At the Intersection of College Access and Spatial Justice: Geographic Accessibility of Broad Access Colleges in Metropolitan Areas

by

KC Deane

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Doctoral Committee:

Professor Michael N. Bastedo, Chair
Professor Stephen L. DesJardins
Professor Joe Grengs
Professor Kevin M. Stange
Dedication

To change over time and space.
Acknowledgements

I wrote this dissertation—at home and on campus—on land that resides in the ancestral and traditional territory of the Anishinaabe, including the Ojibwe, Odawa, and Potawatomi peoples. These nations ceded their land in 1817, some of which was later sold to fund the University of Michigan’s endowment. The dispossession of land from Indigenous peoples to fund the construction of U.S. higher education is foundational evidence of racism’s imprint on the built environment and on the geography of higher education. I acknowledge that, as I grappled abstractly with the intersection of racism and the built environment, I did so on land that sits in this intersection. This truth requires that I hold front of mind that my work benefits from historical patterns of oppression even as Indigenous peoples here and nationwide continue to struggle for self-determination and Indigenous sovereignty.

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Abstract

The built environment creates and sustains unequal access to opportunity across communities—be it to parks, grocery stores or as evidenced in this study, less selective colleges. Studies of accessibility in urban planning document disproportionately lower accessibility to a range of opportunities for low-income communities and communities of color. Accessibility to higher education matters because students who live close to a college are more likely to enroll. Yet, colleges are unequally distributed across the country and within cities.

Drawing on theories of spatial justice, this study examines the relationship between census tract demographics and the geographic accessibility of less selective colleges in two regions—Lansing, Michigan and Chicago, Illinois. In Part I, I employ the non-parametric Kruskal-Wallis (KW) test to examine whether neighborhood demographics differ based on the presence or absence of a less selective college, its sector, and its status as a main versus branch campus. I find that tracts in public college neighborhoods have a lower median income, higher poverty rate, and a higher percentage of Black residents than non-college tracts—suggestive of increased accessibility for these communities. However, retention rates, graduation rates, mean six- and ten-year earnings, and student loan repayment rates are all lowest at the colleges nearest to high poverty tracts or tracts that are predominantly residents of color.

In Part II, I calculate cumulative accessibility to less selective public colleges using an index adapted from the urban planning literature. I then partition tracts into high and low accessibility sub-groups and compare demographics using the KW test. I find that Lansing’s high accessibility tracts have the highest poverty rates and highest percentage of residents of color.
across the region, but low accessibility tracts have the highest percentage of residents with less than an associate degree. In Chicago, low accessibility tracts are lower income, higher poverty, and higher proportion residents of color than high accessibility tracts. When I examine these relationships using a spatial regression, I find a negative relationship between accessibility and potential educational demand in both study areas. In Chicago, the relationship between accessibility and a tract’s poverty rate is also negative. The relationships to accessibility for racial composition measures are less consistent in their magnitude, direction, and statistical significance level.

I conclude that local geographic access is another axis along which spatial processes may accumulate unfavorably for populations historically excluded from or underserved by higher education, though the patterns of accessibility are unlikely to follow a single narrative across metropolitan areas. Patterns will differ depending on the way in which college campus locations intersect with neighborhood level demographic changes over time. Systemic inequalities are embedded in the built environment and likely contribute to lower levels of educational attainment in tracts with low access to less selective colleges in either Lansing or Chicago. Improving student success at less selective colleges, which serve primarily local student populations, requires understanding how geographic accessibility interacts with student outcomes. In pursuit of this goal, I develop a toolkit prototype that institutional practitioners can use to assess how geographic access varies across their student population, and whether this variation is correlated with differences in academic outcomes.
Chapter 1 Introduction

The community in which an individual lives influences their access to resources and opportunities related to education, employment, healthcare, and even leisure. Low-income communities and communities of color—two demographics that often overlap with each other—disproportionately experience spatially induced barriers that limit such access. Individuals in these communities face longer commute times to health care (Brown et al., 2016; Insaf, n.d.), parks (Barbosa et al., 2007), public libraries (Park, 2012), and public K-12 schools (Moreno-Monroy et al., 2018). Long commute times also complicate individuals’ attempts to travel between multiple destinations in a single day, leaving low-wage workers less able to earn more by working multiple jobs (Soja, 2010) and further constraining the schedules of parents who commute between home, work, and daycare (Blumenberg, 2004).

With respect to college enrollment, approximately 60% of students enroll at a college within 20 miles of home (Hillman, 2017), which suggests that an individual’s college access is intricately linked to the set of nearby colleges. Worryingly, given that so many students attend college close to home, over 11.5 million adults live more than a 60-minute drive from the nearest less selective two- or four-year public college (Myers, 2018). For the communities where these individuals live, enrolling in in-person public higher education is synonymous with commuting long distances. Taken together, students’ preferences for colleges close to home and the absence of any college in many communities suggests a geographic tension that limits public higher education opportunities for a large portion of potential college students who cannot or will not relocate to enroll in college (i.e., place-bound students).
The tendency to enroll at a college close to home is more pronounced among students from backgrounds historically underserved by higher education, including low-income students (Card, 1993; Desmond & Turley, 2009; González Canché, 2018b), students of color (Desmond & Turley, 2009), and adult learners (Jepsen & Montgomery, 2009). Familial obligations, work obligations, or price sensitivity are all factors that contribute to a student’s tendency to enroll close to home. This tendency appears to supersede students’ preferences for colleges that align with their academic performance (Dillon & Smith, 2017). These factors manifest as a geographical constraint that leads to place-bound students for whom proximity to home is the primary motivator in college decision-making, often resulting in lower bachelor’s degree attainment than among peers who out-migrate from their community (González Canché, 2018b).

Open access and less selective colleges represent a viable access point to higher education for place-bound students because of the convergence of low selectivity and a commuter-oriented campus setting.\(^1\) Where less selective public institutions diverge from their for-profit and nonprofit counterparts is in their affordability. Average published in-state tuition and fees at these colleges is less than half the amount charged at similar non-public colleges in the four-year sector ($7,900 versus $20,603) and a third of the amount in the non-public two-year sector ($4,400 versus $14,600 in the 2019-20 academic year; author’s analysis of IPEDS data). Higher tuition at for-profit and nonprofit institutions contributes to higher rates of student loan borrowing and increased debt burdens (Cellini & Darolia, 2016), making the choice to enroll in a non-public broad access college when a public option is available a costly one.

Non-public colleges may not satisfy the affordability criterion of an accessible institution of higher education, but they are known competitors to broad access public colleges (Cellini, ...\(^1\) Previous studies define low selectivity as an acceptance rate of 75% or higher (Doyle 2010; Hillman, 2016; Hillman & Weichman, 2016; Rosenboom & Blagg, 2018).
2009; Goodman & Henriques, 2015). For-profit colleges, for example, compete with broad access public colleges by spending an outsized amount of money on recruitment and marketing (Majority Committee Staff Report, 2012) and promising students an educational experience with fewer bureaucratic hurdles than at their local public college (Cottom, 2017; Iloh & Tierney, 2014). In the context of this study, even if non-public colleges are not affordable points of entry for place-bound students, they remain colleges that place-bound students may consider when contemplating whether and where to enroll (Dache et al., 2018). For this reason, understanding a city’s geography of college opportunity requires examining the relative geographic accessibility of less selective colleges by sector.

Geography is embedded in numerous discussions of postsecondary educational access. A suite of studies situated in the economics discipline empirically demonstrate the positive relationship between proximity to a college and propensity to enroll in college (Card, 1993; Do, 2004; Kling, 2001), hypothesizing that this relationship is in part due to students’ needs to limit costs, increase convenience, and integrate schooling with familial obligations (Jepsen & Montgomery 2009; Turley, 2009). Relevant to the study at hand, a subset of scholars view college enrollment through the lens of spatial opportunity, wherein enrollment decisions are foremost the result of geographic proximity to college (Hillman, 2016; Hillman & Weichman, 2016; Jones & Kauffman, 1994; Rosenboom & Blagg, 2018). The accompanying empirical investigations document regional variation in geographic access to public colleges and identify postsecondary education deserts where few, if any, public colleges operate. In many of these education deserts, for-profit colleges are the only option (Beamer & Steinbaum, 2019), providing students with a high-cost alternative to a public education (Ma et al., 2019).
By examining variation in access across regions, inter-regional comparisons make an implicit assumption that geographic access is equivalent for all communities within a region without supporting evidence that this assumption holds. In areas without colleges, this assumption may well hold: Without a college nearby, place-bound students lack geographic access, whether they reside in a city, in the suburbs of a city, or in a rural area. In regions where colleges do operate, the assumption can be tested directly, as several studies have done for single cities (Briscoe & De Oliver, 2006; Dache-Gerbino, 2017; Kenyon, 2011). Each of these studies finds that local variation in access to nearby colleges can result from the location of colleges relative to the populations of individuals most likely to enroll (Briscoe & De Oliver, 2006; Dache-Gerbino, 2017), the available mode(s) of transportation, the reliability of the available transportation, or individual budget constraints (Kenyon, 2011). The Seldin/Haring-Smith Foundation’s Public Transit Map further reinforces that community colleges themselves differ in their relative proximity to transit access: Almost half of all community colleges are more than half a mile from a public transit stop (Crespi et al., 2021). Stated differently, living in a metropolitan area where colleges operate is not a guarantee of postsecondary access.

However, each of these studies focuses only on a single city and/or single college, providing little opportunity to compare local variation in geographic access across cities. Furthermore, the only study to consider public transit is qualitative in nature (Dache, 2022), and therefore cannot quantify the variation in geographic access that results from differential reliance on and access to public transportation. This is the gap I seek to fill. If a community’s geographic access differs within regions and by mode of travel, then evaluations of geographic access to higher education must likewise evaluate access using a measure that acknowledges the variable accessibility borne of car versus public transit reliance.
In support of an intra-metropolitan evaluation of geographic access to postsecondary education that incorporates transit reliance, a 2018 report by the Kresge Foundation identified transportation as the “single biggest pain point” among commuter students (Price & Curtis, 2018). An evaluation of the City University of New York’s (CUNY) Accelerated Study in Associate Programs (ASAP) identified the program’s free public transit passes as contributing to improvements in retention and graduation rates (Scrivener et al., 2015). At 2019 prices, this public transit benefit saved students over $1,500 per year if enrolled year-round ($127 for a 30-day unlimited metrocard; Metropolitan Transit Authority, n.d.), an amount that is equivalent to 29% of annual tuition and fees for a full-time student enrolled at a CUNY community college in the 2019-2020 academic year ($5,120; CUNY, 2019). Elsewhere across the country, colleges invest in transportation solutions to support commuter students for whom transportation is a barrier (Arnett, 2020; Mangan & Schmalz, 2019; Smith, 2016; Wood, 2022). These examples demonstrate that, even for individuals living in metropolitan areas served by broad access public colleges, transportation remains a barrier to accessing postsecondary education.

Purpose of the Study and Research Questions

The purpose of this study is to investigate and document the presence of differential geographic access to less selective colleges within metropolitan areas. Specifically, I seek to understand how college accessibility in metropolitan areas varies across neighborhoods and when adjusted for public transit reliance. To do this, I compare the demographics or relative accessibility of communities for three forms of access: demographics of college neighborhoods, distance to the nearest college by race/ethnicity and poverty rates, and cumulative accessibility to less selective public colleges by neighborhood demographics. This third form of access relies on an accessibility index that I construct. The measure, which I term the postsecondary accessibility
index, has its origins in the transportation planning discipline and allows the researcher to produce an overall measure of geographic access that acknowledges (1) travelers’ tendencies to make fewer trips as travel time increases and (2) the presence of regional variation in the number and quality of opportunities available to residents (Levine et al., 2019).

Gillborn et al.’s (2018) statement of value-add for quantitative studies of race/racism guides this study: My high-level goal is “to chart the wider structures, within which individuals live their everyday experiences, and to highlight the structural barriers and inequalities that differently racialized groups might navigate” (p. 160). In service of this goal, I identify three sub-goals that motivate the research design. First, I want to document differences in the demographic composition of less selective college neighborhoods and document whether average resources and student outcomes are lower at the colleges nearest to populations historically excluded from or underserved by higher education. Second, I seek to diagnose the presence and severity of within-region variation in accessibility to broad access public colleges by comparing accessibility and demographics at the tract level. Through these analyses, I hope to determine for these study areas whether low-income tracts and/or racially diverse tracts have lower postsecondary accessibility than wealthier and/or predominantly White tracts.² Third, I hope to demonstrate how practitioners at broad access public colleges can replicate my analytic approach to diagnose whether students at their institutions experience differential accessibility. Using descriptive analyses and a spatial regression model, I investigate the following questions:

² University of Chicago scholar Eve L. Ewing (2020), whose research includes the study of racism and education, writes, “when we ignore the specificity and significance of Whiteness—the things that it is, the things it does—we contribute to its seeming neutrality and thereby grant it power to maintain its invisibility.” My goal in this study is to contribute in an albeit small way to the identification and dismantling of spatial injustices related to geographic access to higher education. Spatial injustices are not race neutral and identifying the causes of these injustices therefore requires refusing to ignore Whiteness as a powerful influence over the construction of the built environment. For this reason, and in alignment with the emphasis I place on conceptualizing how racialized geographies contribute to variable access to higher education, I opt to capitalize White throughout this study.
1. How do the demographics of less selective colleges’ census tracts, considered separately for public versus non-public less selective colleges, differ from the demographics of census tracts without a less selective college?

2. How do average institutional resources and student outcomes at the colleges that are nearest to low-income neighborhoods and neighborhoods of color compare to the characteristics of less selective colleges that are nearest to high-income and predominantly White neighborhoods in the same metropolitan area?

3. What are the demographics of the census tracts with the highest and lowest levels of accessibility to broad access public colleges?

4. To what extent does postsecondary accessibility to broad access public colleges vary based on a census tract’s race/ethnicity composition, level of poverty, and overall educational attainment?

The first step of the analysis involves developing a census tract-level index of postsecondary accessibility that accounts for differences in mobility when measured by car versus the most direct public transit service. In the second stage of work, I assess each of the research questions. The third and final step involves developing a prototype for a toolkit that institutional practitioners can use to assess, based on their student population, how geographic access varies across their service area and by travel mode. Though the toolkit is targeted at broad access public college practitioners, it can be adapted for use by practitioners at other colleges, K-12 practitioners interested in local college access for their student population, or city officials seeking to coordinate with educational entities to improve college access.
The Policy Case for Broad Access Public Colleges

Although the first two research questions center accessibility to any less selective college, regardless of sector, in the latter two research questions I deliberately shift my focus to less selective public colleges, which I call broad access public colleges. To answer these questions, I create a summative measure of accessibility that accounts for all broad access public colleges in the region. The rationale for this pivot is policy-based: First, broad access public colleges account for an outsized share of total college enrollments. These colleges enroll more than half of all undergraduate students and a disproportionate number of students from populations historically excluded from or underserved by higher education, including low-income students, first-generation students, and Black, Latinx, and Indigenous students (Fryar, 2015; Ginder et al., 2017; Mellow & Heelan, 2008). Relatedly, a substantial portion of the adult population foregoes college enrollment. Twenty-seven percent of all adults aged 25 and older have only a high school diploma or GED (U.S. Census Bureau, 2018) and surveys of adult learners reveal potential costs as central to their consideration of whether to enroll in college (Silliman & Schleifer, 2018). These are some of the individuals for whom geographic access to low-cost higher education may influence their enrollment. Policy that seeks to improve college access benefits from focusing on the relative geographic accessibility of colleges where most students enroll or may enroll.

I shorten “Black or African American” to “Black” to center inclusivity of the large population of African and Caribbean immigrants in the United States (Tamir & Anderson, 2022). I use the term Latinx instead of “Hispanic or Latino” because it has a clearer linkage to its underlying region (Latin America) than the U.S. Census-derived term Hispanic and it is gender neutral unlike the term Latino/a. That said, Latinx remains an umbrella term that homogenizes a population of individuals who self-identify using many, often country-specific, terms (Salinas, 2020). Indigenous references individuals “with pre-existing sovereignty who were living together as a community prior to contact with settler populations” (UCLA Equity, Diversity & Inclusion, 2020), whereas American Indian, Alaska Native, and Native Hawaiian categorizations capture Indigenous peoples living in North America, Alaska, and Hawaii, respectively. These latter categorizations are what the U.S. Census captures in its terminology, and thus I use these specific terms in reference to my analytic sample so that the distinct populations embedded in the general term are not unnamed. When not describing the Census-based categories, I use the general term of Indigenous to ensure that I do not unintentionally classify the referenced population too narrowly.
Second, some community colleges and state universities were founded in part as a means of ensuring geographic access to public colleges for state and local residents. In Illinois, for instance, the Illinois Community College Board was established in 1965 “to create a system of public community colleges that would be within easy reach of every resident” (ICCB, 2020). This notion of ensuring geographic access to college is even present in the 1946 report produced by the Truman Commission, in which members of the commission assessed the purpose and goals of the American higher education system (Katsinas & Hardy, 2012). Evaluating accessibility to broad access public colleges is one way of assessing whether policy goals to bring public colleges within reach of residents are succeeding in their efforts.

Third, state- and local-level free college programs have expanded in recent years, with the majority of programs providing two years of free college to students enrolled at public colleges (Douglas-Gabriel, 2022; Jones et al., 2020). If the goal of free college programs is to increase college enrollment, then their success depends, in part, on whether students have physical access to the institutions where tuition is free. In this way, transportation is a prerequisite for achieving free college policy goals, and thus quantifying the geographic accessibility to these colleges becomes a necessary part of any feasibility analysis.

A justifiable counter to any policy argument in favor of broad access public colleges is outcomes-based. Enrollment is no guarantee that a student will complete, and retention and graduation rates at less selective public colleges are generally low. Fall-to-fall retention rates of first-time full-time graduates range from 62% for community colleges to 71% at public universities, compared to an average of 76% across all institutions (U.S. ED NCES, 2020c;

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4 An analysis of state and local free college programs in the Midwest found that only 15 of the 56 total programs were eligible for use at private institutions (Kelchen, 2017).
author’s calculations of IPEDS, 2019). With respect to completion, 41% of community college students earn any credential within six years of entry (Shapiro, Ryu, Huie, Liu & Zheng, 2019), and an even smaller percentage—17%—earn a baccalaureate degree within six years of entry (Shapiro et al., 2017). At less selective public universities, the average six-year completion rate is 42%. When disaggregated, completion rates at these colleges are lower among populations historically excluded from higher education. At community colleges, 29% of Black students and 37% of Latinx students earn any degree in six years, as compared to 49% of White students (Shapiro et al., 2019). At the average less selective four-year university, 30% of Black students and 37% of Latinx students graduate within six years, as compared to 44% of White students.

I offer two responses to this critique. First, there is similar variability in student outcomes at for-profit and nonprofit colleges, but with the additional burden of increased cost. As I note above, tuition at less selective private colleges exceeds tuition at less selective public colleges. Furthermore, more students at private colleges take out federal student loans (49% and 61% at nonprofit and for-profit less selective colleges, as compared to 22% at less selective public colleges). Even though three-year cohort default rates are comparable between less selective public and for-profit colleges (13% and 12%, versus 7% at nonprofit less selective colleges), the higher borrowing rates at for-profit colleges mean a higher percentage of students at these colleges experience default. Put differently, regardless of whether a college operates as a public or private institution, lower outcomes at less selective colleges complicate any arguments for expanding access at these same institutions (Dache et al., 2018). However, rather than compound the problem of low outcomes with the additional problem of unaffordability, I opt to emphasize institutions that, at the very least, remain more affordable than their private peers.

5 Except where explicitly cited, all figures in the remainder of this chapter derive from the author’s analyses of IPEDS data.
Second, improving geographic access may well contribute to improved retention and completion rates, since transportation accessibility is a meaningful barrier to college enrollment and success for many students (Kenyon, 2011; Price & Curtis, 2018). In a survey of adult students with some college but no degree, 40% of respondents indicated that they view the cost of transportation as a barrier to returning (Silliman & Schleifer, 2018; see also Hagelskamp et al., 2013 for an earlier survey of adults without a college degree). An evaluation of a free transit pass program at a Los Angeles community college found a positive relationship between receipt of the transit pass and credit accumulation, retention, and degree receipt (Clay & Valentine, 2021).

In the K-12 literature, shorter commutes are associated with decreased absences (Stein & Grigg, 2019) and fewer instances of chronic absenteeism (Cordes et al., 2021). Transportation barriers, then, are inseparable from broader efforts to improve outcomes at less selective colleges.

In short, evaluating the accessibility of broad access public colleges is in service of existing policy goals that center these same institutions. An assessment of transportation accessibility to broad access public colleges can catalog the proportion of neighborhoods that experience low transportation access, and whether this access is systematically lower in neighborhoods with populations historically excluded from or underserved by higher education. If geographic access is a function of neighborhood demographics, then the next step is identifying how institutional practitioners, in collaboration with state and local government, can leverage transportation-based solutions to improve access, persistence, and completion at these colleges.

**Significance of the Study**

Addressing the above research questions will contribute to ongoing academic conversations about the geography of college opportunity. The study’s research design, including
its reliance on publicly available data, serves as a blueprint that future scholars can use to evaluate the (un)equal geographic access of less selective colleges in and across urban centers nationwide. Embedded in the blueprint is both a conceptually grounded measure of accessibility and a suite of methodological tools that accommodate the spatial nature of census data. The accessibility index I construct brings into higher education an empirical approach that transportation planning scholars have employed for nearly a century, and the use of spatial statistics and a spatial regression model enables a researcher to quantify the relationship between tract-level demographics and local accessibility without unintentionally attributing to covariates what is instead the result of spatial dependence. As González Canché (2018a) notes, spatial models “remain largely missing within the higher education tradition in general” (p. 171) despite frequent reliance on spatial data. Without addressing spatial autocorrelation according to the underlying source of the spatial dependence, the researcher risks presenting regression results that are biased in their coefficients, standard errors, or both. This bias could distort the perceived magnitude of any documented relationship, overstate the statistical significance, or both.

Second, by addressing the four research questions, I directly engage with two important findings in the geography of opportunity literature. First, Hillman and Weichman (2016) specify what constitutes a postsecondary education desert: any region with no colleges, or with only a single two-year public college. The unstated hypothesis here is that anyone who lives in an area with more than one community college has access to public higher education. By examining the research questions in Lansing—an area that just barely escapes categorization as a desert—the study can evaluate this hypothesis for a single area and, in so doing, contribute to the literature’s identification of the level at which geographic accessibility is most accurately assessed.
In this same vein, Dache-Gerbino’s (2018) case study of Rochester culminates in a typology of local college access: Neighborhoods are either education deserts or oases. In her evaluation, the demographics of college deserts overlap with the demographics of populations historically excluded from or underserved by higher education, including low income, Black, and Latinx students. The story unfolds similarly at the campus level in Briscoe and De Oliver’s (2006) case study of University of Texas – San Antonio (UTSA): Lower-income residents of color are closer to the branch campus, where the authors find there are fewer courses and degree offerings than the main campus. In both studies, the urban core is synonymous with lower income and more racially diverse demographics, and these neighborhoods experience lower levels of college access than the higher income and Whiter suburban periphery. By addressing the above research questions against the backdrop of Dache-Gerbino’s (2018) typology and Briscoe and De Oliver’s (2006) related finding for UTSA campuses, I can assess in two metropolitan areas whether urban/suburban remains synonymous with college desert/college oasis—either when examining the total absence of colleges or when evaluating main versus branch campus locations—and whether college deserts’ demographics are consistently lower income and more racially diverse.

Lastly, I supplement the empirical assessments of accessibility to less selective colleges with a toolkit prototype that institutional practitioners can adapt to their unique contexts. In so doing, I provide a path forward for practitioners and policymakers seeking to implement solutions that temper transportation’s potentially negative effects on student outcomes. Specifically, I offer a way for college leaders to quantify the degree to which transportation is a barrier for the specific student population their institution serves or could serve in the absence of such barriers. This prototype reflects my conscious belief that education research is most
valuable when policymakers and practitioners can discern how to carry the lessons learned into ongoing efforts to better serve students. The toolkit, then, is a deliberate attempt to transform an academic document into a concrete product that directly supports institutional leaders seeking to remove non-academic barriers to student success.

Transportation is just one component that complicates college enrollment for commuter students, but it is an important one. Reliable transportation enables students to integrate their college commute into their daily lives. Its role is even more pronounced for students who balance school enrollment with employment, families, or other time constraints that make the commute more costly—students who are disproportionately low income, Black, and Latinx. That advocates and researchers in higher education are beginning to emphasize the role of non-academic success strategies in improving retention and completion rates is evidence of the study’s relevance to burgeoning academic and policy-focused conversations.
Chapter 2 Literature Review and Conceptual Framework

This chapter begins with a review of the relevant higher education literature, separated into two broad categories: individual-level studies of the relationship between college proximity and student enrollment, and exploratory evaluations of variation in community-level access to college opportunity. Throughout, I emphasize relevant studies’ conceptual and methodological groundings and note key limitations. Next, I consider how space, and transit infrastructure specifically, influences community-level college access. Drawing from three frameworks—Soja’s (2009, 2010) framework of spatial justice, the still-developing notion of transportation justice (Adli et al., 2019; Pereira et al., 2017), and spatial opportunity structures (Galster & Sharkey, 2017)—I construct a conceptual framework that seeks to explain why postsecondary accessibility accrues unevenly within metropolitan areas, and the consequences thereof.

Review of Higher Education Studies of Geography

When choosing a college, geographic proximity to home is an unavoidable consideration for many students in the United States, though its relevance in the choice process varies depending on the student’s circumstances (Turley, 2009; Hillman, 2016). Among traditionally aged students, for example, college enrollment has become increasingly geographically integrated over the preceding decades, with academically prepared students opting for colleges that are further from home than the colleges chosen by their less academically prepared peers (Hoxby, 1997, 2009). However, a large portion of traditionally aged students—as well as the majority of adult learners—are place-bound for financial, familial, or other reasons (Hillman, 2017; Jepsen & Montgomery, 2009; Jones & Kauffman, 1994).
Existing evidence confirms that college enrollment decisions are related to geographic proximity (Turley, 2009; Klasik et al., 2018), with a number of regions in the country lacking broad access public colleges altogether (Hillman & Weichman, 2016). The conceptual explanations for this relationship are many-fold. Individual-level examinations of the role of distance rely on concepts such as convenience effects, spillover effects, and substitution effects, each of which is explored below (Card, 1993; Do, 2004; Frenette, 2006, 2009). More recently scholars have adapted conceptual frameworks from geography and urban planning to explore the relationship between geographic proximity and access to postsecondary education across populations and communities (Briscoe & De Oliver, 2006; Dache-Gerbino, 2017, 2018; Hillman, 2016). In this section, I elaborate on the conceptual approaches wielded by these two higher education literatures and synthesize the empirical findings as they relate to the question of intra-metropolitan variation in geographic access.

**Individual-Level Geographic Preferences Literature**

There are several potential mechanisms through which living near a college might influence an individual’s college enrollment behavior. First, the presence of a college may create spillover effects for nearby residents who, after living near the college, come to value the role of education and therefore become more likely to enroll in college as compared to individuals who do not live near a college (Do, 2004; Griffith & Rothstein, 2009; Turley, 2009). If college proximity influences enrollment through spillover effects, then living near a college will increase an individual’s probability of college enrollment anywhere, not solely in the region where an individual lives prior to college enrollment. Because the concept of spillover effects makes no distinction between enrollment close to home versus far from home, this mechanism misses the potential ways in which geographic proximity influences the location of enrollment.
Depending on the extent to which individuals are price sensitive, a second mechanism, the substitution effect, may explain the interaction between proximity to a college and enrollment behavior. Students with higher price sensitivity than their peers may substitute attendance at a non-local college for enrollment at a lower-cost local college when available (Do, 2004; Frenette, 2009). Often, this substitution effect will occur even though further-away colleges are considered a better academic fit than the local college (Klasik et al., 2018). Taken to its extreme, price-sensitive students in areas without a local college will substitute college enrollment for non-enrollment, the result of an absence of postsecondary opportunity and suggestive of a third, embedded, mechanism: the convenience effect (Rouse, 1995).⁶

With the convenience effect, living closer to a college may induce college enrollment for students who would not otherwise enroll (Card, 1993; Frenette, 2009; 2006; Griffith & Rothstein, 2009; Klasik et al., 2018; Kling, 2001; Rouse, 1995; Turley, 2009) because the close proximity removes the need to incur relocation and/or on-campus housing costs and lowers the degree to which college enrollment disrupts daily life (e.g., transportation costs). Both the substitution and convenience effects would manifest as enrollment gains at local colleges, whereas spillover effects could occur either locally or not. Both substitution and convenience effects are hypothesized to strongly influence enrollment behavior among low-income students for whom the cost of attendance represents a larger portion of household income (Card, 1993; Griffith & Rothstein, 2009). The convenience effect may also disproportionately influence adult learners for whom other life commitments, such as employment and childcare, prevent relocation for the sake of college enrollment (Jepsen & Montgomery, 2009; González Canché, 2018b).

⁶ This discussion considers only two factors relevant to the college choice process, price and location, because these are limiting factors that may disproportionately influence the schools in a student’s choice set. As I discuss in brief in Chapter 6, research on the college choice process demonstrates that other factors also influence students’ choices.
Empirically disentangling these three mechanisms requires detailed data on a student’s primary residence, the list of colleges to which they consider applying and ultimately apply, their preferences about whether to relocate for college, and the college where they ultimately enroll. In the absence of detailed data, some studies document overall changes in the probability of enrollment at any college without investigation of the specific mechanisms at play. Card’s (1993) and Kling’s (2001) instrumental variable investigations of the relationship between education and earnings each use as their first stage the co-location in a county with an accredited four-year college. Both studies found that co-location positively affected an individual’s probability of enrollment, especially for high school students from low-income households or whose parents have fewer years of education. However, neither author observed whether enrollment occurred at a local college and therefore neither study could speak to the specific mechanism driving the relationship between college proximity and subsequent enrollment. This is in part because, in both cases, the authors’ primary interest was to document the effect of college-going on earnings, not students’ collegiate preferences. Furthermore, though the authors included covariates for race/ethnicity in their regression analyses, in neither study did they discuss, either conceptually or empirically, the differential effects of college proximity on enrollment by race/ethnicity.

The next two studies attempted to identify which mechanisms underlie the relationship between geography and enrollment. Griffith and Rothstein’s (2009) assessment of application behavior to selective colleges found that approximately 40% of students who lived within 50 miles of a selective institution applied to the nearest selective institution. They also found that, regardless of income, students who lived closer to a selective college were more likely to apply to a selective college than students who lived further from a selective college. The authors interpret these findings as evidence of spillover effects, wherein living closer to a selective
college encourages enrollment at any selective college, regardless of distance. Do’s (2004) assessment of the relationship between proximity and quality of the college where a student enrolled found evidence of both the spillover and substitution effects among low-income students. Specifically, attending high school in a county with a “high-quality” public college, as defined by the highest quality tier in a ranking of undergraduate programs (the Gourman Report), “spilled over” into the quality of the college a student attended. However, living near a low-tier public college likewise increased a low-income student’s probability of attending a low-tier public college, suggestive of a substitution effect wherein low-income students opt for the more affordable local option. Save for its inclusion as a control variable, neither Griffith and Rothstein (2009) nor Do (2004) considered potential differences in the role of proximity by race/ethnicity.

The preceding studies emphasize the relationship between four-year colleges and the probability of enrollment, however proximity to a community college also affects the probability of college enrollment. Kane and Rouse (1993) and Rouse (1995) incorporate proximity to a two-year college into their investigation of the effects of college enrollment on subsequent outcomes. Findings from Kane and Rouse’s (1993) study lend additional support to the presence of spillover effects: The authors found a positive relationship between distance to the nearest community college and enrollment at a four-year university. However, Rouse (1995) found that living closer to a community college lowered the probability of first enrolling at a four-year college, suggesting that students substitute enrollment at a four-year college for enrollment at the nearer community college. Here, as elsewhere, the authors’ evaluations considered race/ethnicity only insofar as it was included as a control variable.

In a more recent investigation using administrative data from public high schools in Georgia, Alm and Winters (2009) reaffirm Rouse’s (1995) finding that students substitute four-
year college enrollment for community college enrollment when the community college is closer to home. But the inverse is also true: Being further from the nearest community college negatively affected whether a student attended a community college and positively affected whether a student attended a four-year university. This effect remained even among high school graduates with strong academic records, though the authors did not consider whether it remained or varied when disaggregated by race/ethnicity. Klasik et al. (2018) used a nationally representative dataset to conduct a similar investigation of the relationship between proximity and the probability of college enrollment among high school graduates. They found that students who did not live near an institution that was an academic match enrolled at a local college instead of a non-local college that better matched their academic qualifications, again evidence of the substitution effect. The authors further evaluated by race/ethnicity the effects of living in an area without an academic match nearby, finding that Black and White students in these regions behaved similarly whereas Latinx students in these same areas were less likely to apply to or enroll in an academic match institution than their White peers. Though González Canché (2018b) does not directly consider application behavior or academic match, he found that students who attended one of the nearest five bachelor’s degree institutions tended to enroll at institutions with lower average standardized test scores as compared to peers who enrolled further from home. These students, who were disproportionately lower-SES, graduated at lower rates and earned lower salaries than their peers who enrolled at a college further from home.

The preceding studies confirm that, at least for some students, living in close proximity to a college influences enrollment through both the spillover effect and the substitution effect. Living in close proximity also increases enrollment through the convenience effect, wherein students who would not have enrolled in college choose to enroll because of the convenient
proximity of a nearby college. Turley (2009) investigated both application and enrollment behavior, finding that, among high school graduates, closer proximity to more colleges was associated with higher odds that the average student would apply to and enroll in a nearby college as compared to the odds of enrolling in any college. She interprets these results as evidence that the positive relationship between proximity to a college and likelihood of enrollment is driven more by the convenience effect than the spillover effect. She further notes that some of the observed differences in enrollment by race/ethnicity could be the result of differences in geographic access to opportunity.

The convenience effect likely matters most for place-bound and more price-sensitive students for whom relocation is least feasible, in particular adult learners. The preceding studies, which universally observe college enrollment for high school graduates, cannot speak to the mechanisms through which geography influences enrollment for these students. Addressing this limitation, Jepsen and Montgomery (2009) investigated the relationship between proximity and enrollment for place-bound adults residing in the Baltimore, Maryland area. They found that a three-mile increase in the Euclidian distance to the nearest college was associated with a between 9% and 14% decrease in the probability of enrollment among adult learners. This inverse relationship between college proximity and enrollment, which is more pronounced for individuals living in predominantly Latinx census tracts, is present even among students who lived in a region with multiple local college options. In other words, even though there are numerous broad access colleges in the Baltimore area, within-region distance to opportunity still influenced whether students took advantage of enrollment. Because the authors hypothesize that the individuals in their study face financial and personal constraints that limit relocation, this
positive association between proximity and enrollment is hypothesized to be driven by the convenience effect.

The conceptualization of geography as an important driver of college-going behavior contributes to the investigation of spatial opportunity in metropolitan areas in at least two ways. First, because place-bound students’ decisions to enroll in college are in part due to geographic convenience, other things equal, living in a metropolitan area with limited geographic access to broad access colleges will lead to a lower likelihood of enrollment. The greater the number of place-bound individuals in a community, the larger the effect of geographic access on postsecondary opportunity for the community at large. Second, even among price-sensitive individuals who might consider enrollment at a non-local college, a lower-cost option closer to home may compel these individuals to enroll nearby. The aggregation of these individual-level effects at the community level suggests a need to situate an individual’s geographic access within their larger community, to which I turn next.

Spatial Opportunity Literature

Whereas the preceding discussion treats the individual as the unit of analysis, it is also possible to model the relationship between distance and college enrollment at the community level. Hillman (2016) refers to this approach as the geography of college opportunity, wherein the built environment (e.g., humanmade structures that occupy the natural environment) is a barrier to college access (and therefore enrollment) for entire communities (see also Tate, 2008). In this approach, population-level inequality in college access results from the absence of financially and academically suitable colleges in a geographic region. College choice decisions for individuals in these so-called education deserts are constrained foremost by geographic
proximity—students who want to enroll in in-person college classes cannot take advantage of an opportunity that does not exist nearby.

The spatial mismatch hypothesis (SMH) serves as the conceptual basis for many of the spatial opportunity studies explored herein (Briscoe & De Oliver, 2006; Dache-Gerbino, 2017, 2018; Kenyon, 2011). First articulated by Kain (1968), the spatial mismatch hypothesis (SMH) theorizes that high rates of community-level unemployment result from a mismatch between where low-wage workers reside and the jobs for which their skills are suited. Stated simply, geographic access is a barrier to employment opportunity because jobs and workers are not physically co-located, and the travel costs necessary to overcome this spatial mismatch are prohibitive for low-wage workers (Kain, 1992). Applied to postsecondary education, SMH motivates assessments of whether colleges are located in areas that are geographically accessible to all populations, or if these locations favor populations with particular characteristics (Briscoe & De Oliver, 2006; Dache-Gerbino, 2017, 2018).

Whether considered at the state level or nationwide, empirical evidence supports the hypothesis that colleges and universities are unequally distributed across population centers. In the border region of Texas, Jones and Kauffman (1994) found that students were required to travel five times as far to the closest comprehensive university than their peers elsewhere in Texas. This increased distance was in turn associated with lower attendance at these universities, with the negative relationship strongest for Latinx students. The authors surmised that this stronger negative relationship for Latinx students was because they were, on average, lower income, more limited in their transportation options, and more likely than their peers to take on family responsibilities that discouraged relocation. Nationwide, Black and Latinx populations are more likely than White and Asian populations to live in commuting zones with fewer two- and
four-year broad access public colleges, where commuting zones are defined by the U.S. Department of Agriculture as geographic regions with overlapping labor markets (Hillman, 2016). This disparity in access by race/ethnicity merits attention since Hillman (2016) also found that educational attainment was lower in commuting zones with fewer four-year universities. Though the causality is ambiguous—either movement to college neighborhoods is motivated by the presence of a college or people who live in these places are more likely to enroll in college—the consequences to place-bound students in education deserts are clear: Without a college nearby, place-bound students have limited postsecondary access.

The expansion of online education mitigates the geographic isolation of education deserts. Rosenboom and Blagg (2018) found that, whereas approximately 17% of all adults lived in a part of the country that was a physical education desert, only an estimated 1.3% of adults lived in an area that was both a physical education desert and an online education desert (defined using the Federal Communication Commission’s designation for what counts as broadband internet access). Even so, uneven access to broadband internet in particular parts of the country meant that the populations living in physical and online education deserts were disproportionately Alaskan Native and American Indian (Rosenboom & Blagg, 2018).

Furthermore, a causal evaluation of online versus in-person course performance found that students who enrolled in the online version of a course earned a grade that was 0.44 points lower on the traditional four-point grading scale than the grade of their peers who enrolled in the in-person version of the course (Bettinger et al., 2015). Earlier descriptive studies support this

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7 I use the terminology Asian instead of Asian American for two data-based reasons: First, in my analyses, I do not differentiate between people of Asian descent from Asia versus the United States. Therefore, it would be inappropriate to default to classifying all individuals in the Asian racial category as Asian Americans. Second, I do not know whether referenced studies differentiate Asian population demographics by country of origin and do not want to misattribute population demographics to only Asian Americans when the underlying data include individuals of Asian descent from outside the United States. That said, both terms are imprecise and collapse into a single category the many Asian nations of origin. My reliance on the umbrella term is a data constraint, where small sample sizes would limit the ability to compare results across the Asian population by nation of origin.
causal effect: On average, students enrolled in online courses earned lower grades and persisted at lower rates than students in face-to-face classes (Johnson & Mejia, 2014; Xu & Jaggars, 2013, 2014), suggesting that internet access and physical access to postsecondary education are not equivalent opportunities.

Dache-Gerbino’s (2017; 2018) investigations of variation in geographic proximity in a single metropolitan area draw on SMH’s basic premise that there is a mismatch between the locations of opportunities and the populations that would benefit from those opportunities. She extends her conceptual frameworks beyond SMH to single out power dynamics as a critical mechanism that creates this local variation in geographic access to higher education. In her postcolonial geographic epistemological framework, Dache-Gerbino (2017) draws on studies of critical geography to theorize that, over time, individuals use positions of power to create and reinforce the spatial mismatch that Kain (1968) identifies with respect to employment and Hillman (2016), Jones and Kauffman (1994), and others observe in higher education access. She continues that the result of this historical use of power—concentrated among White, wealthy individuals—is the placement of public goods, such as colleges, in predominantly White, high-income communities instead of low-income communities and communities of color. In her critical geographic college access framework, Dache-Gerbino (2018) further notes that, over time, these locational decisions led to the unequal concentration of postsecondary education opportunities in communities with better-resourced populations, leaving populations historically excluded from higher education with more limited access (see also Dache, 2022).

Her accompanying empirical evidence, wherein she presented a series of maps overlaid with institutional enrollment demographics, demonstrated that colleges in the Rochester, New York metropolitan area were not demographically representative of the neighborhoods in which
they were located (Dache-Gerbino, 2017). This mismatch between colleges’ populations and the
demographic characteristics of surrounding neighborhoods makes clear that, even when there
exist postsecondary opportunities within the metropolitan area, residents of the city may not be
able to access these opportunities. Furthermore, the physical distribution of opportunity within
these cities favors some populations more than others. The urban core of Rochester—where
Black and Latinx populations were disproportionately located—was itself an education desert,
with few college options located within a several-mile radius (Dache-Gerbino, 2018). This
contrasts with the suburban periphery, which she described as an education oasis because of the
large number of colleges and universities located less than a mile away. Though these empirical
analyses are limited in their focus on the distance between colleges and neighborhoods—not
accounting for travel time or transportation mode—Dache-Gerbino (2017, 2018) found that,
even within the Rochester region, not all populations benefited from similar geographic access.
Indeed, the burden of limited geographic access falls disproportionately on the populations
historically excluded from or underserved by American higher education.

The geography of opportunity framework as well as Dache-Gerbino’s (2017; 2018)
critical frameworks consider broadly how living in proximity to a college influences a
community’s geographic access to postsecondary education. Conceptual discussions of SMH’s
underlying mechanisms (e.g., Coulson et al., 2001) note that the relationship between geography
and opportunity exists in part because of individual-level costs associated with commuting long
distances, a point which receives less attention in the preceding higher education studies.
Commuter students, for example, incur daily the costs of geographic access, suggestive of the
need to identify in the conceptual framework the ways in which transportation itself, not just
distance, serves as a barrier to access.
Toward that end, Briscoe and De Oliver (2006) articulated and empirically evaluated how variation in transportation mobility created disparities in geographic access to the University of Texas – San Antonio (UTSA) campuses. The authors relied on SMH to make the case that the costs associated with traveling between home and campus create a geographic barrier that affects individuals differentially based on the amount of time required to cover this distance and the individual’s ability to afford reliable transportation. The authors modeled mobility using driving time, finding that students from predominantly non-White census tracts traveled further to UTSA’s main campus in the suburban fringe than their peers from predominantly White census tracts (16.2 miles versus 9.6 miles, respectively). Although the downtown campus was a shorter commute for students from non-White census tracts, it offered fewer courses, majors, and amenities than the suburban campus, leaving these students to either travel further and access more opportunity or travel less far but constrain their choices.

Kenyon’s (2011) qualitative study on the ways in which transportation serves as a barrier to commuter students’ continued enrollment further contextualizes the mobility variation that Briscoe and De Oliver (2006) documented. According to the mobility-related social exclusion framework as applied to higher education, individuals with low transit mobility—in this case, the ability to travel from home to school—are marginalized by colleges that typically cater to residential and more mobile students (Kenyon, 2011). Three factors determine the severity of an individual’s mobility-related social exclusion: person-specific barriers that result from long-standing inequalities in access across different populations (e.g., access to a car is less common among low-income households), the transportation system’s inability to meet certain groups’ needs; and spatial factors relating to the physical distance between home and place (Kenyon, 2011). The greater the distance between home and college, the more mobile an individual will
need to be to overcome that distance. When an individual has more limited mobility, they will experience education- and social-related consequences that result from this social exclusion.

Findings from Kenyon’s (2011) focus groups suggested that transportation barriers result in late arrivals to classes or office hours; an inability to stay on campus late because of limited transit service; the need to commit multiple hours each day to commuting; and the decision to change major or course choices based on what is offered on which campus and when. Mobility-related social exclusion, he noted, disproportionately disadvantaged low-income individuals. This was because low-income students tended to live furthest from colleges, had the lowest rates of car-ownership, and were least well-served by public transportation systems (Kenyon, 2011).

The experiential differences in college access among transit-reliant communities were further outlined in Dache-Gerbino et al.’s (2018) and Dache’s (2022) qualitative evaluations of college access for residents of a predominantly Latinx neighborhood in the Rochester region. Dache-Gerbino et al. (2018) find that, for sixteen female residents of the barrio, the nearest college was most frequently a for-profit college; these institutions likewise advertised at the local high schools. The second-closest institutions, also within walking distance, were community colleges. The authors conclude that this close proximity of particular colleges likely influenced sector of enrollment for the Latina students. Dache (2022) evaluates the experience of riding the bus from the same neighborhood to nearby colleges, finding that that the colleges with the shortest bus commutes were disproportionately community colleges (as opposed to the more-selective colleges, which were in the outer portion of the study area), but these lower travel times were coupled with less clean buses/bus stops, more criminalizing advertising (e.g., gun buy-back programs), and fewer college-oriented advertisements. She concludes that she “[sees] the public transit system as part of racialized college access geographies” (Dache, 2022, p. 25).
The preceding studies point to two specific mechanisms through which an individual’s geographic location influences whether they can access postsecondary educational opportunities. First, place-bound individuals may live in parts of the country (Hillman & Weichman, 2016; Jones & Kauffman, 1994; Klasik et al., 2018) or in a city (Dache-Gerbino, 2017, 2018) without any colleges located nearby. Second, even when individuals live in a city with a nearby college, the time and cost required to commute from home to school may be prohibitively high (Briscoe & De Oliver, 2006; Dache, 2022), leaving individuals with the difficult decision to commit to commuting, choose a college with fewer resources (Briscoe & De Oliver, 2006; Kenyon, 2011; Dache-Gerbino et al., 2018), or drop out altogether (Kenyon, 2011). The next section surfaces, for the collection of higher education studies reviewed here, several conceptual and methodological limitations relevant to the study at hand.

**Methodological Limitations of Higher Education Geography Studies**

There are two primary methodological limitations of existing studies of geographic access to higher education. First, these studies tend to operationalize geographic accessibility in a partial manner. Second, even though spatially proximate regions (such as census tracts) likely share a relationship with each other—which in turn leads to observations that are not statistically independent from each other—few studies in this literature directly account for the potential presence of spatial autocorrelation in the regression analyses.

First, geographic accessibility is often operationalized in ways that either forego consideration of variation in travel distance or time (e.g., contour measures), account for differences in distance but leave travel time unconsidered (e.g., Euclidean distance or driving distance), or disregard the probable mode of transportation (e.g., driving distance or time). Studies that evaluate cross-region variation in geographic access to higher education typically
rely on contour measures of proximity, where proximity is defined as the presence of a two- and/or four-year college in the same geographic region—such as county (Card, 1993; Do, 2004; Kling, 2001), commuting zone (Hillman, 2016; Klasik et al., 2018), or a set radius based on student commuting patterns (Turley, 2009). Such an operationalization of geographic accessibility is not granular enough to observe within-region variation in geographic access. A suite of studies in both higher education (Dache-Gerbino, 2018; Briscoe & De Oliver, 2006) and K-12 (Corcoran, 2018; Talen, 2001) demonstrate that within-region variation exists and disproportionately affects racially and socioeconomically marginalized populations, suggestive of the need to evaluate geographic accessibility within and across study areas.

However, existing within-region evaluations of accessibility in higher education are also constrained by their operationalization of geographic accessibility. Operationalizing geographic access using Euclidean distance (Alm & Winters, 2009; Dache-Gerbino, 2017, 2018; Frenette, 2006, 2009; Jepsen & Montgomery, 2009; Kane & Rouse, 1993; Rouse, 1995) underestimates network distance and ignores required commute time. Operationalizing geographic access as driving distance (Dache-Gerbino, 2017; 2018) is more accurate than Euclidean distance, but still ignores the time costs associated with commuting and favors driving as the primary mode of transportation. The use of driving time provides a clearer depiction of how mobility may vary across a geographic region (Briscoe & De Oliver, 2006). However, driving-based mobility measures overestimate mobility for public transit reliant households, which are disproportionately low-income, Black, and Latinx (Anderson, 2016). Driving-based measures also assume that the relationship between travel time to an opportunity and likelihood of traveling to that opportunity is linear when, as urban planning scholars have found, the likelihood of travel decays exponentially as distance and/or time increase (Grengs et al., 2010). In this case,
a comprehensive evaluation of within-region variation in accessibility must account for differences in mobility by mode of transportation in response to the existing variation in public transit reliance across regions. Several K-12 studies center public transit reliance (Blagg et al., 2018b; Cordes et al., 2021; Corcoran, 2018; Stein & Griggs, 2019; Stein et al., 2020) and, in doing so, document meaningful differences in geographic access by mode of transportation.

The second empirical limitation relates to the consideration of spatial autocorrelation as a source of statistical bias that can affect the coefficients, standard errors, or both. In brief, any given geographic unit shares a spatial relationship with its neighbors, making neighboring units spatially dependent on each other (Darmofal, 2015). This theoretical concept of spatial dependence manifests empirically as spatial autocorrelation, in which observations’ values are no longer independent of each other (Chi & Zhu, 2020). A researcher who does not test for the potential influence of spatial autocorrelation on a relationship of interest—for instance, the relationship between accessibility and neighborhood demographics—risks misestimating the strength of the relationship, either in magnitude or statistical significance (see Chapter 3, p. 100).

The evaluation of within-region accessibility—where accessibility is compared across census tracts within a single geographic area—magnifies the potential severity of spatial autocorrelation’s statistical influence. In exploratory evaluations, the researcher should, at a minimum, document the presence of spatially autocorrelated community demographics prior to comparing census tracts’ accessibility a-spatially; any regression analysis would benefit from more deliberate assessment of how best to accommodate the documented spatial autocorrelation.

The quantitative higher education studies reviewed above make no mention of spatial autocorrelation even as they rely on regression analyses to quantify the size of the statistical

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8 This study is one in a series of think tank reports that measure neighborhood-level mobility to public K-12 schools in a metropolitan area. I highlight these reports, as they employ a-spatial regression analyses. For non-regression-based analyses, see also Blagg et al. (2018a); Stein et al. (2017); and Lincove and Valant (2018).
relationship between covariates in geographic units that are likely spatially related to each other.\(^9\) A review of related K-12 studies finds one instance where the author diagnoses the presence of spatial autocorrelation and incorporates it into the empirical decision-making (Talen, 2001).\(^{10}\) The consequence of unaddressed spatial autocorrelation is bias in the standard errors, coefficients, or both, which renders the findings difficult to interpret and contextualize.

**Conceptual Limitations of Higher Education Geography Studies**

The spatial opportunity literature in higher education frequently grounds its conceptual framing in the Spatial Mismatch Hypothesis (SMH; Briscoe & De Oliver, 2006; Dache-Gerbino, 2018; Klasik et al., 2018). As the preceding literature review notes, SMH was initially put forward as an explanation of high unemployment among low-skilled Black workers living in metropolitan areas (Kain, 1968). Though originally vague in its identification of mechanisms (Blumenberg & Manville, 2004), scholars have since contended that the spatial disconnect between Black workers’ place of residence (historically city centers) and the locations of employers who demand low-skilled labor (historically the suburbs) is a geographic barrier that creates non-zero search and commuting costs (Arnott, 1997; Gobillon, Selod, & Zenou, 2007; Kain, 1992). Search costs are steep because it is difficult to obtain information about job availability, there are fewer opportunities to take advantage of networking, and the time and travel costs associated with the search are higher than for similar jobs located near the city center (Arnott, 1997; Gobillon et al., 2007). Once employed, search costs become daily commuting costs, in the form of both time and money. If these costs are prohibitively high for budget-constrained households, workers may either limit their search to local, potentially more limited,

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\(^9\) Although not included in the detailed literature review here, González Canché (2019a) employs a spatial autoregressive (SAR) model in his evaluation of out-of-state student enrollment.

\(^{10}\) See Cobb (2020) for a comprehensive review of the K-12 literature’s evaluation of the linkage between geography and K-12 educational opportunity in the United States.
job opportunities or refuse job opportunities in the suburban fringe and, in doing so, opt for unemployment as the preferable alternative (Arnott, 1997; Coulson et al., 2001; Gobillon et al., 2007). Put differently, low-skilled workers weigh whether potential earnings sufficiently offset what they must spend to seek and then accept employment.

There are three central limitations to SMH and its applications to higher education. First, applications of SMH to higher education speak broadly about the role of geography in accessing opportunity but do little to adapt SMH’s mechanisms—specifically, commuting costs—to the higher education context. Briscoe and De Oliver (2006) treat as their theoretical framing the basic fact that “the residential location of low-income, urban (and often minority) households inhibits their access to opportunities and services progressively located in the suburban fringe” (p. 205). Dache-Gerbino (2018) provides similarly high-level detail on SMH, noting that she is interested in the locational mismatch between colleges and Black and Latinx student populations. Whereas Briscoe and De Oliver (2006) and Dache-Gerbino (2018) each acknowledge the likely locations of people versus opportunities (urban core versus suburban fringe) and the potential for differential access across populations, Hillman (2016) notes only that not all regions possess colleges, a general point that Klasik et al. (2018) reiterate, though neither study explicitly references SMH.

The exclusion of commuting costs as an individual-level mechanism is not due to a lack of relevance.¹¹ Non-residential students incur daily commuting costs as they travel between home and school to attend classes, participate in extra-curriculars, and access other campus services such as tutoring or office hours (Kenyon, 2011). In fact, commuting costs may serve as

¹¹ Individuals deciding whether and where to enroll in college, even those who remain local, likewise incur search costs associated with gathering information about program offerings and degree requirements, the likely financial cost, and the relative benefits afforded by attending each college in their choice set (Iloh & Tierney, 2014; Toutkoushian & Paulsen, 2016). Both Dache-Gerbino (2018) and Klasik et al. (2018) acknowledge such costs.
a more powerful deterrent to enrollment than to employment since, unlike compensated employment, college enrollment requires a financial investment in the form of up-front payment (tuition and fees) and opportunity costs (time that could be spent working; Becker, 1964). Monetary and time-based commuting costs likely underlie both the substitution and convenience effects, wherein individuals make college enrollment decisions based on price sensitivity and the potential to lower costs by enrolling at a nearby institution.

Second, the structural causes of spatial mismatch receive inconsistent attention across higher education studies of geography. The original hypothesis identifies two structural causes of spatial mismatch as it relates to unemployment: the suburbanization of jobs12 and the pervasive effects of racial housing segregation (Ihlanfeldt & Sjoquist, 1998). Within the higher education studies that reference SMH either explicitly or indirectly, Klasik et al. (2018) center individual choices rather than the structural causes that yield an uneven distribution of colleges. Though Hillman (2016) does not directly reference SMH, he notes that “geographical differences are created and sustained through policy action and political negotiations where spatial inequality is concentrated in areas facing high levels of unemployment, poverty, and social exclusion” (p. 991). This acknowledgement of structural causes is certainly in keeping with SMH and, as Hillman (2016) alludes to in his discussion of future research, more theorizing is necessary to understand the policies that enabled and reinforced spatial inequality in higher education access.

Third, a subset of the higher education adaptations undertheorizes the racialized nature of spatial inequalities. This limitation is notable given the original framework’s emphasis on spatial mismatch for low-skilled Black workers and its thematically consistent expansions to other vulnerable populations (e.g., non-Black racially minoritized populations, among others; Preston

12 Whether and how the suburbanization of jobs manifests depends on the specific context of the city being studied (Blumenberg & Manville, 2004).
& McLafferty, 1999). Each of the higher education geography of opportunity studies incorporates an examination of racial differences into the empirical design, yet only one of these studies (Dache-Gerbino, 2018) theorizes on the racialized creation of space. Dache-Gerbino’s (2018) critical geography college access framework “is used to examine how a county and city are divided across racialized spaces and the spatial relationships these areas have to where local colleges and universities are located” (p. 99). The mismatch is acknowledged and placed in the context of how space becomes an avenue through which race-based inequalities are sustained.

In contrast, the role of racism in the construction of spatial inequalities receives minimal attention in the remaining studies. Hillman’s (2016) geography of opportunity framework acknowledges that “communities are becoming increasingly segregated along lines of race and ethnicity” (p. 991); the author notes that there are college access and completion consequences resulting from this segregation. That said, there is limited discussion of how racially charged or explicitly racist policies and practices contributed to racial segregation and these resultant spatial inequalities, directly or indirectly. Briscoe and De Oliver (2006) allude to race/ethnicity in their consideration of “urban” communities, which they parenthetically acknowledge are “often minority” in their demographics (p. 205). Even with its limited conceptual treatment, their empirical work ultimately finds evidence of racialized spatial decisions. For instance, the initial decision to locate UTSA’s main campus in the suburbs—further away from the Latinx population that the university’s president promised to serve—reflected “the interests of large landholders on the urban periphery, intent on enhancing their own land values” (p. 214). In this case, the authors provide evidence that space serves as a vehicle to maintain racially unequal access to opportunity. However, without deliberate theoretical centering about de facto and de jure racism in policy and practice, these studies and the resultant policy discussions risk
silencing the voices of the exact populations that research demonstrates would most benefit from the reversal of spatial inequalities.

Dache-Gerbino’s (2018) framework, as well as Dache’s (2022) and Dache-Gerbino et al.’s (2018) studies, all serve as examples of how to better incorporate the structural causes of race-based spatial inequalities into a conceptual framework on the geography of opportunity. In these studies, the authors center the experiences of Black and Latinx students to further our understanding of how racially minoritized populations experience unequal geographic access to higher education due to structural decisions about the use of space. Inspired by these studies, I seek to incorporate an awareness of structural causes into the study at hand. To do so, I draw on Velez and Solorzano’s (2017) Critical Race Spatial Analysis (CRSA) framework. CRSA, as defined by its originators, builds from the critical geography literature to:

spatially examine how structural and institutional factors influence and shape racial dynamics and the power associated with those dynamics over time. Within educational research, CRSA is particularly interested in how structural and institutional factors divide, constrict, and construct space to impact the educational experiences and opportunities available to students based on race (Velez & Solorzano, 2017, p. 20).

Put differently, researchers who employ CRSA must move beyond empirical observations of how opportunity varies across space and by community demographics, and into the realm of understanding the structural mechanisms that motivate the uneven accumulation of spatial opportunity by race. This goal is accomplished by adhering to several tenets that Velez and Solarzano (2017) identify, two of which are particularly relevant to this study: Conceptually, CRSA studies “[challenge] race-neutral representations of space by exposing how racism operates to construct space in ways that limit educational opportunity for Students of Color, their
families, and their communities” (p. 21). This exposure of racism’s role in the construction of space can be accomplished, in part, by examining the historical policies and practices that contributed to these inequalities (e.g., redlining). Methodologically, CRSA studies “[emphasize] maps and mapmaking as a point of departure for analyzing the sociospatial relationship between race and space and refusing to allow maps to speak for themselves” (p. 21).

**Developing a Conceptual Framework of Postsecondary Geographic Accessibility**

In this section, I draw on three existing conceptual frameworks, as well as the tenets of CRSA, to build a conceptual framework of geographic accessibility to less selective colleges that centers race- and class-based spatial inequalities. I first introduce the spatial justice framework as articulated by Soja (2009, 2010) and the transportation justice framework, as formulated by Pereira et al. (2017) and Adli et al. (2019). I then draw on these frameworks to argue that less selective colleges’ neighborhoods are likely lower income and more racially diverse than neighborhoods elsewhere in the study area. I further argue that the average less selective college nearest to lower income and racially diverse neighborhoods is lower quality than the one nearest to higher income and White neighborhoods. Furthermore, transportation infrastructure, in particular public transit systems, reinforce geography-based inequalities in access to educational opportunity. I hypothesize that, in the aggregate, lower income and racially diverse neighborhoods experience lower overall accessibility to broad access public colleges. The consequence of these spatial inequalities, I argue using the framework of spatial opportunity structures (SOS), is the accumulation of lower educational attainment in communities that experience comparatively low geographic access to higher education. Drawing from these frameworks, I introduce a series of propositions that seek to answer the following question: To
what degree and through which mechanisms does geographic access to postsecondary education vary across neighborhoods in metropolitan areas?

I develop this framework in two distinct parts, the first of which considers the relative locations of all less selective colleges, both public and non-public (e.g., nonprofit or for-profit). Here, the framework delineates hypothesized patterns in the demographics of neighborhoods surrounding different types of colleges as well as the characteristics of the nearest institution to certain neighborhoods when mode-adjusted travel time is the dominant consideration. The second part of the framework considers overall accessibility to a particular type of college, the broad access public college. This decision is motivated by public policy goals related to universal geographic access to public colleges for state residents (e.g., ICCB, 2020), as well as the recent expansion of free public college programs (Douglas-Gabriel, 2022). The potential effects of free college programs’ improved affordability are necessarily related to the geographic accessibility of participating colleges to potential students (Dache, 2022).

Throughout the development of this framework, I remain attentive to the conceptually minded tenets of CRSA. According to Velez and Solorzano (2017), CRSA evaluations of educational inequalities must first center the linkages between “race, racism, history, and space” (p. 21) and second deliberately view space not as race-neutral but instead as racialized in its construction and therefore in the way that students, families, and communities do (or do not) gain access to educational opportunities. I therefore center theoretical approaches that provide race-conscious explanations for why certain opportunities (e.g., colleges) locate in particular neighborhoods and why metropolitan transportation infrastructure disproportionately inhibits or minimizes access for low income and racially minoritized students, families, and communities.
Spatial Justice and its Complement, Transportation Justice

Soja’s (2009, 2010) spatial justice framework offers a means of unpacking the spatial processes through which “unjust outcomes arise from inherently unjust processes” (p. 86). His central argument is that geography—specifically, the distribution of resources, opportunities, and people across space—contributes to the production and reinforcement of social inequalities. Spatial justice can be summarized through three iterative ideas (p. 20, direct quote):

- justice and injustice are infused into the multiscalar geographies in which we live, from the intimacies of the household to the uneven development of the global economy;
- the socialized geographies of (in)justice significantly affect our lives, creating lasting structures of unevenly distributed advantage and disadvantage;
- these geographies and their effects can be changed through forms of social and political action

Three geography of opportunity studies reviewed above reference Soja (2010) in the construction of their conceptual framework. Hillman (2016) employs Soja’s (2010) basic argument that policies “establish and maintain a social geography of class” (p. 989) where communities with fewer opportunities and resources remain under-resourced not out of desire but because policymakers prevent an alternative course. Likewise emphasizing the social construction of space, Dache-Gerbino (2017, 2018) takes as her foundation Soja’s (2010) argument that “power and domination [is] embedded in the creation of geographic boundaries” (Dache-Gerbino, 2018, p. 22). Here, I build on this foundation with additional details from Soja’s (2010) framework.

When considering the consequences of spatial processes, Soja is primarily concerned with the Rawlsian form of distributive justice (i.e., the difference principle), which posits that

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13 The framework draws its inspiration from geographers such as Lefebvre (1996), who theorized on the “right to the city,” and Harvey (1973), who articulated the idea of territorial justice (Nordquist, 2013).
“departures from equality must benefit everyone, starting with the least advantaged” (Freeman, 2018, p. 2). Addressing distributional injustices, in Soja’s (2010) opinion, requires “shift[ing] attention to the production of [these] injustices and the embeddedness of this production process in the social order” (p. 74). According to Soja (2010), since the built environment is constructed by institutions comprised of individual people, the built environment is not itself a passive actor in social processes. Put another way, everything that is social is also spatial.

Transportation justice is a component of spatial justice, in that it specifically emphasizes transportation infrastructure as a necessary form of urban infrastructure, one which is designed via the political process (Enright, 2019) and contributes to spatially distributed social inequalities (Adli et al., 2019; Pereira et al., 2017). Transportation justice starts from the premise that the spatial distribution of opportunities throughout the built environment is more or less fixed, and it is the job of the transportation system to facilitate equitable access to these opportunities across populations (Bullard, 2004). In other words, transportation infrastructure influences whether individuals and communities can effectively overcome spatial mismatch and, in this way, contributes to the creation and reinforcement of spatial inequalities that Soja (2010) observes.

Central to the transportation justice framework is the acknowledgement that the distribution of transportation infrastructure—and public transit service specifically—is not race-neutral. “Regional transportation planning processes—whether explicitly cast in racial terms, or in neutral technocratic ones—have long produced racialized geographies of advantage and disadvantage and have enforced inequalities of opportunity and power in the built environment” (Enright, 2019, p. 674).\(^4\) Reversing the distributional consequences of transportation injustice

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\(^4\) The consequences of transportation injustice extend beyond differential mobility across communities. For instance, as America expanded its interstate system beginning in the 1950s, historically Black communities—with lower car ownership rates—were often the ones displaced by construction or, among those who remained, walled off by the sudden presence of a highway and negatively affected by the resultant increase in air and noise pollution.
requires policies that “prioritise vulnerable groups and thereby mitigate morally arbitrary advantages that systematically reduce their accessibility levels” (Pereira et al., 2017, p. 184).\textsuperscript{15} Although Soja (2009, 2010) does not speak as explicitly about racism’s role in the construction of spatial inequalities, empirical evidence reinforces the disproportionate accrual of spatial injustices on communities of color, in particular Black, Latinx, Asian, and Indigenous populations (Dache 2022; Grengs, 2015; Le, 2018; Rosenboom & Blagg, 2018). Thus, it is difficult to employ the spatial justice framework without also centering the racial composition of the populations most affected by the spatial inequalities that the framework seeks to identify, explain, and eradicate.

Soja (2010) identifies three avenues through which spatial injustices—and, by extension, transportation injustices—manifest. Two of these—endogenous and exogenous decisions—are relevant to the study at hand and therefore introduced here.\textsuperscript{16} First, spatial injustice can result from endogenous, or individual-level, “processes of locational decision making and the aggregate distributional effects that arise from them” (Soja, 2010, p. 47). This mechanism yields distributional injustice from the bottom up and is comprised of two components: the geography of privilege and the geography of choice. The geography of privilege is any geographic decision that an individual makes because they have the privilege (typically financial resources) to do so.\textsuperscript{17} For example, wealthy parents seeking a high-quality school for their children can exercise

\textsuperscript{15} Although I focus here on the distributive inequalities that burden low-income communities and racially diverse communities, transportation planning scholars likewise center the elderly and people with disabilities in their appraisal of justice in urban transportation systems.

\textsuperscript{16} Spatial injustice can develop at the mesogeographical level as well, which occurs when regions and/or nations develop unevenly. Since I focus on within-region variation, I cannot observe mesogeographical spatial inequalities.

\textsuperscript{17} Relevant to this discussion, Israel and Frenkel (2018) link Bourdieu’s theorizing on economic, social, and cultural capital to the concept of spatial justice. The authors hypothesize that these interrelated forms of capital, “which are formed in an individual’s living environment, determine their life choices, thus influencing spatial equality of
their geographic privilege by purchasing a more expensive home in their preferred school
district—what Holme (2002) refers to as the “‘unofficial’ choice market” (p. 179). In contrast, a
geography of choice is one in which the individual makes a geography-based decision that
reflects personal preference, regardless of one’s privilege. Either form of locational decision-
making results in distributional inequality when aggregated.

Spatial injustice also manifests exogenously, through decisions by those who hold
influence over the “political organization of space” (Soja, 2009, p. 3). Soja (2010) notes that
exogenously introduced spatial injustices exert significantly more influence over the totality of
spatial injustice than the collection of individual-level endogenous decisions. This is because
exogenous decisions wield greater influence over who has access to what and at what cost.
Examples of exogenous decisions that manifest as spatial injustices within metropolitan areas
include the secession of suburban areas from urban school districts as occurred in Memphis City-
Shelby County (Siegel-Hawley et al., 2018), boundary-setting for community college districts
(Baker et al., 2021), and, relevant to the study at hand, decisions about where to locate new
college campuses (Briscoe & De Oliver, 2006).

Looking at transportation infrastructure specifically, exogenous decisions encompass the
relative investment in infrastructure for roads or new public transit (e.g., light rail) versus
available revenue for public transit service expansions. Roads and highways receive more
infrastructure funds than public transit (Oliff, 2015), which means populations with lower rates
of car ownership receive less benefit from public transportation investments (Bullard, 2004).
Dollars that are invested in public transit favor capital investments for services that tend to serve
wealthier communities (e.g., rail lines) rather than maintenance or expansions of bus service on

opportunity” (p. 647). Future work could adapt Israel and Frenkel’s (2018) conceptual framework to the specific
context of geographic access to higher education.
routes that service primarily transit-reliant populations (Congressional Budget Office, 2022; Taylor & Morris, 2015). When public transit experienced a budget shortfall early in the pandemic, the first cuts were to service frequency and routes, which most affected disproportionately transit-reliant essential workers (Davies & Marshall, 2020; He et al., 2022; Hu & Chen, 2021). These exogenous decisions about the built environment, both those unique to education and those that relate to transportation, create a spatially unequal distribution of educational opportunity that disadvantages racially minoritized and low-income populations.

The Inequitable Distribution of Colleges in Metropolitan Areas

At least two categories of land-use decisions could result in a spatially unequal distribution of accessibility to college campuses across metropolitan neighborhoods: first, the segregation of particular populations in neighborhoods where less selective colleges are already located, through either endogenous or exogenous decisions; second, the deliberate placement of new college campuses in certain neighborhoods. To the first point, higher-income and White individuals continue to use their geography of privilege (endogenous decision) to avoid living in lower-income and more racially diverse neighborhoods (Frey, 2021). Notably, gentrification remains concentrated in a small number of cities, with the effects of gentrification felt unevenly across historically Black or Latinx neighborhoods in these cities (Richardson et al., 2020).

Exogenous decisions such as exclusionary zoning force lower-income residents away from certain neighborhoods and into physically small regions of the city resulting in a high concentration of poverty (Jargowsky, 2015). If less selective colleges are located in the same neighborhoods as low-income housing or are located in historically non-White neighborhoods,

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18 These modern-day policies are in addition to the more overtly racist and since-outlawed policies such as racial zoning ordinances and red-lining that contributed to the historical establishment of spatial segregation (Jones-Correa, 2000; Trounstine, 2018).
then such policies could reinforce socio-economic and racial segregation even as doing so increases proximity to postsecondary educational opportunity for the neighborhood’s residents.

If the nearest institution to low-income and racially diverse neighborhoods were instead a more selective institution, then it could result in a mismatch between the demographics of the college and its surrounds. Although increased accessibility to more selective colleges is unlikely to result in increased enrollment at these colleges for most students, especially low-income and racially minoritized students who have long attended selective colleges at lower rates (Carnevale & Van Der Werf, 2017; Nichols, 2020), it could increase overall college enrollment or even selective college enrollment through the spillover effect (Griffith & Rothstein, 2009; Turley, 2009). In contrast, if the most accessible college is a less selective institution, then the convenience effect could lead to a direct relationship between geographic accessibility and college enrollment (Dache, 2022; Do, 2004).

The second category of land-use decisions relates to formal decisions about where to locate new or relocate existing college campuses, specifically among the less selective institutions that are the focus of this study. Campus location decisions are embedded in the time in which they were made, which makes a cross-sectional evaluation of the relationship between present-day locations and nearby demographics necessarily constrained. For instance, in their case study of UTSA, Briscoe and De Oliver (2006) observed that the 1960s decision about where to locate the main campus initially focused on downtown options that would maximize geographic access for Latinx students before shifting to a suburban site that appealed to landowners seeking increased property values. Similarly, as Dache-Gerbino (2017) chronicled in her evaluation of college locations in Rochester, several colleges in the study area relocated their existing campuses between the 1940s and 1960s, reflective of “how community educational
resources in the north of the city, where more Blacks and Latinxs lived, moved south, where more wealthy and White residents lived” (p. 377). One of these colleges was Rochester’s only community college; its decision to relocate from the city to the suburbs “left the city without a community college for 23 years” (p. 377). In both cases, historical decisions about (re)-location negatively affected access for historically marginalized populations.

More recent evidence suggests that institutional leaders at for-profit colleges may deliberately place new campuses in low-income or non-White neighborhoods in an effort to improve accessibility for prospective students with otherwise limited access to educational opportunity.¹⁹ Dache-Gerbino et al. (2018) find that for-profit institutions in Rochester locate in neighborhoods that are disproportionately low income and have the highest percentage of Black and Latinx residents. A report by the Student Borrower Protection Center (2021) found that nationwide, majority-Black and majority-Latinx zip codes are more likely to house at least one for-profit college than non-majority Black or Latinx zip codes. In Chicago, 53% of zip codes with the largest Black populations and 41% of zip codes with the largest Latinx populations have at least one for-profit college, as compared to only 6% of zip codes with the largest White populations. These findings are based on a dataset that includes all Title IV colleges, regardless of degree-granting status.

There is, however, inconsistency in these findings about the placement of less selective colleges generally, and for-profit colleges specifically. Fisher (2012) observes in her study of college locations in the DC area what she terms “‘race avoidance’ in for-profit location decisions. That is, for-profits locate in areas with mixed ethnicity, but not in areas with an overwhelming percentage of black residents” (p. 108). When she examines branch versus main

¹⁹ Fisher (2012) hypothesizes a similar argument, though not with the explicit use of Soja’s (2010) spatial justice framework, in her master’s thesis that assesses the locations of for-profit and community college main and branch campuses in the Washington, DC metropolitan area.
campus locations for community colleges in DC, she finds still different patterns: Main campuses in her study were located in areas more accessible to many minority populations, in particular the region’s Black population, whereas branch campus locations were seemingly chosen “to target the Asian, Hispanic, and foreign-born minority groups” (p. 108). Even though the demographics of populations accessible to main versus branch campuses differed, in both instances community college locations increased access for racial populations historically excluded from or underserved by higher education. (Fisher (2012) does not assess the location of colleges relative to neighborhood median income.) These patterns in the distribution of opportunity across neighborhoods suggest:

*Proposition 1:* Less selective colleges are located in neighborhoods with a higher proportion of low-income residents and/or residents of color than the remainder of the study area, however less selective colleges’ neighborhood demographics likely differ based on the sector of the institution.

At first blush, this strategic placement of educational opportunity in neighborhoods with low access could be construed as beneficial to the low-income residents and residents of color in the communities where these less selective colleges are located. There are at least two caveats to the potential benefits of this co-location. First, it is unlikely that all low-income neighborhoods or neighborhoods of color are co-located with a less selective college. If co-location is the only consideration of geographic access, then these neighborhoods would be left without an opportunity—especially if location decisions strategically sidestep certain populations, as Fisher (2012) observes. Even looking beyond co-location to a broader treatment of accessibility such as travel time, unequally distributed transportation infrastructure may still stymie access to the closest less selective college. In this way, the issue is not whether colleges are in certain neighborhoods but, taking the built environment as given, whether the transportation system can overcome the spatial mismatch for populations who do not live near a less selective college.
Second, less selective colleges are not a monolith in their resources and outcomes, and existing research suggests that when multiple opportunities are present in the metropolitan area, the higher-quality opportunities are disproportionately located in better-resourced neighborhoods (Block & Kouba, 2006; Cooksey-Stowers et al., 2017; Fleischhacker et al., 2011; Franco et al., 2008; Chapman et al., 2021). For instance, food “swamps,” or areas where accessible grocery options provide “high-calorie fast food and junk food” (Cooksey-Stowers et al., 2017), are predominantly lower income and comprised of racially minoritized populations (Fleischhacker et al., 2011; Franco et al., 2008). Block and Kouba (2006) find similar disparities in the quality of goods available when examining grocery stores across neighborhoods in Chicago. Furthermore, not only do low-income communities and communities of color have fewer walking-accessible parks nearby, but when parks are accessible, they are, on average, half and a quarter of the size, respectively, and serve almost five times as many people (Chapman et al., 2021).

If the nearest park or grocery store to low-income neighborhoods or neighborhoods of color are lower quality, then it is possible that the nearest less selective college to these neighborhoods is lower quality than the less selective college nearest to higher-income or predominantly White neighborhoods (e.g., fewer resources, lower student outcomes). The second half of Briscoe and De Oliver’s (2006) UTSA case study, as well as Kenyon’s (2011) case study, find that branch campuses, the locations of which were deliberately chosen to serve students for whom the main campus is geographically inaccessible, offer fewer support services than the main campuses and were therefore less comprehensive access points to postsecondary education. This is not to imply causality in the relationship between demographics and the quality of nearby opportunities but could suggest systemic underinvestment of resources in certain communities that in turn influences quality. The tendency for the quality of the most accessible opportunity to
differ across neighborhoods, with lower-quality opportunities disproportionately more accessible to low-income neighborhoods and/or neighborhoods of color, suggests the following:

**Proposition 2:** In metropolitan areas with multiple less selective colleges, the colleges most geographically accessible to low-income neighborhoods and/or neighborhoods of color will have, on average, fewer student resources and lower student outcomes than the less selective colleges most accessible to other neighborhoods in the study area.

**Overall Accessibility to Broad access Public Colleges**

Whereas the preceding section is concerned with conceptualizing the likely demographic patterns associated with accessibility to individual less selective colleges, this portion of the conceptual framework considers how overall accessibility to broad access public colleges may vary across a metropolitan area. The difference is subtle: Above, I consider geographic access as it relates to the region immediately surrounding a less selective college, and as it relates to the time required to travel to the nearest less selective college. Here, I consider how cumulative accessibility to all broad access public colleges may vary across key demographics.

Though a neighborhood’s relative accessibility differs depending on the focal opportunity and the assumed travel mode, low accessibility areas are disproportionately comprised of low-income households or households of color (Brown et al., 2016; Ermagun & Tilahun, 2020; Grengs, 2010, 2012). Brown et al. (2016) assess geographic access to healthcare providers in Philadelphia, finding that overall access is lower in neighborhoods with a high proportion of Black households. Shen (1998) compares job accessibility in neighborhoods across Boston, finding that many low-income households live nearer to the more densely populated central business district (which improves proximity to opportunity), but the benefits of proximity are only realized in the presence of car ownership. Furthermore, residence near the central business district does not guarantee proximity to a desired opportunity. Grengs (2010, 2012) compares job accessibility in Detroit, Michigan based on mode of travel. He finds that, despite living near the
central business district, Black households and lower-income households in this area have low job accessibility due to the intersection of low car ownership rates and the disproportionate concentration of jobs outside of the central business district.

Within higher education, a recent study of driving accessibility in six metropolitan areas using U.S. Census American Community Survey (ACS) 5-year estimates (2011-2015) found variable accessibility by income and race/ethnicity (Krause, 2017). Even though overall college accessibility favored upper-socioeconomic status census block groups in four of the six metropolitan statistical areas (MSAs; Krause, 2017), the patterns were less consistent by race/ethnicity, due in part to the higher accessibility of for-profit institutions to predominantly Black, Asian or Latinx census block groups in some metropolitan areas. When examining access to public colleges specifically, access was higher for Black and Asian populations than for White populations in only two of the six MSAs; in the four remaining MSAs, the median number of accessible broad access colleges was equivalent across race/ethnicity groups. In only one MSA did the median number of accessible public colleges for Latinx populations exceed the number of accessible colleges for White populations. Fewer Black households and low-income households report having access to a vehicle (Berube et al., 2006; Bureau of Transportation Statistics, 2011), which means that, even with a similar number of public colleges located nearby, different populations may still experience differential access. However, because Krause (2017) employed a contour measure of accessibility, it is not possible to evaluate the variation by race/ethnicity and mode of transportation.

The combination of distance to opportunities and a household’s degree of mobility creates disparities in neighborhood-level accessibility, with higher-income and/or predominantly White neighborhoods often experiencing increased overall accessibility. Building from the
perspectives of distributive justice in accessibility, I hypothesize that the conditions of transportation justice are not met as it relates to the overall geographic accessibility of broad access public colleges for low-income and racially minoritized communities. Specifically, documented disparities in overall accessibility to other opportunities suggest the following:

**Proposition 3:** High-accessibility neighborhoods are disproportionately comprised of White and/or higher-income households, whereas low-accessibility neighborhoods are disproportionately comprised of low-income residents and/or residents of color.

**The Consequences of Spatial Mismatch in Education**

Individuals are shaped by their built environment because, when they lack geographic access to opportunity, it affects their short- and long-term outcomes. Galster and Sharkey (2017) refer to this relationship between the built environment, which includes transportation infrastructure, and an individual’s outcomes as the spatial opportunity structure (SOS). The SOS framework is relevant in that it provides a means of understanding how spatial and transportation inequalities lead to social inequalities in, for example, educational attainment. Within SOS, spatial confinement affects individuals’ socioeconomic outcomes in two ways: First, it can directly alter the payoff an individual can achieve from a particular opportunity. For example, jobs for college-educated workers may pay lower wages in some communities than in others. Second, spatial confinement indirectly affects outcomes by modifying the “bundle of attributes that individuals develop over time” (Galster & Sharkey, 2017, p. 2). This modification occurs because the built environment shapes what an individual is exposed to (similar to spillover effects) as well as the individual’s perceptions of what is attainable based on the available information. Early decisions then affect subsequent decisions, thereby contributing to incremental adjustments that further limit the potential attributes that an individual can accrue (Galster & Killen, 1995).
When aggregated at the neighborhood level, limited local opportunities and minimal transportation accessibility can shape an entire neighborhood’s access to opportunity (Briggs, 2005; Galster & Sharkey, 2017). This spatial variation in turn creates variation in the degree to which different neighborhoods can benefit from private and public opportunities (e.g., job availability) and resources (e.g., high-quality K-12 schools; Galster & Killen, 1995). Further extended, this uneven accrual of resources can give way to the idea of spatial opportunity hoarding (Green et al., 2017), wherein particular communities or individuals are able to accumulate an outsized proportion of a given opportunity by trading on existing privileges and powers. As evidenced by investigations of neighborhood-level access to grocery stores (Block & Kouba, 2006) or services like healthcare (Brown et al., 2016), accessibility to opportunity accrues unevenly across neighborhoods. Low-income households and households of color are disproportionately located in neighborhoods that can access fewer opportunities than the neighborhoods where high-income and predominantly White households reside.

These spatial inequalities in overall access to educational opportunity can eventually manifest in neighborhood-level outcomes with long-term consequences for individuals’ educational attainment and social mobility (Chetty et al., 2014). Clay and Valentine (2021) employ propensity score matching (PSM) with administrative records at Rio Hondo College in Los Angeles, California to estimate the causal effect of receiving a universal transit pass. The authors found that the overall rate of next-semester and next-year enrollment among students who received the pass was approximately 5 percentage points (pp) higher than observed in the matched comparison group. Increases in credit accrual and degree attainment were modest, but statistically significant (3.6pp increase in the percentage of students who earned 12 credits by the end of the first semester; 2.7pp increase in the percentage of students who earned an associate
degree). At the regional level, Hillman (2016) finds a positive relationship between the number of nearby colleges and the region’s educational attainment.

The above studies document a relationship between a high-level measure of access (a transit pass, Clay & Valentine, 2021; a nearby college, Hillman 2016) and college outcomes. Several studies in the K-12 space emphasize the relationship between a more granular measure of access (commute times) and student outcomes. Two studies evaluate the relationship between public transit mobility and either absenteeism (Stein & Grigg, 2019) or transfer (Stein et al., 2020). In both studies, the authors rely on administrative student-level data from the Baltimore Public School System and, in both cases, changes in mobility are associated with changes in student outcomes. A ten minute increase in the estimated commute time increases day-long absences by 2.6% (approximately 1/3 of a day for the average student; Stein & Grigg, 2019) and increases the probability of transfer by 17%, with transfer students disproportionately Black and/or in need of special education services (Stein et al., 2020).20

These results suggest that even when students are choosing between local options, there is an incentive to decrease the commute time. This is effectively a within-region manifestation of the convenience effect and mirrors Jepsen and Montgomery’s (2009) findings regarding adult learners’ sensitivity to distance when choosing to enroll at a local community college. Put simply, students’ enrollment decisions are sensitive to local variation in geographic accessibility. If there exists a relationship between educational attainment and college access across metropolitan areas (Hillman, 2016), and between K-12 outcomes and transportation access within regions (Cordes et al., 2021; Stein et al., 2020), then it is equally possible that there is a

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20 Similar analyses in other city contexts affirm the increased likelihood of transfer for students with longer commute times. In NYC, students with long bus rides are disproportionately Black; these long bus rides are associated with increased absences and chronic absenteeism (Cordes et al., 2021). Among kindergarten students in Washington, DC, 7.2% of those with a 15-minute driving commute transfer schools compared to 3.9% of those with a three-minute driving commute (Blagg et al., 2018).
relationship between within-region accessibility of broad access colleges and neighborhood-level rates of educational attainment. All the above suggests the following:

**Proposition 4:** The concentration of lower educational attainment in communities comprised of lower-income residents and/or residents of color means that the decreased accessibility of postsecondary education in these communities disproportionately affects metropolitan households with the greatest potential demand for college enrollment.

**Summary of the Proposed Framework**

Opportunity—be it employment, education, or other public goods—tends to accrue unevenly across neighborhoods, with low-income, Black, and Latinx individuals disproportionately located in neighborhoods with fewer or lower-quality opportunities (Soja, 2010; Galster & Killen, 1995). This uneven accrual of opportunity within the built environment is the result of historical inequalities that favor the accumulation of resources and power in primarily White and higher-income neighborhoods (Soja, 2010; Dache-Gerbino, 2017, 2018). As understood in higher education, large regions of the United States lack any nearby public colleges (Hillman, 2016) and, even within metropolitan areas, the exogenous decision of where to locate college campuses preferences some demographic populations over others (Briscoe & De Oliver, 2006; Dache-Gerbino et al., 2018).

There are two basic mechanisms through which geography influences access to opportunity: the spatial distribution of opportunities across neighborhoods, and the level of transportation accessibility within neighborhoods. First, the presence (or absence) of opportunity within the neighborhood in which an individual lives has an immediate and direct effect on an individual’s ability to access a particular opportunity. In many cases, existing evidence points to the likely co-location of less selective colleges and low-income and/or Black and Latinx neighborhoods. However, evidence also points to the potential for the opportunities that are most accessible to these neighborhoods to be lower quality than those closest to higher-income and
predominantly White neighborhoods (Briscoe & De Oliver, 2006; Kenyon, 2011). Furthermore, the combined forces of geographic segregation and lower rates of car ownership among low-income, Black, and Latinx households could result in overall lower accessibility to broad access public colleges regionwide.

The ramifications for lower accessibility to broad access public colleges are both immediate and long term. In the immediate, lower access could dampen the potential effects of policy initiatives such as free college programs which seek to remove affordability as a barrier to access; if geography remains a barrier, then the potential benefits to completion could remain unachieved. When the negative consequences of lower accessibility accrue over time, the result could be decreased educational attainment in these same communities. In the chapters that follow, I translate this conceptual framework and its propositions into a quantitative research design that evaluates multiple forms of accessibility in two Midwestern cities.
Chapter 3 Data and Study Area Overviews

This chapter provides an overview of the data sample and outlines how I operationalize key terms as well as the selection process I employ to select the two focal study areas. Following this description of the selection process, I introduce the two study areas by examining the overall and tract-level demographics. I also provide a high-level overview of the higher education landscape embedded in each area. The chapter closes with a discussion of limitations.

Data Sources

*Integrated Postsecondary Education Data System*

Information on an institution’s characteristics draw from the Integrated Postsecondary Education Data System (IPEDS), which includes institutionally submitted aggregate data for all colleges and universities that are eligible to participate in Title IV financial aid programs. Institutions are identified as less selective using three years of IPEDS data on selectivity and open access designation (see below for additional detail). I draw on 2019 IPEDS surveys for institutional characteristics, expenditures, and student outcomes. The desirability measure in the accessibility index relies on IPEDS data related to program offerings by four-digit Classification of Instruction Programs (CIP) code and published in-district and in-state tuition and fees. Comparisons of college characteristics rely on institution-level data on per-full time equivalent (FTE) expenditures, retention and graduation rates, earnings, and borrower outcomes. I identify the census tract in which a college’s main campus is located using data from the Urban Institute’s Education Data Center, which draws on IPEDS data; branch campuses are identified by inputting the campus address into the U.S. Census Geocoder.
Because institutions sometimes report to IPEDS differently depending on whether the campus is a “parent” or “child” (Jaquette & Parra, 2014)—and depending on how the institution chooses to report campus-level information—I must take care in understanding the appropriate reporting entity for each institution in my sample. First, each of the 41 institutions that I identify as “main” campuses independently submits to IPEDS for all but one of the surveys used in my analyses. In this survey (finance), my sample of 41 main campuses includes 10 partial-child records, meaning some, but not all, of the finance survey is completed by campuses that are main campuses in my sample but are globally considered “child” campuses in a larger system. Seven of these ten records are for the colleges within the City Colleges of Chicago System (the system office is not included); the remaining three records correspond to campuses of multi-state institutions with at least one location in the study area. For all ten records, the child location (i.e., the location in my sample) reports the information necessary to calculate per-FTE expenditures.

Second, in no instance do the branch campus locations that I manually identify for these 41 institutions independently report any survey data to IPEDS. Therefore, any reporting for these locations is rolled into the reporting for the main campus with which the branch campus is affiliated. By way of example, I include in my sample of 41 main campuses the DeVry University – Illinois unitid (482477). Within the IPEDS universe, this unitid is a child institution to the parent institution, DeVry University – Administrative Office (144777). When I examine the DeVry University website, I find that in Illinois, there are six locations, all within the geographic boundary of the Chicago study area. Since DeVry University – Illinois submits independent IPEDS surveys, including a partial-child record for finance, I assume that DeVry University – Illinois’ IPEDS survey responses cover all six Illinois locations, even though none of these locations are listed independently within the IPEDS universe.
**U.S. Census Data**

Metropolitan statistical area and census tract characteristics draw from the U.S. Census American Community Survey (ACS) 5-year Estimates (2015-2019). Variables of interest include population percentage by race/ethnicity (White, Black, Latinx, Asian, and American Indian/Alaska Native/Pacific Islander/Native Hawaiian/Multiracial/Other); median household income; poverty rate; percentage of residents who are veterans; and potential educational demand measured as the percentage of the population 25 years and older with less than an associate degree. Variables on the number of vehicles available per household are used to determine the degree of transit reliance in each tract. Census tracts include an average of 4,000 individuals (U.S. Census, n.d.b) and are collections of census block groups, which are themselves collections of census blocks (the smallest geographic unit employed by the U.S. Census). Also drawn from the U.S. Census are shape files with boundaries for geographies of interest (census tracts, counties, urbanized areas, and metropolitan areas).

**CDAC Origin-Destination Matrix**

The ongoing COVID-19 pandemic has affected transportation along a host of dimensions that interact with data collection. Traffic volumes declined precipitously in spring 2020 due to stay-at-home orders (Tomer & Fishbane, 2020). Though overall volumes are recovered, morning travel peaks are less pronounced, midday travel is increasing, and evening rush hours unfold over more hours (TomTom, 2022). These patterns all likely reflect changes in travel behavior borne of work from home policies; not only is the commute either gone or its timing more flexible—both of which affect morning and evening rush hour volumes—but employees who work from home can and often do conduct non-work travel throughout the day (Su et al., 2021), which increases midday traffic volumes. Public transit service is a skeleton of its former self in many cities, due to reductions in frequency, routes, and operating times (Mondry, 2020; Pascale, 2020). For these
reasons, I rely on two sources of travel time estimates that precede the start of the pandemic. First, I use the pre-computed publicly available origin-destination (O-D) matrix calculated by researchers at the University of Chicago’s Center for Data and Computing (CDAC). These matrices were developed using OpenStreetMap data and OpenTripPlanner in September 2019 and include driving and public transit travel times from each origin tract to all destination tracts within 100km (approximately 62 miles) of the boundary of the county in which the origin tract is located (Saxon & Snow, 2020). Time estimates are calculated from the population centers, or weighted centroids, of origin and destination tracts.

For tract pairings with missing time estimates in the CDAC O-D matrix, I supplement the dataset with driving times calculated using the Stata program osrmroute and historical OpenStreetMaps (OSM) files as well as transit times calculated using ArcGIS’s Network Analyst toolkit and historical General Transit Feed Specification (GTFS) files for the transit agencies operating in the study areas.21 Archived OSM files are from January 2020, the archive date closest to the CDAC O-D matrix’s September 2019 timeframe. GTFS files are drawn from two websites that specialize in the archiving of transit agencies’ publicly available files (if available): transit.land and transitfeeds.com. I use these alternative data collection approaches as supplemental rather than primary because my preference is that most time estimations are calculated using the same program. In the case of the CDAC data, the researchers used OSM data to calculate both driving and public transit time estimates. Furthermore, because of feasibility constraints with the ArcGIS approach, I am unable to incorporate walk time into the public transit travel estimates. For this reason, the ArcGIS-derived travel times for public transit likely have more misestimation than the CDAC data.

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21 GTFS refers to a data specification that public transportation agencies can use to publish transit data so that developers (i.e., Google Maps, HERE, OSM) can write tools related to transit service.
To calculate intrazonal (e.g., within tract) travel times, I adhere to an approach first recommended by the U.S. Department of Commerce (1965) for traffic demand modeling and that is still in use within the transit planning literature (Bhatta & Larsen, 2011): I calculate the average by-mode travel time between the focal census tract and its adjacent neighbors using a Queen’s contiguity neighbor definition (i.e., any tract that shares an edge or vertex with the focal area is a neighbor). I then divide this value by two. Though this approach is less sophisticated than more recent approaches employed for formal traffic demand modeling (e.g., Hu et al., 2020; Kordi et al., 2012; Manout & Bonnel, 2019), there does not appear to be consensus within the literature about the relative benefits of increased complexity. In contrast, the U.S. Department of Commerce’s (1965) approach is both computationally simple and, by its design, adjusts intrazonal travel time based on the size of the focal census tract. Since travel times between large tracts and their neighbors will be higher than travel times between small census and their neighbors, the intrazonal travel time for large tracts will be higher than for small tracts. This approach is conservative, in that it is more likely to over- rather than under-estimate travel time.

Operationalizing Key Terms

Less Selective Colleges

From the universe of colleges operating in the United States, I first limit the sample to only those institutions that offered undergraduate degrees (e.g., associate or baccalaureate degree) and enrolled undergraduate students in the 2018-2019 academic year, according to IPEDS data. I then categorize an institution as less selective if it was either open access or had a low selectivity rate (accepted more than 75% of students) in at least two of the three admission cycles that preceded the start of the pandemic (2017-18, 2018-19, 2019-20). This definition of less selective is consistent with the approach taken in recent higher education geography of opportunity studies (see Hillman, 2016, 2019; Rosenboom & Blagg, 2018).
I make one exception to this definition: I include the University of Illinois Chicago (UIC), a minority-serving institution with a high admission rate, to better capture the landscape of less selective college opportunities available to Chicago residents, especially residents of color. Even though UIC has an admission rate above 75% in only one of the three years I consider (2017-18), its admission rate is within three percentage points of this cut-off in the two remaining years (2018-19, 2019-20) and exceeds 75% in several preceding years (2016-17, 2014-15). Put differently, a slight change in the choice of years would result in its inclusion, making its exclusion here arbitrary if not data driven.

**Broad Access Public College**

A broad access public college (BAC) is any less selective college, two- or four-year, that operates as a public institution. Public community colleges (e.g., two-year colleges) are open-access institutions that offer associate degree programs in addition to non-credit workforce training and continuing education courses (Bai& & Baum, 2016); an increasing number also offer bachelor’s degree programs that target local workforce needs (Fulton, 2015).

There is no widely agreed-upon definition for less selective public four-year colleges (Dalbey, 1995; Fryar, 2015) but many colloquial names, including the regional public university and the people’s university (Henderson, 2009). Henderson (2009) depicts these institutions as lower-selectivity universities that provide local student populations with degree programs focused on employment in the local labor market. To maintain a data-driven selection process, I opt to define broad access public universities as any public university that is likewise categorized as a less selective college using the above criteria. Included in the final sample are only those broad access public colleges with a main campus in one of the two study areas.
Non-Public Competitor Colleges

Non-public competitor colleges (or less selective private colleges) are any less selective colleges that operate either as a for-profit or nonprofit institution. From the final list of non-public competitor colleges, I exclude seminaries, niche colleges with limited degree offerings (e.g., Worsham College of Mortuary Science), and institutions that have closed since the 2018-19 academic year (Argosy University – Chicago, Flashpoint Chicago, Career Quest College).

Branch Campuses

Branch campuses for each less selective college in the study areas are identified by visiting college websites. Any branch campus outside of the study area is excluded. I further exclude any learning centers (typically located on high school campuses) or university centers (located on other college campuses) as well as any specialty campuses (e.g., law) that would service only graduate students. This decision preserves the inclusion of specialty campuses such as dentistry that offer undergraduate degrees but would only service a subset of students. I make this decision since many of these specialty campuses offer degrees in high-demand fields like healthcare that may be desirable to place-bound students.

Neighborhood

I operationalize neighborhoods as census tracts, which are areal units designated by the U.S. Census. This decision reflects a need to balance the granularity of the geographic unit with the level of information available in ACS as well as in the CDAC O-D Matrix. Specifically, many population characteristics in the ACS 5-year estimates are only available at the census tract level. Furthermore, the CDAC O-D matrix with nationwide coverage considers only tract-to-tract travel times. Throughout the text, I reference neighborhoods, tracts, and areal units; in all instances, I am referring to the base unit of a census tract. In RQ1, I refer to collections of census tracts as neighborhood units (for more, see Chapter 4).
**Accessibility Index**

For use in RQs 2-4, I develop a postsecondary accessibility index using a gravity-based model employed in the transportation planning literature (Levine et al., 2019: see also Chapter 6). Estimated for each census tract is a summative value of the postsecondary accessibility index, derived using equation 6.3 (page 161), as well as a pairing-specific accessibility value for the most accessible less selective college to each census tract (see pages 112-113 for details).

**Terminology for Race/Ethnicity Sub-Populations**

Institutions are required to ask students a two-part question on race/ethnicity identification: First, the student indicates whether they identify as Hispanic/Latino; then they select the racial categories (one or more) with which they identify (U.S. ED NCES, 2021). When reporting to IPEDS, all students who select Hispanic/Latino, regardless of their racial identification, are categorized as such. Additional categories capture non-resident aliens (for whom race/ethnicity information is not collected) and unknown race/ethnicity (U.S. ED NCES, 2021). In the presentation of institutional statistics on the percentage of the student body that identifies as a particular race/ethnicity, I opt to preserve the full nine IPEDS reporting categories, adjusted to align with the terminology used elsewhere in the study: Latinx (any race) and, for non-Latinx students, American Indian or Alaska Native; Black; Multiracial; Native Hawaiian or Other Pacific Islander; White; non-resident alien; and race/ethnicity unknown.\(^{22}\)

In the U.S. Census ACS, information on individuals’ race/ethnicity is collected through the survey instrument; individuals self-report their race and ethnicity separately (U.S. Census, n.d.f.; U.S. Census, n.d.e), with the individual who completes the form determining the appropriate racial categories for all members of the household. As in IPEDS data collection, rather than refer to individuals with multiple races as “2 or more races,” I opt for the term “multiracial.” This is not because the term comprehensively captures individuals’ nuanced racial identities (Baker et al., 2022) but because it reflects modestly improved consciousness of multiracial identities than the administrative labeling employed by IPEDS and the U.S. Census.
individuals can select whether their ethnicity is Hispanic/Latino, which ACS defines as “a person of Cuban, Mexican, Puerto Rican, South or Central American, or other Spanish culture or origin, regardless of race” (U.S. Census, n.d.e). Individuals can also select one or more of 15 racial categories. In the construction of my analytic dataset, I rely on ACS racial/ethnic categorizations for two variables: percent of the total population in a census tract, and percent of a given population living in poverty. Privacy-based data suppression and small cell sizes that constrain statistical power make it difficult to preserve the complete list of racial/ethnic categories. Therefore, in both by-race/ethnicity Census variables, I collapse categories to ensure that populations with small or suppressed counts are not completely excluded from the analyses. I acknowledge that, in doing so, I limit my ability to surface the full range of variation in geographic accessibility by race/ethnicity.

For the population percentage variable, I rely on conceptually motivated categorizations to guide the combination of the 15 sub-categories into five racial categories: White, Black, Latinx, Asian, and AI/AN/PI/MR/Other. This final group includes all individuals who identify as American Indian (AI), Alaska Native (AN), Pacific Islander (PI), as well as those who identify as multiracial (MR) and those who write in another unlisted race (Other). I avoid the simplified “other” to preserve the acknowledgement of disenfranchised identities within this combined category. The existing higher education geography and accessibility literatures emphasize disparities in access primarily for White versus Black and Latinx residents (Brown et al., 2016; Dache-Gerbino et al., 2018; Dache, 2022; Grengs, 2015; Hillman, 2016; Jones & Kauffman, 1994), with a small subset of studies further examining accessibility among Asian populations (Fisher, 2012; Hillman, 2016; Krause, 2017). By maintaining separate sub-groups for these
populations wherever possible, I can better observe whether geographic accessibility of public colleges differs based on a census tract’s distinct racial/ethnic composition.

Whereas tract-level sample sizes allow me to examine total population estimates broken out separately for Black, Latinx, and Asian individuals, I am not able to do so for the poverty rate measure. Therefore, I estimate poverty rates for White residents, then combine all remaining race and ethnicity categories into a single category and calculate the poverty rate for these individuals. I refer to this poverty rate as either the POC (“people of color”) poverty rate or the poverty rate for residents of color. This terminology cannot capture individuals’ nuanced preferences for self-identification but consciously avoids defining certain race/ethnicities in relation to Whiteness (e.g., non-White). For the research question where I use this same combination of racial/ethnic subgroups to identify tracts with a high percentage of residents of color (RQ2), I term the sub-group high proportion POC. I do not label this sub-group “racially diverse,” since the phrasing could reasonably be interpreted as signifying a representative proportion of all racial sub-groups rather than a predominance of select racial/ethnic populations.

**Study Area Selection**

I evaluate accessibility to broad access public colleges across neighborhoods in the Lansing/East Lansing, Michigan metropolitan area and the portion of the Chicago, Illinois urbanized area located in the state of Illinois. Although the ultimate geographic boundary employed in each study area differs according to its unique geographic context, the initial selection process focuses on core based statistical areas (CBSAs), which are collections of counties designed by the U.S. Census based on association with at least one urban area and “a high degree of social and economic integration” with the main urban area (U.S. Census, n.d.d).²³

---

²³ There are two types of urban areas: (1) An urbanized area (UA) is “a densely settled core of census tracts and/or blocks” that includes at least 50,000 people; (2) urban clusters include between 2,500 and 50,000 people (U.S. Census, n.d.a).
I begin with CBSAs for several reasons. First, broad access public colleges may be located outside of the urban core but within the CBSA. Using the boundaries of the CBSA ensures that I do not artificially decrease the number of broad access public colleges I observe across cities.24 Second, I rely on CBSAs instead of commuting zones as are employed elsewhere in the education desert literature (Hillman, 2016; Rosenboom & Blagg, 2018) because commuting zones, which are based on work commuting patterns, typically cover substantially larger geographic areas than would be reasonably serviced by public transit systems. That said, because CBSAs are delineated based on existing county boundaries, population density varies across each study area, which requires explicit consideration in any regression modeling.

My selection strategy aligns with what Seawright and Gerring (2008) refer to as diverse case selection, in which I identify cases that are representative of a range of values on the primary construct of interest (number of educational opportunities) to test the strength of the relationship of interest under varying conditions. The choice of two diverse study areas—one that just barely exceeds the criteria for an education desert laid out in the existing literature, and one that vastly exceeds these criteria—can make “the process of interest ‘transparently observable’” (Eisenhardt, 1989, p. 537). My decision to select a study area with few broad access public colleges is likewise a form of theoretical sampling. In theoretical sampling, cases are “selected because they are particularly suitable for illuminating and extending relationships and logic among constructs” (Eisenhardt & Graebner, 2007, p. 27). I seek to test an implied assumption in Hillman and Weichman’s (2016) evaluation of postsecondary education deserts:

24 CBSA boundaries are updated in non-Census years, which can result in changes over time in the set of counties associated with a given CBSA. Of the two study areas, the Chicago-Joliet-Naperville, IL-IN-WI CBSA did not experience any changes in the composition of counties during the five-year ACS period, but a fourth county was added to the Lansing/East Lansing, MI metropolitan area in 2018. I opt to include this fourth county as part of the study area since it is included in the ACS 5-Year estimates (2015-2019) for the MSA. Its inclusion results in no additional BACs added to the sample.
whether an entire geographic region has access to postsecondary education so long as a certain number of educational opportunities are present within the region. Testing this assumption requires that I evaluate accessibility within such a region.

Beyond these deliberate sampling decisions, I prioritize the selection of CBSAs with high levels of potential transit access so that I can evaluate the distribution of transportation accessibility, overall and by race/ethnicity and poverty rates, under the most generous transit service conditions. Other, smaller decisions within case selection are in service of the goal of identifying areas in which future research can be conducted (e.g., focusing on a Michigan region) or in which accessibility to broad access public colleges has the potential to influence educational attainment for the greatest number of residents (e.g., focusing on a populous CBSA with high potential demand for broad access colleges). Throughout, I refer to these study areas in short (i.e., Lansing, Chicago) or more formally based on the underlying Census designation (Lansing MSA, Chicago UZA). I also refer to both study areas as regions or, in the relevant research questions, in- or out-of-district sub-regions. In these instances, I am drawing on the general definition of region, relating to a geographically defined area, rather than the formal Census-designated collections of states called census regions.

Selection of a Marginal Education Desert

Selection of the first study area is motivated by Hillman’s (2016) and Hillman and Weichman’s (2016) use of co-location in a CBSA or commuting zone as an indicator of accessibility (see also Klasik et al., 2018). I argue that living in a CBSA with another college is an insufficient indication of accessibility because it does not account for the possibility that geographic accessibility varies within the region. To test my critique directly, I select a CBSA that just barely escapes classification as an education desert in the literature; I term this a
marginal education desert. Hillman and Weichman (2016) classify a CBSA as an education desert if there are either zero broad access colleges or only one broad access two-year college. Therefore, a marginal education desert is any CBSA that just barely exceeds these criteria based on the presence of: (1) one broad access public four-year college, (2) two public community colleges, or (3) one broad access public four-year college and one public community college.

Selection of a marginal education desert begins from a sample of all CBSAs that include at least one urbanized area (UA) or urban cluster (UC) included in the American Public Transportation Association’s (APTA) 2020 Factbook (n=352). APTA aggregates data from the Federal Transit Administration’s National Transit Database based on the UA or UC in which each individual transportation agency operates (APTA, 2020). From this sample, I keep only the five marginal education deserts located in Michigan (Ann Arbor, Jackson, Kalamazoo, Lansing/East Lansing, and South-Bend-Mishawaka, IN-MI). This decision to limit the sample to marginal education deserts in Michigan is forward-looking; using existing approval for access to Michigan student administrative data, I can directly test in future studies the distance elasticity of enrollment demand among recent high school graduates.

Of these five CBSAs, I exclude Jackson because the region’s only broad access college, Jackson College, offers baccalaureate degrees (hence the CBSA’s classification as a marginal education desert) but is historically and predominantly a two-year degree-granting institution. I exclude South Bend-Mishawaka, IN-MI because its presence in multiple states complicates future studies in which I would observe geographic enrollment patterns using Michigan student administrative data. I exclude Ann Arbor because the presence of a highly selective public university alongside multiple broad access public colleges likely influences neighborhood-level
demographics, especially as it relates to educational attainment and potential demand for a broad access college education.

Between the remaining two options, Lansing/East Lansing and Kalamazoo, I opt for Lansing/East Lansing because the largest public transit agency in this CBSA has higher rankings on two APTA metrics (total ridership and ridership per capita) than the largest public transit agency in the Kalamazoo CBSA. Higher rankings could mean that Lansing/East Lansing’s transit-reliant households are better served than transit-reliant households in Kalamazoo. If this is the case, then selecting Lansing/East Lansing gives the unstated assumption in the education desert literature—that co-location within a CBSA ensures sufficient access—the best chance of being proven correct regardless of transportation mode.

**Selection of an Opportunity-Rich City**

I select a second CBSA based on the desire to test the hypothesis that even in an opportunity-rich and populous region, unequal geographic accessibility can arise (and therefore undermine college access). Here, as in the previous selection process, I begin with the full sample of CBSAs that include at least one UA or UC included in APTA’s 2020 Factbook (n=352). I then limit my choice set to the 20 CBSAs with the largest populations. Next, from these 20 CBSAs, I consider only the seven CBSAs with an above-average percentage of households without access to a vehicle (average = 9.3%). Of these seven remaining CBSAs, I limit the final selection to the two CBSAs with the highest proportion of the population with less than an associate degree (Chicago-Joliet-Naperville, IL-IN-WI, 54.7%; Philadelphia-Camden-Wilmington, PA-NJ-DE-MD, 55.1%). These three decisions in combination allow for an evaluation of accessibility in a region with relatively high public transit reliance, as well as a large number and percentage of residents with potential demand for a less selective college. The
final selection of Chicago is due to its Midwestern alignment with Lansing and better coverage of public transit data in the CDAC O-D matrix, as compared to Philadelphia.

I constrain the geographic boundaries of the Chicago study area in two ways. First, I include only those portions of the CBSA in Illinois. This decision is motivated by the high incidence of in-state enrollment among freshmen at less selective colleges in the sample. At all BACs or non-public competitors in the Chicago CBSA, the average in-state enrollment rate is 88% (98% when limited to BACs); among those colleges within the boundaries of the final study area, the average rate is 85% (98% when limited to BACs). Second, I include only those census tracts with weighted centroids located within the geographic boundary of the urbanized area. This decision is motivated by the desire to exclude less-dense census tracts with large land areas in the outlying regions of the CBSA. Whereas in Lansing, an explicit goal is to examine accessibility using a geographic categorization employed elsewhere in the literature—thereby necessitating the inclusion of outlying tracts—here I seek to understand whether and how accessibility varies in a region known to be opportunity-rich. This question can be answered without the inclusion of sparsely populated outlying census tracts.

I make modest inclusion/exclusion exceptions to the requirement that a tract’s weighted centroid fall within the UZA boundary: I include three origin tracts with weighted centroids close to but outside the boundary because their removal would result in legitimate origin tracts without adjacent neighbors; zero-neighbor tracts would complicate subsequent spatial analyses. Second, I exclude three tracts in DeKalb county because, though their weighted centroids are within the UZA boundary, the tracts have low population densities and the majority of the land area resides outside the UZA. Third, among destination tracts (e.g., tracts with less selective colleges), I include two tracts with weighted centroids outside of the Chicago urbanized area (GEOID:
17097861106, College of Lake County main campus; GEOID 17111870902, McHenry County College main campus). In both cases, this inclusion ensures that every origin tract has in its destination choice set an in-district community college.

**Exploratory Spatial Data Analyses and Study Area Overviews**

In this section, I briefly introduce the exploratory spatial data analyses (ESDAs) that I employ in the examination of both study areas. I then provide an overview of each study area’s demographics and less selective college landscape. The analytic dataset used in this section and throughout is unique at the census tract level. It includes census tracts in the Illinois portion of the Chicago urbanized area ($n=1,885$) and the Lansing/East Lansing metropolitan area ($n=139$) that have a population of at least 500 and a minimum of 200 housing units (Folch et al., 2016). These criteria eliminate anomalous census tracts that capture national parks, bodies of water, prisons, or large college dormitories ($n=9$ in Lansing and $n=11$ in Chicago; Folch et al., 2016).

**Empirical Approach for ESDAs**

A common first step in ESDA involves overlaying variables, or attributes, of interest on top of geospatial data, in this case census tracts within each study area. Mapping data in this way enables the researcher to visually identify clusters where similar attribute values congregate, or outlier areas with an attribute value that appears to differ markedly from nearby areas. Since visual inspections cannot, on their own, statistically quantify the strength or significance of a spatial relationship, ESDA also involves calculating the presence of spatial autocorrelation across attributes.\(^{25}\) There are two approaches to calculating the presence and severity of spatial autocorrelation: globally, to identify spatial autocorrelation for the study area as a whole; and

\(^{25}\) In practice, spatial autocorrelation is a measure of the correlation between two values of the same variable in different, but nearby, locations, and is present when the variance between the values in neighboring areas is non-zero (Darmofal, 2015, p. 31). Positive spatial autocorrelation results when like values are clustered with like values, and negative spatial autocorrelation occurs when attribute values in neighboring areas are dissimilar (Anselin & Bera, 1998).
locally, to identify spatial autocorrelation within specific areas (Darmofal, 2015). To measure
global spatial autocorrelation for each covariate, I rely on the Moran’s \( I \) global statistic. To
measure each covariate’s local spatial autocorrelation, I rely on the local Moran’s \( I \) statistic (Chi
& Zho, 2020).\(^{26}\) In both cases, I use the same queen’s contiguity spatial weights matrix, wherein
any adjacent census tract is treated as a focal census tract’s neighbor.

Formally, the global Moran’s \( I \) is defined as (Darmofal, 2015):

\[
I = \frac{N}{S} \sum_i \sum_j w_{ij} (y_i - \bar{y})(y_j - \bar{y}) \frac{1}{\sum_i (y_i - \bar{y})^2}
\]

(3.1)

where

- \( N \) is the number of observations (i.e., census tracts)
- \( S \) is the sum of the weights
- \( w_{ij} \) is the accompanying \( i-j \) element of the spatial weights matrix, \( W \)
- \( y_i \) and \( y_j \) are values on the variable of interest at locations \( i \) and \( j \)
- \( \bar{y} \) is the mean value of \( y \) across all areas

The global Moran’s \( I \) sums across all focal areas \( i \) the difference between the focal area’s value
on a variable and the mean value of this variable multiplied by the difference between each
neighbor \( j \)’s value on this variable and the mean value. The value derived from each \( i-j \) pair of
locations is weighted based on the corresponding value in the spatial weight matrix, \( w_{ij} \). This
summative value is divided by the squared difference between the attribute value in focal area \( i \)
and the mean value of the attribute across all areas in the study area. It is then multiplied by the
ratio of the total number of observations and the sum of the weights across all observations. The
null hypothesis for the global Moran’s \( I \) is that no spatial autocorrelation is present (i.e., a value
of zero). Positive values of Moran’s \( I \) signal the presence of positive spatial autocorrelation in the

\(^{26}\) The Geary’s \( C \) is another diagnostic with both global and local versions used to estimate the degree of spatial
autocorrelation. Rather than observing the difference between the mean and the observed value, Geary’s \( C \) compares
an area’s value to its neighbor’s value (Ward & Gleditsch, 2008). However, both the global and local versions of
Geary’s \( C \) are more sensitive to outliers and therefore are used less frequently than the Moran’s \( I \). Because of the
treatment of outliers, as well as the decision to adhere to spatial modeling conventions, I opt for the Moran’s \( I \) and
the local Moran’s \( I \) for my diagnosis of the presence and severity of spatial autocorrelation.
data, and vice versa. Statistical significance of the resulting value can be tested with a $z$-statistic, with an expected value of $I$ as $-\left(\frac{1}{n} - 1\right)$ (Chi & Zho, 2020).

I calculate the global Moran’s $I$ values using the raw ACS estimates. Increasingly, however, demographers emphasize the inherent short-comings of raw ACS estimates and instead encourage researchers to both acknowledge the variable margin of error in measurement across census tracts (Folch et al., 2016) and re-estimate raw values using an Empirical Bayesian (EB) smoothing strategy (Jung et al., 2019b). In adherence to these best practices, I calculate the global Moran’s $I$ with both the raw and EB-smoothing estimates where possible.\(^{27}\) Since, with one exception, there are no discernible differences in the global Moran’s $I$ values, I proceed to the local Moran’s $I$ calculation using only the raw ACS estimates (see Table 3.3 and Table 3.7).

The local Moran’s $I$ statistic measures the (dis)similarity between a focal area and its neighbors, rather than the (dis)similarity overall. Formally, the local Moran’s $I$—which foregoes the summation of values derived for each area $i$—is (Darmofal, 2015):

$$I_i = \frac{\sum_j w_{ij}(y_i - \bar{y})(y_j - \bar{y})}{(y_i - \bar{y})^2}$$

(3.2)

where
- $w_{ij}$ is the element of the spatial weights matrix, $W$, corresponding to the $i$-$j$ pair
- $y_i$ and $y_j$ are values on the variable of interest at locations $I$ and $j$
- $\bar{y}$ is the mean value of $y$ across all areas

Here again, the null hypothesis is zero spatial autocorrelation, and values can range from -1 to 1, with negative values suggesting negative spatial autocorrelation and positive values suggesting positive spatial autocorrelation. Once the local Moran’s $I$ values are calculated for each area, I can then map these values to observe visually the presence of statistically significant clusters of positive spatial autocorrelation (“hotspots” if high values are clustered with high values,

\(^{27}\) EB smoothing rates are calculated using the HCEB library (Jung et al., 2019b) in R.
“coldspots” if low values are clustered with low values). These tract-level maps of attribute values and statistically significant clusters of spatial autocorrelation accompany the study area overviews that follow.

**Lansing Study Area Overview**

Lansing, located in southeast Michigan, has a population of nearly half a million people, ranking third among 33 CBSAs in the state. The CBSA is comprised of four counties, one of which is designated as outlying by the U.S. Census. It is a marginal education desert with two broad access colleges across 7 campuses (Lansing Community College [LCC] and Michigan State University [MSU]; Figure 3.1). According to APTA data, the primary UZA in the region (Lansing/East Lansing, MI UZA) ranks outside of the top 50 UZAs on two measures (total ridership, revenue miles), but within the top 50 on ridership per capita. Put differently, even though Lansing has public transit, it is unclear from these rankings whether commuting on public transit is a feasible option for the majority of the region’s residents.

Study area descriptive statistics are included in three tables: Table 3.1 provides details for the entirety of the study area (e.g., the CBSA); Table 3.2 provides tract-level summary statistics for land area and population density, as well as a number of demographic variables; Table 3.3 includes the global Moran’s $I$ for each of the demographic covariates, estimated using a Queen’s contiguity matrix. The global Moran’s $I$ value is presented separately based on whether estimates were derived using raw values or EB-smoothing values (when available). Since in all but one case, these values are identical to three decimal points (percent veterans; difference of 0.001), I focus my discussion and subsequent estimation on raw values. As a reminder, positive values of the global Moran’s $I$ signal positive spatial autocorrelation (like values clustered with like values), with values closer to one indicative of a higher level of spatial autocorrelation. Figure
3.2, Panels A-M map tract-level demographic covariates’ raw values (sub-panel a) and statistically significant local Moran’s I values (sub-panel b). These analyses afford an opportunity to identify clusters of positive spatial autocorrelation.

Across the study area, approximately 7% of households lack access to any vehicle (Table 3.1), though the percentage of households without access to a vehicle varies by census tract. At the high end, 43% of households in a census tract lack access to vehicle (Table 3.2); these tracts are concentrated in the central city portion of the MSA (Figure 3.2, Panel B). Lansing is predominantly White (78% of the total population, Table 3.1), with an additional 8% and 6% of residents identifying as Black and Latinx, respectively. Outlying census tracts skew heavily White (Figure 3.2, Panel H) with concentrated pockets of Black, Latinx, and Asian populations in the central city (Figure 3.2, Panels I-K). In the census tracts with the highest proportion of Black residents, more than 40% identify as Black; the maximum observed percentage of residents in a census tract who identify as Asian nears 60% (Figure 3.2). Median household income in the region is $57,925, though here again, there is geographic variation. Clusters of lower-income census tracts are more central, whereas higher income tracts are dispersed throughout the outlying tracts (Figure 3.2, Panel C). Approximately 15% of residents in the CBSA live in poverty based on Census definitions (Table 3.1), with the poverty rate exceeding 50% in a small number of census tracts (n=5). Fifty-eight percent of all individuals aged 25 and over have less than an associate degree (Table 3.1), suggestive of a large population of individuals with potential demand for college enrollment.

All of the covariates presented here have positive global Moran’s I values (Table 3.3), though the level of spatial autocorrelation varies. Among the race/ethnicity measures, spatial autocorrelation is highest in the percentage of White and Black residents in a census tract (0.724
and 0.737, respectively). Spatial autocorrelation is lower, but still substantial, for the distribution of Latinx (0.476) and Asian (0.263) residents. Potential educational demand (e.g., the percentage of residents aged 25 or older with less than an associate degree) as well as median income is positively spatially autocorrelated (0.613 and 0.424, respectively). The percentage of households in living in poverty (all residents) exhibits positive spatial autocorrelation (0.420), though the global Moran’s $I$ values for the by-race poverty rates are lower (0.283 for percentage of residents of color living in poverty, 0.358 for percentage of White residents living in poverty).

**Table 3.1 Summary Statistics for Lansing Study Area (2019)**

<table>
<thead>
<tr>
<th></th>
<th>Lansing, MI MSA</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Total population</strong></td>
<td>464,036</td>
</tr>
<tr>
<td><strong>Land area (mi$^2$)</strong></td>
<td>2,228</td>
</tr>
<tr>
<td><strong>Census demographics</strong></td>
<td></td>
</tr>
<tr>
<td>Households with zero vehicles</td>
<td>0.07</td>
</tr>
<tr>
<td>White</td>
<td>0.78</td>
</tr>
<tr>
<td>Black</td>
<td>0.08</td>
</tr>
<tr>
<td>Latinx</td>
<td>0.06</td>
</tr>
<tr>
<td>Asian</td>
<td>0.04</td>
</tr>
<tr>
<td>AI/AN/PI/MR/Other</td>
<td>0.04</td>
</tr>
<tr>
<td>Median household income</td>
<td>$57,925</td>
</tr>
<tr>
<td>Poverty rate (all residents)</td>
<td>0.15</td>
</tr>
<tr>
<td>Poverty rate (residents of color)</td>
<td>0.25</td>
</tr>
<tr>
<td>Poverty rate (White residents)</td>
<td>0.12</td>
</tr>
<tr>
<td>Veterans</td>
<td>0.07</td>
</tr>
<tr>
<td>Residents aged 25+ with less than an AA</td>
<td>0.58</td>
</tr>
<tr>
<td><strong>Transit service</strong></td>
<td></td>
</tr>
<tr>
<td>Total ridership rank (out of 488)</td>
<td>64</td>
</tr>
<tr>
<td>Ridership per capita rank (out of 488)</td>
<td>39</td>
</tr>
<tr>
<td>Revenue miles rank (out of 378)</td>
<td>73</td>
</tr>
<tr>
<td><strong>Broad access public colleges</strong></td>
<td></td>
</tr>
<tr>
<td>Two-year college main campuses (branch campuses)</td>
<td>1 (5)</td>
</tr>
<tr>
<td>Four-year college main campuses (branch campuses)</td>
<td>1 (0)</td>
</tr>
<tr>
<td>Total UG enrollment at broad access public colleges</td>
<td>58,878</td>
</tr>
<tr>
<td>BAC enrollment as a proportion of total college enrollment in the Region</td>
<td>84%</td>
</tr>
<tr>
<td><strong>Non-public competitor colleges</strong></td>
<td></td>
</tr>
<tr>
<td>Two-year college main campuses (branch campuses)</td>
<td>0 (0)</td>
</tr>
<tr>
<td>Four-year college main campuses (branch campuses)</td>
<td>1 (0)</td>
</tr>
</tbody>
</table>

*Sources: Author’s calculations from U.S. Census ACS 5yr Estimates 2015-2019; APTA 2020; IPEDS 2019*

*Notes: Unless expressly noted with a unit of measurement (e.g., $), all demographic values are proportion variables.*
Table 3.2 Demographic Summary Statistics for Census Tracts in Lansing (N = 139; ACS 5-Year Estimates 2015-2019)

<table>
<thead>
<tr>
<th></th>
<th>N</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Land area (mi^2)</td>
<td>139</td>
<td>15.90</td>
<td>23.64</td>
<td>0.22</td>
<td>110.32</td>
</tr>
<tr>
<td>Tract population</td>
<td>139</td>
<td>3,828</td>
<td>1,267</td>
<td>1,356</td>
<td>7,268</td>
</tr>
<tr>
<td>Population density</td>
<td>139</td>
<td>2,151</td>
<td>2,417</td>
<td>35</td>
<td>16,232</td>
</tr>
<tr>
<td>Households with zero vehicles</td>
<td>139</td>
<td>0.07</td>
<td>0.07</td>
<td>0.00</td>
<td>0.43</td>
</tr>
<tr>
<td>Median household income</td>
<td>139</td>
<td>$59,020</td>
<td>$20,719</td>
<td>$12,378</td>
<td>$130,385</td>
</tr>
<tr>
<td>Poverty rate (all residents)</td>
<td>139</td>
<td>0.16</td>
<td>0.14</td>
<td>0.00</td>
<td>0.77</td>
</tr>
<tr>
<td>Poverty rate (residents of color)</td>
<td>139</td>
<td>0.21</td>
<td>0.16</td>
<td>0.00</td>
<td>0.79</td>
</tr>
<tr>
<td>Poverty rate (White residents)</td>
<td>139</td>
<td>0.14</td>
<td>0.14</td>
<td>0.00</td>
<td>0.80</td>
</tr>
<tr>
<td>Residents aged 25+ w less than AA</td>
<td>139</td>
<td>0.58</td>
<td>0.17</td>
<td>0.09</td>
<td>0.87</td>
</tr>
<tr>
<td>White</td>
<td>139</td>
<td>0.77</td>
<td>0.18</td>
<td>0.22</td>
<td>0.98</td>
</tr>
<tr>
<td>Black</td>
<td>139</td>
<td>0.08</td>
<td>0.10</td>
<td>0.00</td>
<td>0.43</td>
</tr>
<tr>
<td>Latinx</td>
<td>139</td>
<td>0.07</td>
<td>0.05</td>
<td>0.01</td>
<td>0.28</td>
</tr>
<tr>
<td>Asian</td>
<td>139</td>
<td>0.04</td>
<td>0.08</td>
<td>0.00</td>
<td>0.59</td>
</tr>
<tr>
<td>AI/AN/PI/MR/Other</td>
<td>139</td>
<td>0.04</td>
<td>0.03</td>
<td>0.00</td>
<td>0.23</td>
</tr>
<tr>
<td>Veterans</td>
<td>139</td>
<td>0.07</td>
<td>0.02</td>
<td>0.00</td>
<td>0.14</td>
</tr>
</tbody>
</table>

Sources: Author’s calculations from U.S. Census ACS 5yr Estimates 2015-2019  
Notes: Population density calculated as tract population divided by land area. Unless expressly noted with a unit of measurement (e.g., mi^2, $), all demographic values are proportion variables.

Over 96% of all undergraduates in the Lansing MSA attend one of the region’s two broad access public colleges (BAC; Table 3.1). LCC, the region’s only two-year BAC, enrolled approximately 16,380 students in the 2018-2019 academic year, the majority of whom identify as White (69%; Table 3.4, Column 1). Black and Latinx students make up 9% and 8% of the student body, respectively. Nearly all first-time enrollees are in-state (99%). Fall-fall retention rates for full-time students (64%) and part-time students (43%) are slightly above the national averages of 62.5% and 44.3 in that same year (US ED NCES, 2020c). Only 19% of first-time degree-seeking students graduate within 150% time (3 years). In-district students paid $3,690 in tuition and fees in 2019-2020 as compared to $6,930 for in-state students; 15 of the 46 school districts that have any degree of overlap with the CBSA boundary are eligible for in-district tuition and fees. The main campus offers degrees in 87 fields of study, whereas the average number of fields of study across the institution’s five branch campuses is 6.6, indicative of far more limited offerings at branch campuses relative to the main campus.
Undergraduate unduplicated enrollment at MSU, the region’s four-year BAC, was approximately 42,500 in the 2018-2019 academic year, with the majority of students at the institution identifying as White (67%; Table 3.4, Column 2). Eight percent of undergraduates identify as Black, and 5% identify as Latinx. Among first-time enrollees, 76% are from the state of Michigan. The fall-fall retention rate for full-time (part-time) students is 91% (57%), with 81% of students graduating within six years of enrollment. In-state tuition and fees at MSU was $14,460 in 2017-2018, and the institution conferred degrees in a total of 102 fields of study, 15 more than offered at LCC.
At Great Lakes Christian College (GLCC), a four-year nonprofit competitor college, enrollment is significantly lower (163) than at either BAC (Table 3.4, Column 3). Out-of-state tuition—which all students pay, regardless of residency—is higher than tuition and fees for in-state students at either BAC ($17,220). Fall-to-fall retention rates for full-time students are lower than those observed at MSU, but higher than observed at LCC. Although GLCC’s per-FTE instructional expenditures are on par with LCC for lowest in the study area, its academic support expenditures per FTE are lowest in the region and its student services expenditures per FTE are highest. Mean earnings six and ten years post-entry are lowest at GLCC by $8,400 and $6,100 respectively (as compared to LCC), and the percentage of undergraduates who borrow is highest (61% versus 42% at MSU and 21% at LCC). Borrower three-year default rates are comparable to those observed at LCC (14% at GLCC; 15% at LCC).

**Table 3.3 Global Moran’s I Values for Census Covariates in Lansing/East Lansing (ACS 5-Year Estimates 2015-2019)**

<table>
<thead>
<tr>
<th></th>
<th>Raw Values</th>
<th></th>
<th>EB Values</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$I$</td>
<td>$p$</td>
<td>$I$</td>
<td>$P$</td>
</tr>
<tr>
<td>Land area (mi$^2$)</td>
<td>0.560</td>
<td>0.000</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Tract population</td>
<td>0.178</td>
<td>0.000</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Population density</td>
<td>0.578</td>
<td>0.000</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Households with zero vehicles</td>
<td>0.301</td>
<td>0.000</td>
<td>0.301</td>
<td>0.000</td>
</tr>
<tr>
<td>Median household income</td>
<td>0.424</td>
<td>0.000</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Poverty rate (all residents)</td>
<td>0.420</td>
<td>0.000</td>
<td>0.420</td>
<td>0.000</td>
</tr>
<tr>
<td>Poverty rate (residents of color)</td>
<td>0.283</td>
<td>0.000</td>
<td>0.283</td>
<td>0.000</td>
</tr>
<tr>
<td>Poverty rate (White residents)</td>
<td>0.358</td>
<td>0.000</td>
<td>0.358</td>
<td>0.000</td>
</tr>
<tr>
<td>Residents aged 25+ w less than AA</td>
<td>0.613</td>
<td>0.000</td>
<td>0.613</td>
<td>0.000</td>
</tr>
<tr>
<td>White</td>
<td>0.724</td>
<td>0.000</td>
<td>0.724</td>
<td>0.000</td>
</tr>
<tr>
<td>Black</td>
<td>0.737</td>
<td>0.000</td>
<td>0.737</td>
<td>0.000</td>
</tr>
<tr>
<td>Latinx</td>
<td>0.476</td>
<td>0.000</td>
<td>0.476</td>
<td>0.000</td>
</tr>
<tr>
<td>Asian</td>
<td>0.263</td>
<td>0.000</td>
<td>0.263</td>
<td>0.000</td>
</tr>
<tr>
<td>AI/AN/PI/MR/Other</td>
<td>0.268</td>
<td>0.001</td>
<td>0.268</td>
<td>0.001</td>
</tr>
<tr>
<td>Veterans</td>
<td>0.395</td>
<td>0.000</td>
<td>0.394</td>
<td>0.000</td>
</tr>
</tbody>
</table>

*Sources:* Author’s calculations from U.S. Census ACS 5yr Estimates 2015-2019

*Notes:* EB values calculated using the HCEB.est function in R’s HCEB library. EB values not estimated for land area, total population, population density, and median household income because the function only calculates these values for rate-based variables (e.g., those with a numerator and denominator).
Figure 3.2 Covariate and Local Moran’s I Maps for U.S. Census Covariates (Lansing; ACS 5-Year Estimates 2015-2019)

Panel A: Tract Population
(a) Covariate
(b) Local Moran’s I

Panel B: Households with Zero Vehicles
(a) Covariate
(b) Local Moran’s I

Panel C: Median Household Income
(a) Covariate
(b) Local Moran’s I
Panel D: Poverty Rate (All Residents)
(a) Covariate

Panel E: Poverty Rate (Residents of Color)
(a) Covariate

Panel F: Poverty Rate (White Residents)
(a) Covariate
Panel G: Residents aged 25 and older with Less than an Associate Degree
(a) Covariate
(b) Local Moran's I

Panel H: White Residents
(a) Covariate
(b) Local Moran's I

Panel I: Black Residents
(a) Covariate
(b) Local Moran's I
Panel J: Latinx Residents
(a) Covariate

Panel K: Asian Residents
(a) Covariate

Panel L: AI/AN/PI/MR/Other Residents
(a) Covariate

(b) Local Moran's I

High-High  Low-Low  Not Sig.
Panel M: Veterans

(a) Covariate

(b) Local Moran’s I

Sources: U.S. Census 2010 census tract shape files; MSA shape files; UZA shape files; state shape files; U.S. Census ACS 5-year estimates 2015-2019

Notes: Created in R. For each covariate, I include two maps: The (a) sub-panels plot the values of the covariate by census tract, with the underlying value corresponding to the color on the gradient legend. The (b) sub-panels plot the statistically significant clusters of census tracts where neighbors share like values, either high values clustered with high values (“High-High” in the above legends) or low values clustered with low values (“Low-Low” in the above legends). Clusters are identified using the local Moran’s I statistic, which measures the (dis)similarity between a focal area and its neighbors.
<table>
<thead>
<tr>
<th>Variable</th>
<th>(1) Lansing Community College</th>
<th>(2) Michigan State University</th>
<th>(3) Great Lakes Christian College</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tuition and Enrollment</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>In-district tuition &amp; fees</td>
<td>$3,690</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>In-state tuition &amp; fees</td>
<td>$6,930</td>
<td>$14,460</td>
<td>$17,220</td>
</tr>
<tr>
<td># of CIP-4 degrees offered at main campus</td>
<td>87</td>
<td>136</td>
<td>11</td>
</tr>
<tr>
<td># of CIP-4 degrees offered at branch campuses</td>
<td>6.6</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>Total undergraduate unduplicated enroll.</td>
<td>16,382</td>
<td>42,492</td>
<td>163</td>
</tr>
<tr>
<td>White</td>
<td>0.69</td>
<td>0.67</td>
<td>0.65</td>
</tr>
<tr>
<td>Black</td>
<td>0.09</td>
<td>0.08</td>
<td>0.21</td>
</tr>
<tr>
<td>Latinx</td>
<td>0.08</td>
<td>0.05</td>
<td>0.06</td>
</tr>
<tr>
<td>Asian</td>
<td>0.03</td>
<td>0.06</td>
<td>0.01</td>
</tr>
<tr>
<td>Native Hawaiian/Pacific Islander</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>American Indian</td>
<td>0.00</td>
<td>0.00</td>
<td>0.02</td>
</tr>
<tr>
<td>Multiracial</td>
<td>0.04</td>
<td>0.03</td>
<td>0.02</td>
</tr>
<tr>
<td>Unknown</td>
<td>0.04</td>
<td>0.01</td>
<td>0.00</td>
</tr>
<tr>
<td>Non-resident alien</td>
<td>0.02</td>
<td>0.10</td>
<td>0.04</td>
</tr>
<tr>
<td>Pell Grant recipients</td>
<td>0.28</td>
<td>0.22</td>
<td>0.61</td>
</tr>
<tr>
<td>First-time enrollments in-state</td>
<td>0.99</td>
<td>0.76</td>
<td>.</td>
</tr>
<tr>
<td>Per-FTE Expenditures</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Instructional</td>
<td>$5,723</td>
<td>$17,743</td>
<td>$5,800</td>
</tr>
<tr>
<td>Academic support</td>
<td>$2,777</td>
<td>$3,836</td>
<td>$1,992</td>
</tr>
<tr>
<td>Student services</td>
<td>$2,002</td>
<td>$1,429</td>
<td>$10,717</td>
</tr>
<tr>
<td>Student Outcomes</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fall-fall retention rate (full-time)</td>
<td>0.64</td>
<td>0.91</td>
<td>0.71</td>
</tr>
<tr>
<td>Fall-fall retention rate (part-time)</td>
<td>0.43</td>
<td>0.57</td>
<td>.</td>
</tr>
<tr>
<td>150% graduation rate</td>
<td>0.18</td>
<td>0.81</td>
<td>0.22</td>
</tr>
<tr>
<td>Mean earnings 6yrs post-entry</td>
<td>$29,100</td>
<td>$45,200</td>
<td>$20,700</td>
</tr>
<tr>
<td>Mean earnings 10yrs post-entry</td>
<td>$36,100</td>
<td>$63,200</td>
<td>$30,000</td>
</tr>
<tr>
<td>Borrowing rate (undergraduates)</td>
<td>0.21</td>
<td>0.42</td>
<td>0.61</td>
</tr>
<tr>
<td>Borrower 3-year repayment rate</td>
<td>0.31</td>
<td>0.67</td>
<td>0.36</td>
</tr>
<tr>
<td>Borrower 3-year cohort default rate</td>
<td>0.15</td>
<td>0.03</td>
<td>0.14</td>
</tr>
</tbody>
</table>

Sources: Author’s calculations from IPEDS 2019
Notes: Unless expressly noted with a unit of measurement (e.g., #, $), all demographic values are proportion variables.
Chicago Study Area Overview

The Chicago urbanized area spans two states (IL and IN), however the analyses here limit the geographic area to only those tracts within the Illinois state boundary (see Study Area Selection for discussion of rationale; see Figure 3.4 for geographic detail). Unlike in Lansing, which has only 2 BACs and is therefore designated a marginal education desert, there are 21 broad access public colleges across a total of 33 campuses in the Chicago study area (Figure 3.4). There are an additional 16 non-public competitor colleges across 31 campuses. Over 70% of the undergraduates in the region attend one of the broad access public colleges (Table 3.5).

Thirteen percent of households region-wide report that they do not have access to a vehicle (Table 3.5). However, when this figure is examined at the census tract level, there is significant variation in vehicle access. At the extreme, three-quarters of households lack access to a vehicle (Table 3.6). Geographically, census tracts with a higher percentage of households lacking access to a car are concentrated in the central city (Figure 3.4, Panel B). According to APTA rankings for transit service in the UZA, Chicago ranks in the top 10 UZAs for total ridership and revenue miles and is just outside the top 10 (#11) for ridership per capita.

More than 8 million people live in this region, with 49% of the total population identifying as White, 17% Black, and 24% Latinx. Racial/ethnic populations are not evenly distributed across the city, as evidenced by the census tract-level summary statistics for the study area (Table 3.6); the global Moran’s $I$ values, which indicate substantial spatial autocorrelation (Table 3.7); and the plots of covariate values and local Moran’s $I$ values (Figure 3.4, Panels A-M). For all covariates, the global Moran’s $I$ values exceed 0.50, with the highest values recorded for the percentage of census tract residents that identify as White (0.843) and Black (0.867). The average census tract is 46% White and 22% Black, but the geographic distribution is uneven.
The southeastern corner of the study area (which includes the lower portion of the City of Chicago) is predominantly Black (Figure 3.4, Panel I); visually, this pattern is a near perfect inverse of the distribution of White residents throughout the study area (Figure 3.4, Panel H). There are several clusters of high-percentage Latinx and Asian census tracts scattered throughout the study area (Figure 3.4, Panels J and K).

Overall poverty in the study area is 12%, with poverty rates higher among residents of color (18%) than among White residents (6%). Across census tracts, poverty rates range from zero to 75% (overall); when considered separately for residents of color versus White residents, tract-level poverty rates reach 75% for residents of color and 100% for White residents. Low-income census tracts and high-poverty census tracts are both clustered in the southeastern portion of the study area. Small pockets of high-income census tracts are located in the northern portion of the study area along the coastline (Figure 3.4, Panel C). Clusters of census tracts along the western periphery are likewise high-income. Region-wide, 53% of residents aged 25+ have less than an associate degree, though the level of potential educational demand varies within census tracts; in some tracts, more than 90% of residents have less than an associate degree, whereas in others, fewer than 10% do. A large cluster of tracts with few residents with less than an associate degree is visible on the northeastern edge of the study area (near Northwestern University, a highly selective R1 university; Figure 3.4, Panel G).
### Table 3.5 Summary Statistics for Chicago Study Area (2019)

<table>
<thead>
<tr>
<th></th>
<th>Chicago UZA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total population</td>
<td>7,972,951</td>
</tr>
<tr>
<td>Land area (mi&lt;sup&gt;2&lt;/sup&gt;)</td>
<td>2,482</td>
</tr>
</tbody>
</table>

**Census Demographics<sup>a</sup>**

<table>
<thead>
<tr>
<th>Demographic Category</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Households with zero vehicles</td>
<td>0.13</td>
</tr>
<tr>
<td>White</td>
<td>0.49</td>
</tr>
<tr>
<td>Black</td>
<td>0.17</td>
</tr>
<tr>
<td>Latinx</td>
<td>0.24</td>
</tr>
<tr>
<td>Asian</td>
<td>0.07</td>
</tr>
<tr>
<td>AI/AN/PI/MR/Other</td>
<td>0.04</td>
</tr>
<tr>
<td>Mean household income&lt;sup&gt;b&lt;/sup&gt;</td>
<td>$150,354</td>
</tr>
<tr>
<td>Poverty rate (all residents)</td>
<td>0.12</td>
</tr>
<tr>
<td>Poverty rate (residents of color)</td>
<td>0.18</td>
</tr>
<tr>
<td>Poverty rate (White residents)</td>
<td>0.06</td>
</tr>
<tr>
<td>Veterans</td>
<td>0.04</td>
</tr>
<tr>
<td>Residents 25+ with less than an AA</td>
<td>0.53</td>
</tr>
</tbody>
</table>

**Transit Service<sup>c</sup>**

<table>
<thead>
<tr>
<th>Service Category</th>
<th>Rank (out of 488)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total ridership</td>
<td>2</td>
</tr>
<tr>
<td>Ridership per capita</td>
<td>11</td>
</tr>
<tr>
<td>Revenue miles</td>
<td>3</td>
</tr>
</tbody>
</table>

**Broad Access Public Colleges**

<table>
<thead>
<tr>
<th>College Category</th>
<th>Count (Campuses)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Two-year college main campuses (branch campuses)</td>
<td>20 (12)</td>
</tr>
<tr>
<td>Four-year college main campuses (branch campuses)</td>
<td>1 (0)</td>
</tr>
<tr>
<td>Total BAC UG enrollment</td>
<td>327,888</td>
</tr>
</tbody>
</table>

**Non-Public Competitor Colleges**

<table>
<thead>
<tr>
<th>College Category</th>
<th>Count (Campuses)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nonprofit college main campuses (branch campuses)</td>
<td>8 (6)</td>
</tr>
<tr>
<td>For-profit college main campuses (branch campuses)</td>
<td>9 (9)</td>
</tr>
</tbody>
</table>

*Sources: Author’s calculations from U.S. Census ACS 5yr Estimates 2015-2019; APTA 2020; IPEDS 2019

*Notes: Unless expressly noted with a unit of measurement (e.g., $), all demographic values are proportion variables. <sup>a</sup>Census demographics for Chicago UZA calculated manually using guidance outlined in Chapter 8 of the U.S. Census’ Understanding and Using American Community Survey data (U.S. Census, 2020). This manual calculation is done to accommodate the exclusion of portions of the UZA that reside outside of IL. <sup>b</sup>Median Household Income cannot be re-calculated for new geographies using publicly available data due to data suppression for privacy reasons. I therefore opt to display mean household income for the study area by summing tract-level aggregate income values, then dividing this summative value by the total number of households in the study area. This final value is likely higher than the median household income in the derived study area due to the disproportionate influence of high-income households in the summation of aggregate income. <sup>c</sup>Rankings for the Chicago UZA include transit service providers that operate in Indiana. On all rankings, the IL-based agencies account for a minimum of 97% of total ridership/miles/hours in the UZA.*
Figure 3.3 Geographic Outline of Chicago Study Area (2019)

Sources: U.S. Census 2010 census tract shape files; MSA shape files; UZA shape files; state shape files; IPEDS 2019
Notes: Created in ArcGIS.
### Table 3.6 Summary Statistics for Census Tracts in the Chicago UZA (ACS 5-Year Estimates 2015-2019)

<table>
<thead>
<tr>
<th></th>
<th>N</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Land area (mi²)</td>
<td>1885</td>
<td>1.32</td>
<td>2.98</td>
<td>0.00</td>
<td>75.26</td>
</tr>
<tr>
<td>Tract population</td>
<td>1885</td>
<td>4230</td>
<td>2050</td>
<td>579</td>
<td>29089</td>
</tr>
<tr>
<td>Population density</td>
<td>1885</td>
<td>10792</td>
<td>16837</td>
<td>138</td>
<td>552750</td>
</tr>
<tr>
<td>Households with zero vehicles</td>
<td>1885</td>
<td>0.15</td>
<td>0.15</td>
<td>0.00</td>
<td>0.75</td>
</tr>
<tr>
<td>Median household income</td>
<td>1885</td>
<td>$76,180</td>
<td>$38,889</td>
<td>$11,146</td>
<td>$250,001</td>
</tr>
<tr>
<td>Poverty rate (all residents)</td>
<td>1885</td>
<td>0.14</td>
<td>0.12</td>
<td>0.00</td>
<td>0.75</td>
</tr>
<tr>
<td>Poverty rate (residents of color)</td>
<td>1885</td>
<td>0.16</td>
<td>0.13</td>
<td>0.00</td>
<td>0.74</td>
</tr>
<tr>
<td>Poverty rate (White residents)</td>
<td>1853</td>
<td>0.12</td>
<td>0.18</td>
<td>0.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Residents aged 25+ w less than AA</td>
<td>1885</td>
<td>0.55</td>
<td>0.23</td>
<td>0.03</td>
<td>0.96</td>
</tr>
<tr>
<td>White</td>
<td>1885</td>
<td>0.46</td>
<td>0.31</td>
<td>0.00</td>
<td>0.97</td>
</tr>
<tr>
<td>Black</td>
<td>1885</td>
<td>0.22</td>
<td>0.32</td>
<td>0.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Latinx</td>
<td>1885</td>
<td>0.23</td>
<td>0.25</td>
<td>0.00</td>
<td>0.99</td>
</tr>
<tr>
<td>Asian</td>
<td>1885</td>
<td>0.07</td>
<td>0.09</td>
<td>0.00</td>
<td>0.86</td>
</tr>
<tr>
<td>AI/AN/PI/MR/Other</td>
<td>1885</td>
<td>0.02</td>
<td>0.02</td>
<td>0.00</td>
<td>0.16</td>
</tr>
<tr>
<td>Veterans</td>
<td>1885</td>
<td>0.04</td>
<td>0.02</td>
<td>0.00</td>
<td>0.20</td>
</tr>
</tbody>
</table>

**Sources:** Author’s calculations from U.S. Census ACS 5yr Estimates 2015-2019

**Notes:** Population density calculated as tract population divided by land area. Unless expressly noted with a unit of measurement (e.g., mi², $), all demographic values are proportion variables.

### Table 3.7 Global Moran’s I Values for Chicago Covariates of Interest (ACS 5-Year Estimates 2015-2019)

<table>
<thead>
<tr>
<th></th>
<th>Raw Values</th>
<th>EB Values</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>I</td>
<td>p</td>
</tr>
<tr>
<td>Land area (mi²)</td>
<td>0.531</td>
<td>0.000</td>
</tr>
<tr>
<td>Tract population</td>
<td>0.386</td>
<td>0.000</td>
</tr>
<tr>
<td>Population density</td>
<td>0.344</td>
<td>0.000</td>
</tr>
<tr>
<td>Households with zero vehicles</td>
<td>0.772</td>
<td>0.000</td>
</tr>
<tr>
<td>Median household income</td>
<td>0.697</td>
<td>0.000</td>
</tr>
<tr>
<td>Poverty rate (all residents)</td>
<td>0.668</td>
<td>0.000</td>
</tr>
<tr>
<td>Poverty rate (residents of color)</td>
<td>0.518</td>
<td>0.000</td>
</tr>
<tr>
<td>Poverty rate (White residents)</td>
<td>0.301</td>
<td>0.000</td>
</tr>
<tr>
<td>Residents aged 25+ w less than AA</td>
<td>0.816</td>
<td>0.000</td>
</tr>
<tr>
<td>White</td>
<td>0.843</td>
<td>0.000</td>
</tr>
<tr>
<td>Black</td>
<td>0.867</td>
<td>0.000</td>
</tr>
<tr>
<td>Latinx</td>
<td>0.776</td>
<td>0.000</td>
</tr>
<tr>
<td>Asian</td>
<td>0.645</td>
<td>0.000</td>
</tr>
<tr>
<td>AI/AN/PI/MR/Other</td>
<td>0.223</td>
<td>0.001</td>
</tr>
<tr>
<td>Veterans</td>
<td>0.419</td>
<td>0.000</td>
</tr>
</tbody>
</table>

**Sources:** U.S. Census ACS 5yr Estimates 2015-2019

**Notes:** EB values calculated using the HCEB.est function in R’s HCEB library. EB values not estimated for land area, total population, and population density because the function only calculates these values for rate-based variables (e.g., those with a numerator and denominator).
Figure 3.4 Covariate, Local Moran’s I, and CV Maps for Chicago (ACS 5-Year Estimates 2015-2019)

Panel A: Tract Population
(a) Covariate
(b) Local Moran’s I

Panel B: Households with Zero Vehicles
(a) Covariate
(b) Local Moran’s I

Panel C: Median Household Income
(a) Covariate
(b) Local Moran’s I
Panel D: Poverty Rate (All Residents)

(a) Covariate

(b) Local Moran's I

Panel E: Poverty Rate (Residents of Color)

(a) Covariate

(b) Local Moran's I

Panel F: Poverty Rate (White Residents)

(a) Covariate

(b) Local Moran's I
Panel G: Residents aged 25 and older with Less than an Associate Degree

(a) Covariate

(b) Local Moran's I

Panel H: White Residents

(a) Covariate

(b) Local Moran's I

Panel I: Black Residents

(a) Covariate

(b) Local Moran's I
Panel M: Veterans

Sources: U.S. Census 2010 census tract shape files; MSA shape files; UZA shape files; state shape files; U.S. Census ACS 5-year estimates 2015-2019

Notes: Created in R. For each covariate, I include two maps: The (a) sub-panels plot the values of the covariate by census tract, with the underlying value corresponding to the color on the gradient legend. The (b) sub-panels plot the statistically significant clusters of census tracts where neighbors share like values, either high values clustered with high values (“High-High” in the above legends) or low values clustered with low values (“Low-Low” in the above legends). Clusters are identified using the local Moran’s I statistic, which measures the (dis)similarity between a focal area and its neighbors.
Table 3.8 Summary Statistics for Less Selective Colleges in Chicago (IPEDS 2019)

<table>
<thead>
<tr>
<th>Variable</th>
<th>N</th>
<th>Mean</th>
<th>SD</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Tuition and Enrollment</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>In-district tuition &amp; fees</td>
<td>20</td>
<td>$3,889</td>
<td>$524</td>
<td>$3,180</td>
<td>$5,093</td>
</tr>
<tr>
<td>In-state tuition &amp; fees</td>
<td>21</td>
<td>$10,074</td>
<td>$1,303</td>
<td>$8,894</td>
<td>$13,874</td>
</tr>
<tr>
<td># of CIP-4 degrees offered at main campus</td>
<td>21</td>
<td>42.10</td>
<td>21.04</td>
<td>12.00</td>
<td>104.00</td>
</tr>
<tr>
<td># of CIP-4 degrees offered at branch campus</td>
<td>12</td>
<td>7.17</td>
<td>8.45</td>
<td>1.00</td>
<td>31.00</td>
</tr>
<tr>
<td>Total UG unduplicated enroll.</td>
<td>21</td>
<td>15,614</td>
<td>8,550</td>
<td>4,607</td>
<td>41,901</td>
</tr>
<tr>
<td>White</td>
<td>21</td>
<td>0.30</td>
<td>0.20</td>
<td>0.03</td>
<td>0.63</td>
</tr>
<tr>
<td>Black</td>
<td>21</td>
<td>0.21</td>
<td>0.24</td>
<td>0.02</td>
<td>0.81</td>
</tr>
<tr>
<td>Latinx</td>
<td>21</td>
<td>0.36</td>
<td>0.19</td>
<td>0.12</td>
<td>0.85</td>
</tr>
<tr>
<td>Asian</td>
<td>21</td>
<td>0.06</td>
<td>0.06</td>
<td>0.01</td>
<td>0.20</td>
</tr>
<tr>
<td>Native Hawaiian/Pacific Islander</td>
<td>21</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.01</td>
</tr>
<tr>
<td>American Indian</td>
<td>21</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Multiracial</td>
<td>21</td>
<td>0.02</td>
<td>0.01</td>
<td>0.01</td>
<td>0.04</td>
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<tr>
<td>Unknown</td>
<td>21</td>
<td>0.03</td>
<td>0.03</td>
<td>0.00</td>
<td>0.13</td>
</tr>
<tr>
<td>Non-resident alien</td>
<td>21</td>
<td>0.01</td>
<td>0.01</td>
<td>0.00</td>
<td>0.07</td>
</tr>
<tr>
<td>Pell Grant recipients</td>
<td>21</td>
<td>0.29</td>
<td>0.10</td>
<td>0.17</td>
<td>0.51</td>
</tr>
<tr>
<td>First-time enrollments in-state</td>
<td>21</td>
<td>0.98</td>
<td>0.02</td>
<td>0.90</td>
<td>1.00</td>
</tr>
<tr>
<td><strong>Per-FTE Expenditures</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Instructional</td>
<td>21</td>
<td>$7,897</td>
<td>$4,823</td>
<td>$2,285</td>
<td>$26,515</td>
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<tr>
<td>Academic support</td>
<td>21</td>
<td>$1,605</td>
<td>$1,442</td>
<td>$436</td>
<td>$6,478</td>
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<td>Student services</td>
<td>21</td>
<td>$1,951</td>
<td>$581</td>
<td>$1,246</td>
<td>$3,425</td>
</tr>
<tr>
<td><strong>Student outcomes</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fall-fall retention rate (full-time)</td>
<td>21</td>
<td>0.64</td>
<td>0.10</td>
<td>0.45</td>
<td>0.79</td>
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<tr>
<td>Fall-fall retention rate (part-time)</td>
<td>21</td>
<td>0.43</td>
<td>0.11</td>
<td>0.14</td>
<td>0.59</td>
</tr>
<tr>
<td>150% graduation rate</td>
<td>21</td>
<td>0.26</td>
<td>0.09</td>
<td>0.17</td>
<td>0.61</td>
</tr>
<tr>
<td>Mean earnings 6yrs post-entry</td>
<td>21</td>
<td>$29,167</td>
<td>$4,597</td>
<td>$23,100</td>
<td>$43,100</td>
</tr>
<tr>
<td>Mean earnings 10yrs post-entry</td>
<td>21</td>
<td>$36,657</td>
<td>$7,111</td>
<td>$27,900</td>
<td>$61,300</td>
</tr>
<tr>
<td>Borrowing rate (undergraduates)</td>
<td>21</td>
<td>0.06</td>
<td>0.08</td>
<td>0.00</td>
<td>0.38</td>
</tr>
<tr>
<td>Borrower 3-year repayment rate</td>
<td>20</td>
<td>0.38</td>
<td>0.13</td>
<td>0.12</td>
<td>0.69</td>
</tr>
<tr>
<td>Borrower 3-year cohort default rate</td>
<td>20</td>
<td>0.13</td>
<td>0.05</td>
<td>0.03</td>
<td>0.23</td>
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</table>
### Panel B. Nonprofit Competitor Colleges (N=8)

<table>
<thead>
<tr>
<th>Tuition and Enrollment</th>
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<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Out-of-state tuition &amp; fees</td>
<td>8</td>
<td>$23,963</td>
<td>$11,060</td>
<td>$11,010</td>
</tr>
<tr>
<td># of CIP-4 degrees offered at main campus</td>
<td>8</td>
<td>24.38</td>
<td>20.63</td>
<td>5.00</td>
</tr>
<tr>
<td># of CIP-4 degrees offered at branch campus</td>
<td>6</td>
<td>9.17</td>
<td>3.60</td>
<td>2.00</td>
</tr>
<tr>
<td>Total UG unduplicated enroll.</td>
<td>8</td>
<td>2,217</td>
<td>2,362</td>
<td>247</td>
</tr>
<tr>
<td>White</td>
<td>8</td>
<td>0.32</td>
<td>0.25</td>
<td>0.01</td>
</tr>
<tr>
<td>Black</td>
<td>8</td>
<td>0.22</td>
<td>0.22</td>
<td>0.02</td>
</tr>
<tr>
<td>Latinx</td>
<td>8</td>
<td>0.31</td>
<td>0.24</td>
<td>0.06</td>
</tr>
<tr>
<td>Asian</td>
<td>8</td>
<td>0.04</td>
<td>0.02</td>
<td>0.01</td>
</tr>
<tr>
<td>Native Hawaiian/Pacific Islander</td>
<td>8</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>American Indian</td>
<td>8</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Multiracial</td>
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<td>0.02</td>
<td>0.01</td>
</tr>
<tr>
<td>Unknown</td>
<td>8</td>
<td>0.02</td>
<td>0.03</td>
<td>0.00</td>
</tr>
<tr>
<td>Non-resident alien</td>
<td>8</td>
<td>0.05</td>
<td>0.07</td>
<td>0.00</td>
</tr>
<tr>
<td>Pell Grant recipients</td>
<td>8</td>
<td>0.54</td>
<td>0.19</td>
<td>0.21</td>
</tr>
<tr>
<td>First-time enrollments in-state</td>
<td>6</td>
<td>0.69</td>
<td>0.29</td>
<td>0.23</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Per-FTE Expenditures</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Instructional</td>
<td>8</td>
<td>$7,807</td>
<td>$3,771</td>
<td>$3,046</td>
</tr>
<tr>
<td>Academic support</td>
<td>8</td>
<td>$2,009</td>
<td>$1,558</td>
<td>$622</td>
</tr>
<tr>
<td>Student services</td>
<td>8</td>
<td>$4,622</td>
<td>$2,626</td>
<td>$1,420</td>
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</table>

<table>
<thead>
<tr>
<th>Student outcomes</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Fall-fall retention rate (full-time)</td>
<td>7</td>
<td>0.62</td>
<td>0.22</td>
<td>0.30</td>
</tr>
<tr>
<td>Fall-fall retention rate (part-time)</td>
<td>8</td>
<td>0.42</td>
<td>0.28</td>
<td>0.20</td>
</tr>
<tr>
<td>150% graduation rate</td>
<td>8</td>
<td>0.39</td>
<td>0.26</td>
<td>0.11</td>
</tr>
<tr>
<td>Mean earnings 6yrs post-entry</td>
<td>8</td>
<td>$31,638</td>
<td>$8,029</td>
<td>$22,500</td>
</tr>
<tr>
<td>Mean earnings 10yrs post-entry</td>
<td>8</td>
<td>$39,888</td>
<td>$11,101</td>
<td>$29,000</td>
</tr>
<tr>
<td>Borrowing rate (undergraduates)</td>
<td>8</td>
<td>0.57</td>
<td>0.25</td>
<td>0.06</td>
</tr>
<tr>
<td>Borrower 3-year repayment rate</td>
<td>7</td>
<td>0.45</td>
<td>0.23</td>
<td>0.16</td>
</tr>
<tr>
<td>Borrower 3-year cohort default rate</td>
<td>7</td>
<td>0.10</td>
<td>0.08</td>
<td>0.01</td>
</tr>
</tbody>
</table>
Panel C. For-Profit Competitor Colleges (N=9)

<table>
<thead>
<tr>
<th>Tuition and Enrollment</th>
<th>4</th>
<th>$17,625</th>
<th>$2,368</th>
<th>$14,325</th>
<th>$19,900</th>
</tr>
</thead>
<tbody>
<tr>
<td>Out-of-state tuition &amp; fees</td>
<td>5</td>
<td>$23,865</td>
<td>$4,453</td>
<td>$17,316</td>
<td>$28,377</td>
</tr>
<tr>
<td># of CIP-4 degrees offered at main campus</td>
<td>9</td>
<td>5.44</td>
<td>5.39</td>
<td>2.00</td>
<td>19.00</td>
</tr>
<tr>
<td># of CIP-4 degrees offered at branch campus</td>
<td>10.00</td>
<td>7.04</td>
<td>1.00</td>
<td>17.00</td>
<td></td>
</tr>
<tr>
<td>Total UG unduplicated enroll.</td>
<td>9</td>
<td>5,604</td>
<td>9,729</td>
<td>211</td>
<td>23,604</td>
</tr>
<tr>
<td># of CIP-4 degrees offered at main campus</td>
<td>9</td>
<td>5.44</td>
<td>5.39</td>
<td>2.00</td>
<td>19.00</td>
</tr>
<tr>
<td># of CIP-4 degrees offered at branch campus</td>
<td>9</td>
<td>5.44</td>
<td>5.39</td>
<td>2.00</td>
<td>19.00</td>
</tr>
<tr>
<td>Per-FTE Expenditures</td>
<td>9</td>
<td>$4,729</td>
<td>$3,127</td>
<td>$1,615</td>
<td>$11,813</td>
</tr>
<tr>
<td>Instructional</td>
<td>9</td>
<td>$1,785</td>
<td>$1,582</td>
<td>0</td>
<td>$4,111</td>
</tr>
<tr>
<td>Academic support</td>
<td>9</td>
<td>$1,531</td>
<td>$1,848</td>
<td>0</td>
<td>$5,651</td>
</tr>
<tr>
<td>Student services</td>
<td>9</td>
<td>$34,786</td>
<td>$16,489</td>
<td>$18,500</td>
<td>$69,800</td>
</tr>
<tr>
<td>Student outcomes</td>
<td>7</td>
<td>$41,414</td>
<td>$11,665</td>
<td>$25,200</td>
<td>$60,400</td>
</tr>
<tr>
<td>Mean earnings 6yrs post-entry</td>
<td>7</td>
<td>$41,414</td>
<td>$11,665</td>
<td>$25,200</td>
<td>$60,400</td>
</tr>
<tr>
<td>Mean earnings 10yrs post-entry</td>
<td>7</td>
<td>$41,414</td>
<td>$11,665</td>
<td>$25,200</td>
<td>$60,400</td>
</tr>
<tr>
<td>Borrowing rate (undergraduates)</td>
<td>9</td>
<td>0.59</td>
<td>0.25</td>
<td>0.01</td>
<td>0.86</td>
</tr>
<tr>
<td>Borrower 3-year repayment rate</td>
<td>9</td>
<td>0.36</td>
<td>0.16</td>
<td>0.14</td>
<td>0.60</td>
</tr>
<tr>
<td>Borrower 3-year cohort default rate</td>
<td>9</td>
<td>0.13</td>
<td>0.06</td>
<td>0.04</td>
<td>0.23</td>
</tr>
</tbody>
</table>

Source: Author’s calculations from IPEDS 2019
Notes: Unless expressly noted with a unit of measurement (e.g., #, $), all demographic values are proportion variables.
Over seventy percent of students (more than 320,000) attend one of the region’s 21 broad access public colleges (Table 3.5), where institutional enrollment averages approximately 15,600 (Table 3.8). These BACs, all but one of which are two-year colleges, are predominantly POC: On average, 21% of students are Black and 36% Latinx; 30% are White. In-state enrollment rates among first-time students average 98%, though no BAC enrolls fewer than 90% in-state first-year students. Average fall-to-fall retention for full-time (part-time) students enrolled at BACs is 64% (43%). Three-year graduation rates (150% time) range from a low of 17% to a high of 61% (mean = 26%, s.d. = 9%). Average in-district tuition and fees is $3,889 at the 20 community colleges, whereas average in-state tuition and fees across all BACs is $10,074. These colleges offer degrees in as few as 12 fields of study and as many as 104 (mean = 42, s.d. = 21). Branch campuses, of which there are twelve, offer degrees in an average of 7.17 fields of study.

As in Lansing, two-year colleges in the Chicago region charge different tuition depending on whether a student’s place of residence is in- versus out-of-district. Students residing in the census tracts within the boundaries of the City of Chicago (see the solid black outline in Figure 3.3) are eligible for in-district tuition at all eleven City Colleges of Chicago main and branch campuses. Students residing in census tracts outside the City of Chicago are eligible for in-district tuition at one of the remaining 16 two-year BACs.

Due to the larger number of competitor colleges in the Chicago study area, I present institutional summary statistics separately for nonprofit competitor colleges (NFP; Table 3.8, Panel B) and for-profit competitor colleges (FP; Table 3.8, Panel C). Average tuition and fees at NFP competitor colleges is more than double the in-state amount at BACs. Out-of-state tuition and fees that charge a single rate regardless of program are less than half the level at BACs; at
the five FP competitors with differential pricing by program, the average of the top three programs is nearly identical to the NFP tuition and fees.

The average competitor college—regardless of sector—has lower unduplicated undergraduate enrollment than the observed average at BACs (2,217 at NFPS, 5,604 at FPs, and more than 15,000 at BACs). Racial demographics at NFP competitor colleges parallel the demographics at BACs (32% White, 22% Black, 31% Latinx), though a smaller proportion of first-time students are Illinois residents (average of 69% across NFP competitor colleges). The percentage of Black students is highest at FP competitor colleges (36%), whereas the percentage of White students is lowest at these same institutions (24%), in keeping with documented evidence that for-profit colleges enroll Black students at disproportionately high rates (US ED NCES, 2020b). Although the average in-state enrollment rate at the five FP competitor colleges that report data is high—80%—the minimum value is 9% (DeVry University – Illinois, which enrolls students primarily through distance education programs). Average per-FTE expenditures are highest at NFP competitor colleges for academic support and student services expenditures. Average per-FTE instructional spending is comparable at BACs and NFPS ($7,897 versus $7,807). Per-FTE academic support expenditures are comparable at BACs and FP colleges, and student services expenditures are slightly higher at BACs than FP colleges.

With respect to student outcomes, fall-to-fall retention rates are similar between BACs and NFPS for both full- and part-time students (64% full-time in both sectors; 43% and 42% for part-time retention at BACs and NFPS, respectively. Part-time retention rates are highest at FP competitor colleges (57%). Rates of 150% graduation are highest at FP competitor colleges (50%) and lowest at BACs (26%). Likewise, six and ten-year mean earnings are highest at FPs and lowest at BACs. A much higher percentage of students borrow at NFP and FP colleges (57%
and 59%, respectively, versus 6% at BACs), though three-year default rates among those who borrow are lower at NFPs than at BACs or FPs (10% versus 13% in both sectors).

Limitations

Before turning to a detailed accounting of the methodologies and findings, I first survey the limitations that underlie the study, of which there are several related to data availability, study design, and the linkage of theory and methodology. I begin by examining three central data limitations. First, because I rely on publicly available U.S. Census data, I cannot incorporate into my accessibility measure the number of students from a given census tract enrolled at each local institution. Without this information, I cannot examine variation in accessibility for the set of students enrolled at a specific broad college. I also cannot identify the census tracts where currently enrolled commuter students reside. By example, accessibility may be high in census tracts where few, if any, students enroll in a local college, but I cannot differentiate tracts with many versus few commuter students using these data. Second, I cannot capture trip-chaining or parking availability in the measure of geographic accessibility. Trip-chaining is the practice of incorporating multiple destinations into the same trip (Primerano et al., 2008). As is true for mobility generally, trip-chaining behavior on public transit requires a greater time commitment than trip-chaining when the car is the primary mode of transportation. This additional time commitment can lead transit-reliant individuals to adapt their behavior to minimize the need to trip-chain (Blumenberg & Agrawal, 2014). Future research could address this limitation by surveying students about their travel behavior then, using this information, investigate how accessibility varies depending on an individual’s degree of trip-chaining.

Third, ACS is itself limited in its capacity to provide detailed information on population demographics. ACS replaced the decennial census in 2000, providing researchers with annual
updates to information on local geographies (e.g., census tracts). However, the expansion in frequency comes with a decrease in precision (Jung et al., 2019a). Fewer households are sampled each year than were sampled in the decennial census, resulting in larger and more variable margins of error (MOE; Folch et al., 2016). MOEs are typically smaller in suburban than in rural areas, and higher in low- versus high-income areas (Spielman et al., 2014). Scholars have acknowledged this increased uncertainty by calculating and mapping for each covariate the by-tract coefficient of variation (CV; Folch et al., 2016) and by adjusting covariate estimates using an EB-smoothing estimator that accounts for varying MOEs, then re-calculating the Global Moran’s I (Anselin, 2018; Jung et al., 2019a; Jung et al., 2019b). The former visually displays the scale of the uncertainty, whereas the latter incorporates into adjusted covariate values the degree of uncertainty. CV maps for the covariates in each study area are included in Figure A.3 and Figure A.4; included in Table 3.3 and Table 3.7 above are Global Moran’s I values calculated using both the raw and EB-smoothed values of each covariate.

As it relates to study design, there are at least four limitations. First, the study is purely descriptive and thus exploratory in nature; though transportation is likely a barrier to both enrollment and subsequent persistence (e.g., Clay & Valentine, 2021), I am not able to descriptively link student-level enrollment behavior to transportation, nor can I causally assess either hypothesis. Second, I exclude for-profit and nonprofit colleges from the sample for which I calculate a summative accessibility index value (see Chapter 6). I do this because I am interested in better understanding geographic accessibility to a set of institutions that are particularly relevant in current policy conversations about free college programs. That said,

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28 The CV “measures the relative amount of sampling error that is associated with a sample estimate. The CV is calculated as the ratio of the SE for an estimate to the estimate itself (Xhat)” (U.S. Census, 2020, p. 55).
estimating separate accessibility indices for each sector could allow for exploration of whether and how summative accessibility varies across sectors.

Third, the study is cross-sectional and only for two geographic regions. Both accessibility and its relationship to neighborhood demographics change dynamically alongside population migration and shifts in the built environment (Williams & Wang, 2014). Furthermore, local conditions will almost certainly yield different results across regions (e.g., Krause, 2017). These time and place choices serve as a test case for the presence of variable accessibility but are limitations in that they constrain external validity. Analyses in more study areas and for post-pandemic travel would offer additional evidence of the continued variability of accessibility.

Lastly, the results of my analyses are almost necessarily influenced by my choice of the census tract as the areal unit of analysis. Census tracts exist for the purposes of data gathering (Wong, 2009) and their boundaries are not designed to correspond to socially enumerated neighborhoods. Because boundaries “are often created artificially or in an ad hoc manner and thus can be changed” (Wong, 2009, p. 105), the results of analyses that rely on different areal units could likewise change (see also Manley, 2014). This problem, known as the modifiable areal unit problem (MAUP), can manifest in two ways: the scale effect or the zonation effect. With the scale effect, “units that are too large may mis-specify context by missing important within-unit variation. . . . Conversely, units that are too small may mis-specify context by including local variation that is not meaningfully experienced by residents of a particular context” (Fowler et al., 2020, p. 157). The zonation effect occurs when the total number of areal units remains constant but the results change as the boundaries change (Wong, 2009).

In this study, the MAUP could manifest through my choice of census tract as the analytic unit, as opposed to county (larger areal unit that nests census tracts) or census block group
(smaller, nested in census tracts). One strategy for diagnosing the severity of the MAUP is to treat the scale of the areal unit as an object of interest; in this case, the researcher re-runs the analyses at several different scales, then compares the results. I do not conduct such a robustness check because the use of county would mask much of the variation in accessibility that I anticipate observing and demographic information is not publicly available at the block group level. That said, Fowler et al. (2020) contend that MAUP is only a problem in those cases where “the degree to which zoning and scale choices affect the context that is ultimately assigned to individuals” (p. 158). Using restricted Census data that enables demographic comparisons between block groups and tracts, the authors find that “tracts are probably not over-generalizing context by grouping dissimilar context together” (p. 162). Based on their findings, the reliance on census tracts, though imperfect, limits the scale of measurement error and does not appear to worsen the MAUP. A second strategy, beyond the scope of this study, is to allow respondents to choose the scale; here, the closest parallel would be estimating accessibility to broad access colleges based on the home addresses of residents considering whether to enroll in college. Neither strategy, nor others explored by spatial analysts, fully removes the potential for the MAUP to influence analytic results (Floch & Le Saout, 2018; Manley, 2014).

Though a conceptual rather than methodological limitation, the choice of census tract likewise reflects a compromise in the operationalization of neighborhoods. Treating the census tract as a neighborhood side-steps the long-standing debate among urban scholars about how best to define neighborhood boundaries (Coulton et al., 2013; Hwang, 2016). Census tracts are inadequate proxies in that their boundaries do not reflect residents’ perceptions (Coulton et al., 2013). The most straightforward adaptation would be to link census tracts to established delineations of neighborhoods within the study areas to understand how transportation
accessibility does or does not cluster within these neighborhoods. Doing so would require the incorporation of neighborhood boundaries explicitly derived to better capture the social construction of the neighborhood, though this approach would still require methodological choices related to whose conception of neighborhood boundaries ought to be prioritized.
Chapter 4 Empirical Approach to Examining the Relative Accessibility of Less Selective Colleges

In this chapter, I detail the methodologies employed in Part I of the study, in which I examine the demographics of areas surrounding less selective college campuses and compare average outcomes at the colleges most accessible to census tract sub-groups. In the first RQ, I differentiate between campus neighborhoods based on the college’s sector (public versus non-public). In the second RQ, I identify census tracts that have high versus low poverty rates and tracts with a high proportion of people of color (POC) and tracts with a high proportion of White residents, then compare average outcomes at the most accessible institutions to each sub-group.

RQ1: Evaluation of College Locations

The first research question evaluates the demographics of the areas immediately surrounding public and private less selective colleges’ physical locations, seeking to understand whether the demographics of these areas differ depending on the type of college located within the neighborhood. I hypothesize that less selective colleges will be located in neighborhoods that are lower-income and that have a larger population of Black, Latinx, Asian, or American Indian/Alaska Native/Pacific Islander/Multiracial/Other (AI/AN/PI/MR/Other) residents. When examining neighborhood demographics by sector, it is less clear whether for-profit colleges will be in neighborhoods that are disproportionately Black (Dache-Gerbino et al., 2018; Student Borrower Protection Center, 2021) or whether these colleges will avoid predominantly Black neighborhoods (Fisher, 2012). I draw on Fisher’s (2012) findings to hypothesize that main campuses will have a higher percentage of Black residents whereas branch campuses will have a
higher percentage of Asian and Latinx residents. I further hypothesize that income will be lower in the neighborhoods surrounding broad access public colleges’ branch campuses than in the areas surrounding main campuses (Briscoe & De Oliver, 2006; Kenyon, 2011).

This analysis begins by identifying the census tracts in which college campuses are located (e.g., destination census tracts). The orientation to the college’s census tract as the unit of analysis can result in data anomalies if the college physically comprises the entirety of a census tract and/or offers residential housing. In these cases, the ACS-reported demographics would either be filtered out using the housing criteria or capture the college’s student population rather than the population of the adjacent community. To ensure that I capture the demographics of each college campus’s surrounding area, I first identify the tract in which each campus is located then evaluate two questions: (1) whether the college offers on-campus housing, and (2) whether the geography of the census tract is dominated by the physical footprint of the campus. In all but six cases, the college does not offer housing and the campus does not physically dominate the census tract; for these non-residential campuses, I keep the focal census tract in the analytic sample since I expect that the ACS demographics reflect residential areas rather than the college itself. Five of the six remaining colleges offer residential housing, though the housing is either not in the college’s census tract (n=1) or comprises a very small part of the tract, either by population or land area (n=4). Therefore, in these five cases, I follow the same procedure as above; the focal census tract is preserved in the analytic sample despite the likelihood that its population is both on-campus students and surrounding residences. The final college, a four-year BAC in Lansing, physically dominates its census tract as well as several neighboring census tracts. Although I will ultimately exclude these college-dominated census tracts from the analytic sample for this research question, I first use them to identify the college’s set of neighbor tracts.
The next step involves identifying which nearby census tracts should be part of the college’s “neighborhood unit.” Perceptions of neighborhood size vary based on individual and environmental factors. In Los Angeles, California, most residents view their neighborhood as being no larger than the area within a 15-minute walk (Pebley & Sastry, 2009); in Seattle, Washington, most residents say their neighborhood is no bigger than a half-mile radius around home (Guest & Lee, 1984; see also Coulton et al., 2013, who find a median neighborhood size of 0.98 sqmi across multiple cities). Furthermore, suburban residents’ perceptions of neighborhood size exceed those of residents in densely populated urban areas (Haney & Knowles, 1978).

Since I rely on census tracts as my operationalization of neighborhood—a limitation that I discuss at the end of this chapter—I must consider how variation in perceptions of neighborhood size intersects with the size of tracts in which college campuses are located. Census tracts vary widely in their geographic scale because the U.S. Census attempts to identify a target population size rather than a target land area. Since many of the college campuses in my sample are in densely populated areas, the tracts in which these campuses are located are often geographically small (a median size of 0.74 square miles; the cut-off size for a census tract to be considered “urban” is 3.0 square miles; U.S. Census, n.d.c). Therefore, in most cases, treating only each campus’s tract as the unit of analysis would result in some college “neighborhoods” that are geographically smaller than individual perceptions and others that are substantially larger than these same perceptions. Inversely, a generalized approach that identifies all neighbor tracts using a common neighbor definition, such as the queen’s contiguity matrix, may sufficiently proxy for neighborhood size in densely populated areas but would result in too-large neighborhood areas for campuses located in less-dense tracts.
Given the shortcomings of each of these strategies, I instead opt for a hybrid approach. First, I identify all census tracts with a weighted centroid that is within ¾ of a mile, measured by network distance, from the weighted centroid of the tract in which each college is located. This distance is chosen based on (1) the average walking speed assumed in the CDAC OD data (3 miles per hour) and (2) Pebley and Sastry’s (2009) finding that the majority of residents identify their neighborhoods as the area within a 15-minute walk of home.

Second, for college census tracts without any neighbors within a ¾ mile radius, I identify any nearby census tract where the weighted centroid is within a certain straight-line distance of the college tract’s weighted centroid. This distance differs in the two study areas and is chosen based on the largest college-occupying tract in the region. I use as my distance the radius of the smallest circle required to fully encompass the census tract’s land area. In Chicago, where the largest tract with a college is 29.6 square miles, this radial distance is 4.4 miles; no college tracts in Lansing satisfy this secondary criterion. In the extreme case, this approach would result in the inclusion of only the census tract in question, though this does not ultimately occur in the analytic sample. Although I cannot claim that the neighborhood units identified with this two-pronged process precisely correspond to residents’ perceptions, it better captures potential neighborhood size than using either colleges’ census tracts alone or a college’s census tract and all its neighboring census tracts.

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29 This process is done using the Minimum Bounding Geometry tool in ArcGIS Pro.
30 Analysis of these two alternative definitions of college neighborhoods reveals that the results in both study areas are generally robust to the adjacent-neighbor definition or college tract-only definition. There are a total of 6 variables in the Lansing study area and 8 in the Chicago study area where the results of the KW test are not consistently aligned across all three definitions. In four of the Lansing variables, the p-value for the KW test is statistically significant using the preferred definition and the queen’s contiguity neighbor definition, but not statistically significant when using the college’s census tract alone. In the fifth case, the test statistic is significant in the preferred definition and in the college tract only definition. In the sixth case, only in the preferred definition does the p-value on the KW test signal statistical significance at the 5% level. In Chicago, two of the variables only have statistically significant differences in rank-sum means in the preferred definition; in both cases, the mean values across the three neighbor specifications are similar. In the remaining six cases, the rank-sum means of the variable is
Having identified all tracts that comprise each college’s neighborhood unit, I compare the demographics of less selective public colleges’ neighborhood tracts to the demographics of three additional census tract groups: (1) less selective for-profit colleges’ neighborhood tracts, (2) less selective nonprofit colleges’ neighborhood tracts, and (3) all remaining tracts in the study area. Among broad access public colleges in Chicago, I further evaluate whether there are demographic differences between broad access colleges’ main versus branch campus neighborhood tracts.31 The first stage of the comparison is done using the Kruskal-Wallis (1952) test, which is a non-parametric version of an ANOVA that compares the rank means between two or more sub-groups to determine the likelihood that the sub-samples draw from the same population (see its application in Hegerty, 2016; see also Coshall, 1988). The non-parametric nature of the test is especially important when comparing samples with non-normal distributions and heterogeneity of variance, two conditions present in the analytic sample.32 Because the test compares the rank-means between groups, the results cannot be interpreted as a difference in group means but instead a difference in groups’ average rankings on a given variable.

Next, for variables where the results of the KW are statistically significant at the 5% level, I conduct a post-hoc Conover-Iman pairwise test with the stepwise Holm adjustment for multiple hypothesis testing. The KW collapses to a Mann-Whitney U test in the presence of only statistically significantly different across groups in both the preferred specification and in the queen’s contiguity neighbor definition.

31 I present unweighted, rather than population-weighted, tract-level summary statistics throughout the study because my central interest is in the demographic composition of census tracts with shared traits (e.g., all tracts around broad access colleges) and whether tract-level composition differs based on these traits. As a sensitivity check, I re-estimate all proportion variables with population weighting and find only 24 instances across a total of 374 summary statistics in which the observed averages differ by more than two percentage points. In no cases would the differing results using population-weighted estimates change the overarching narrative presented throughout.

32 Using the Shapiro-Wilk test, I can reject the null hypothesis of normal distribution for all covariates and sub-groups in the Chicago study area. In the Lansing study area, I can reject the null hypothesis in 28 of the 45 tests. I can reject the Levene’s test null hypothesis of equal variance in eight of the 15 covariates for Lansing, and 13 of the 15 covariates in Chicago.
two groups; therefore, there is no need to conduct any post-hoc testing in the supplemental
evaluation of broad access public colleges’ main versus branch campus neighborhood
demographics in Chicago. Post-hoc testing enables me to determine, for variables with a
statistically significant difference in rank-sum means across the three sub-groups, which pairs of
sub-groups have statistically significant differences in rank-sum means. The Conover-Iman
(1979) test, which uses rank sums much like the KW test to determine whether sub-groups are
drawn from the same population, balances the trade-off between Type I and Type II errors when
conducting post-hoc comparison tests (Conover & Iman, 1979).

Because post-hoc pairwise tests involve testing multiple hypotheses using the same data,
the researcher risks an increase in the family wise error rate (FWER), or the probability of at
least one Type I error (false positive) across all tests (Schochet, 2008). To correct for this, I
employ a family wise error rate (FWER) adjustment procedure—specifically, the Holm stepwise
correction method—that adjusts the p-values on the pairwise tests iteratively based on the total
number of tests and the size-based ranking of a given test’s p-value (Porter, 2018). I rely on the
Holm correction here and in subsequent analyses because it preserves statistical power while still
lowering the chances of a Type I error (Holm, 1979; Abdi, 2010).33

An additional note on multiple hypothesis testing: This study is exploratory. At no point
are the statistical comparisons considered confirmatory. A U.S. Department of Education
technical methods report on multiple hypothesis testing indicates that “[m]ultiplicity adjustments
are not required for exploratory analyses” (Schochet, 2008, p. 6). The report notes that the

33 The statistically significant results are robust to the choice of correction method, including a commonly employed
false discovery rate approach, the Benjamini-Hochberg adjustment. In one of the 45 comparisons in Lansing, the BH
adjustment would yield statistical significance and the Holm adjustment would not. In four of the 90 comparisons in
Chicago, the BH adjustment would yield statistical significance and the Holm adjustment would not. Because I opt
against adjusting p-values based on the total number of covariate-subgroup tests, which would be a more
conservative approach, I make the decision to instead rely on a more conservative FDR adjustment even though the
BH FWER adjustment would suffice.
researcher can employ such adjustments if there is sufficient statistical power to do so, but the results “should be reported as providing preliminary information on relationships in the data that could be subject to more rigorous future examination” (p. 6). In other words, an adjustment does not enable the researcher to interpret exploratory results as confirmatory. Translated to this context, were I conducting confirmatory analyses, I would implement the previously described adjustment procedure based on the total number of post-hoc comparison tests conducted across all variables of interest. Instead, for these exploratory analyses, I implement the procedure based on the number of comparison tests conducted for each individual variable (e.g., 4 comparison tests conducted to identify differences in rank-sum means for each individual covariate). Although making this adjustment is not strictly necessary, I do so because it is good practice and, in most cases, there is sufficient sample size to do so. At no point, however, can these results be interpreted as anything other than exploratory, or results that can “identify hypotheses that could be subject to more rigorous future examination” (Schochet, 2008, p. 4).

**RQ2: Evaluation of Most Accessible Institution by Neighborhood**

The second research question examines key measures at the collection of less selective colleges that are most accessible to census tracts that differ from each other on demographic variables related to poverty and race/ethnicity. I hypothesize that institutional resources and key student outcome measures will be, on average, lower at the set of institutions that are most accessible to high poverty and high proportion POC tracts than at the set of institutions that are most accessible to low poverty and high proportion White census tracts. Setting up the analysis for this research question is a two-pronged process involving the categorization of census tracts based on race/ethnicity demographics and overall poverty rate, and the identification of which less selective institution is most geographically accessible to each census tract.
First, I categorize tracts into sub-groups based on ACS-reported race/ethnicity demographics and the tract-level poverty rate.\textsuperscript{34} For the poverty sub-groups, I categorize as high poverty any tract with a poverty rate in the top quartile (estimated separately for each study area) and low poverty any tract with a poverty rate in the bottom quartile; the remaining two quartiles are categorized as “all other.” I rely on the poverty rate rather than median income since a family’s poverty status is adjusted based on familial composition (U.S. Census, 2021).\textsuperscript{35} For the race/ethnicity sub-groups, I define two sub-groups of interest: high proportion POC and high proportion White, estimated separately for the two study areas.\textsuperscript{36} The high proportion POC sub-group is any tract in the top quartile for the proportion of residents who identify as Black, Latinx, Asian, AI/AN/PI/MR/Other. Census tracts in the top quartile for the percentage of residents who identify as White comprise the high proportion White sub-group. All other tracts are categorized as such. The use of quartiles reflects a desire to partition the data in a straightforward manner that allows for comparisons between tracts in the outer portions of the distribution for each respective underlying variable while simultaneously maximizing sub-group sample size.\textsuperscript{37}

Second, I identify which less selective college is most geographically accessible to each census tract using a simplified version of the accessibility index. In this version, I calculate for

\textsuperscript{34} As a preliminary analysis, I examined the intersection of a tract’s racial composition and poverty rate for that racial sub-population (e.g., high-proportion white residents and high poverty rate among white residents). The largest sub-groups in both cities were for high proportion POC, high POC poverty rate and high proportion white, low white poverty rate. Sub-group sizes for high proportion POC, low poverty rate and high proportion white, high poverty rate were 4 and zero, respectively, in Lansing. In Chicago, these same sub-groups had cell sizes of 5 and 14, respectively. Given the small or null cell sizes in many sub-groups as well as the exploratory nature of the analyses, I opt to maintain separate analyses by race/ethnicity and poverty rate.

\textsuperscript{35} Poverty rate and median family income are strongly negatively correlated in both study areas, but overlap is not perfect (Lansing: \(r_{s} = -0.845, p = 0.000\); Chicago: \(r_{s} = -0.846, p = 0.000\)). In Lansing, eight of the 34 high-poverty tracts would not be categorized as low-income, and 12 of the 35 low-poverty tracts would not be categorized as high-income. In Chicago, of the 472 low-poverty tracts, 146 would not be categorized as high-income. Of the 472 high-poverty tracts, 105 would not be categorized as low-income.

\textsuperscript{36} I use the language “high proportion,” rather than “majority” or “predominantly” because the minimum observed percentage of residents of color in a Lansing high proportion POC tract is 38%, which is not a majority.

\textsuperscript{37} Tract-level summary statistics for each sub-group are similar using either a quartile or quantile decision rule. Furthermore 71% of the high- and low-poverty tracts and 89% of the high proportion POC and high proportion white tracts maintained consistent classification when estimated using the ACS 2014 5-year estimates.
each tract-institution pairing the mode-adjusted accessibility value, excluding desirability. The following equation is used to calculate each census tract-institution’s paired index value (for complete details on the construction of the summative accessibility index, see Chapter 6):

\[
A_{ij} = (D_{ij}^{-\beta} \times PropCar) + (T_{ij}^{-\beta} \times PropNoCar)
\]

(4.1)

where
- \(A_{ij}\) is the paired postsecondary accessibility for location \(i\) and college \(j\)
- \(D_{ij}\) is the driving travel time associated with traveling between the weighted centroids of census tract \(i\) and college \(j\)’s census tract
- \(PropCar\) is the proportion of households in census tract \(i\) that report having access to at least one vehicle
- \(T_{ij}\) is the public transit travel time associated with traveling between the weighted centroids of census tract \(i\) and college \(j\)’s census tract
- \(PropNoCar\) is equal to \(1 - PropCar\) for census tract \(i\)
- \(\beta\) is the distance-decay factor associated with travel for work-based trips (constant across travel modes; 0.10157)

I exclude the desirability measure from this estimation of paired accessibility because I use its values to compare accessibility under the extreme condition in which a tracts’ residents only enroll at the geographically most accessible institution. Including the desirability measure, which distinguishes between colleges in the summative index, would result in a tract-institution accessibility value that is not singularly reflective of geographic access.

Having categorized census tracts by their demographics and identified each tract’s most accessible college, I can now compare average institutional resources and key outcome measures across the collection of institutions identified as most accessible to the set of census tracts in each sub-group. In doing so, I can evaluate whether high poverty and high proportion POC tracts are, on average, more geographically proximate to colleges with fewer resources and lower student outcomes than low poverty and high proportion White census tracts. I examine per-student spending (instructional, academic support services, student support services), as well as full- and part-time retention rates and 150% graduation rate. Longer-term outcomes included in these
comparisons are mean earnings six and 10 years after initial enrollment, federal student loan borrowing rates and, among borrowers, 3-year repayment rates and cohort default rates. Based on the IPEDS reporting patterns identified for my sample (see pages 55-56), I rely on institution-level IPEDS data for the comparison of resources and outcomes regardless of whether the nearest campus to any given census tract is a main or branch campus. Since the IPEDS data for the institutions in my sample do not disaggregate at a more granular level to the manually incorporated “branch campuses,” this approach acknowledges that I cannot isolate main campus outcomes any better than I can isolate branch campus outcomes.

Especially in Lansing, where there are few BACs, a given college can appear as the most accessible institution to multiple census tracts in the same sub-group as well as tracts in both sub-groups. The repeated inclusion of individual colleges is not considered a violation of the independence of observations assumption for the KW test because, in these analyses, the tract is the unit of analysis. Put differently, each college is included because it is closest to a particular census tract, and each census tract is included in the sub-groups only once. This treatment of the tract as the underlying unit of analysis parallels the approach taken in studies that compare the colleges that students attend (e.g., Alm & Winters, 2009); multiple students may attend the same school, thereby resulting in the repeated inclusion of any given school, but the students themselves appear only once. For this reason, nothing specific is adjusted in the analysis to address the repeated presence of institutions. However, in the case of Lansing, the small amount of variation in the sample of colleges renders the analyses indeterminate.

Because the underlying institutional data demonstrate non-normality in distribution and variance,\textsuperscript{38} I rely on the same non-parametric testing protocol outlined for RQ1: a KW omnibus

\textsuperscript{38} In Lansing, I can reject the Shapiro-Wilk null hypothesis of normality of distribution in 24 of the 36 tests for institution-level covariates in the poverty rate comparisons and 35 of the 36 tests for race/ethnicity comparisons. In
test followed by a Conover-Ivan post-hoc test with the Holm adjustment. I conduct these
analyses separately by study area. In Lansing, where there are only three institutions in total,
there is too little variation in the institutional data to productively compare the average
characteristics of institutions across sub-groups of tracts.\textsuperscript{39} In Chicago, the number of institutions
is large enough to observe whether there are statistically significant differences in the average
institutional measures across-sub-groups. The results of these tests provide evidence of whether
average student outcomes for the set of colleges most accessible to sub-groups of tracts differ
between high-poverty, low-poverty, and all other tracts, as well as high proportion POC tracts,
high proportion White tracts, and all other tracts. In the next chapter, I present the findings for
research questions one and two which, together, comprise Part I of the study.

\textsuperscript{39} This inability to compare characteristics within Lansing is to be expected. Research question two emphasizes the
potential for the quality of the most-accessible opportunity to vary by neighborhood demographics \textit{when multiple
opportunities are present}. I chose Lansing, a marginal education desert, because of the small number of broad
access colleges (and, indeed, less selective colleges overall) within the region. Though there are technically multiple
opportunities in Lansing, there are very few as compared to an opportunity-rich study area like Chicago.
Chapter 5 Results on the Relative Accessibility of Less Selective Colleges

This chapter presents the results for Part I, in which I examine the relative accessibility of less selective colleges in two ways: based on the demographics of the census tracts in the immediate vicinity of a college campus, and by identifying average outcomes at the institutions most accessible to census tracts with a high proportion of residents in a demographic sub-group of interest. Lansing and Chicago are considered separately in each question.

RQ1: Evaluation of College Locations

In this section, I present the findings for research question one (RQ1), in which I seek to understand whether the demographics of less selective colleges’ census tracts, considered separately for public versus non-public less selective colleges, differ from the demographics of census tracts without a college. As a reminder, I hypothesize that less selective college tracts are more racially diverse than non-college tracts, though it is less clear from the literature whether or how these less selective college tracts will differ when examined by sector. To address this question, I investigate the demographics of less selective colleges’ neighborhoods.

Lansing

College neighborhoods in Lansing are clustered mostly near the central region of the Lansing MSA (within the cities of Lansing/East Lansing; see Figure 5.1). The one non-public competitor college (GLCC, a small nonprofit institution) is on the western edge of the region, and several LCC branch campuses are outside the central portion of the MSA. Because Lansing
does not have for-profit competitor colleges,\textsuperscript{40} it is not possible to evaluate whether for-profit institutions locate in neighborhoods with particular racial/ethnic demographics.

That said, it is possible to compare the overall differences in demographics between BAC neighborhood units and GLCC’s neighborhood unit. Focusing on sub-group pairings for which the results of the Conover-Iman test are statistically significant, the proportion of households without access to a vehicle is higher in BAC tracts (10%; Table 5.1) as compared to non-college tracts (6%). In BAC tracts, median income is more than $10,000 lower compared to non-college tracts, and the average poverty rate is more than 10 percentage points (pp) higher than in both competitor college tracts and all other tracts (26% in BAC tracts versus 10% and 14% in competitor college tracts and non-college tracts, respectively). When poverty rates are considered separately by race/ethnicity, here again there are large differences in racial subgroup poverty rates between the tracts. Twenty-nine percent of residents of color in the average BAC census tract live in poverty, as compared to 12% of residents of color in competitor college residents. The average poverty rate for White residents in BAC tracts is 23%, compared to 8% in competitor college tracts and 13% in non-college tracts.

Less selective college tracts—whether BACs or the competitor college—have a higher percentage of Black residents than non-college tracts. The average proportion of Black residents is highest in BAC tracts and lowest in non-college tracts (17% and 5%); the inverse is true for White residents (61% and 84%). Latinx residents are similarly distributed within broad access and competitor college tracts (10% in each group). The highest average percentage of American Indian/Alaska Native/Pacific Islander/Multiracial/Other (AI/AN/PI/MR/Other) residents are in

\textsuperscript{40} One qualifying institution with a campus in Lansing closed in Fall 2021 (Career Quest College). Another potentially eligible institution (Baker College) had an admission rate more than 20pp below the cut-off in 2017-18 and 4pp below the cut-off in 2019-20. In the 2020-21 AY, the acceptance rate was again more than 20pp below the cut-off. Furthermore the college made changes to its admission practices in 2016 to become more selective (Allen, 2019).
BAC tracts (6%, as compared in 3% in competitor college and non-college tracts). Non-college tracts have the lowest proportion of Latinx residents (6%) and Asian residents (3%). Results of the Conover-Iman post-hoc tests confirm that differences in the rank-sum means between BAC tracts and the competitor college’s tracts are not statistically significant on measures of race/ethnicity, but the differences are statistically significant between both college tract groups and the non-college tract group for all racial sub-groups except the AI/AN/PI/MR/Other racial group (Table 5.2, Columns 2 and 3).

Figure 5.1 Map of Neighbor Census Tracts in Lansing (2019)

Sources: Author’s calculations from U.S. Census ACS 5yr Estimates 2015-2019; APTA 2020; IPEDS 2019
Notes: Created in ArcGIS.
Table 5.1 Census Tract Summary Statistics and Results of KW Test for Lansing (ACS 5-Year Estimates 2015-2019)

<table>
<thead>
<tr>
<th></th>
<th>Broad Access College Tracts (n=34)</th>
<th>Competitor College Tracts (n=8)</th>
<th>Non-College Tracts (n=99)</th>
<th>K-W H Statistic (P-Value)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>SD</td>
<td>Mean</td>
<td>SD</td>
</tr>
<tr>
<td>Land area (mi²)</td>
<td>2.09</td>
<td>2.92</td>
<td>1.98</td>
<td>1.43</td>
</tr>
<tr>
<td>Tract population</td>
<td>3,605</td>
<td>1,458</td>
<td>3,445</td>
<td>773</td>
</tr>
<tr>
<td>Population density</td>
<td>4,215.65</td>
<td>3,498.67</td>
<td>2,300.33</td>
<td>1,060.30</td>
</tr>
<tr>
<td>Households with zero vehicles</td>
<td>0.10</td>
<td>0.08</td>
<td>0.07</td>
<td>0.05</td>
</tr>
<tr>
<td>Median household income</td>
<td>$48,586</td>
<td>$22,249</td>
<td>$64,284</td>
<td>$22,179</td>
</tr>
<tr>
<td>Poverty rate (all residents)</td>
<td>0.26</td>
<td>0.20</td>
<td>0.10</td>
<td>0.06</td>
</tr>
<tr>
<td>Poverty rate (residents of color)</td>
<td>0.29</td>
<td>0.21</td>
<td>0.12</td>
<td>0.08</td>
</tr>
<tr>
<td>Poverty rate (White residents)</td>
<td>0.23</td>
<td>0.21</td>
<td>0.08</td>
<td>0.06</td>
</tr>
<tr>
<td>Residents aged 25+ w less than AA</td>
<td>0.57</td>
<td>0.18</td>
<td>0.53</td>
<td>0.12</td>
</tr>
<tr>
<td>White</td>
<td>0.61</td>
<td>0.16</td>
<td>0.68</td>
<td>0.11</td>
</tr>
<tr>
<td>Black</td>
<td>0.17</td>
<td>0.12</td>
<td>0.14</td>
<td>0.04</td>
</tr>
<tr>
<td>Latinx</td>
<td>0.10</td>
<td>0.05</td>
<td>0.10</td>
<td>0.06</td>
</tr>
<tr>
<td>Asian</td>
<td>0.07</td>
<td>0.09</td>
<td>0.05</td>
<td>0.04</td>
</tr>
<tr>
<td>AI/AN/PI/MR/Other</td>
<td>0.06</td>
<td>0.05</td>
<td>0.03</td>
<td>0.03</td>
</tr>
<tr>
<td>Veterans</td>
<td>0.06</td>
<td>0.03</td>
<td>0.08</td>
<td>0.02</td>
</tr>
</tbody>
</table>

Sources: Author’s calculations from U.S. Census ACS 5yr Estimates 2015-2019

Notes: Unless expressly noted with a unit of measurement (e.g., #, $), all demographic values are proportion variables.
Table 5.2 P-Values from Post-Hoc Pairwise Conover-Iman Tests with Holm Correction for Lansing

<table>
<thead>
<tr>
<th></th>
<th>(1) BAC v. Competitor Tracts</th>
<th>(2) BAC v. Non-College Tracts</th>
<th>(3) Competitor v Non-College Tracts</th>
</tr>
</thead>
<tbody>
<tr>
<td>Land area (mi²)</td>
<td>0.19</td>
<td>0.00</td>
<td>0.03</td>
</tr>
<tr>
<td>Tract population</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>Population density</td>
<td>0.12</td>
<td>0.00</td>
<td>0.06</td>
</tr>
<tr>
<td>Households with zero vehicles</td>
<td>0.34</td>
<td>0.00</td>
<td>0.26</td>
</tr>
<tr>
<td>Median household income</td>
<td>0.05</td>
<td>0.00</td>
<td>0.49</td>
</tr>
<tr>
<td>Poverty rate (all residents)</td>
<td>0.02</td>
<td>0.00</td>
<td>0.32</td>
</tr>
<tr>
<td>Poverty rate (residents of color)</td>
<td>0.02</td>
<td>0.03</td>
<td>0.08</td>
</tr>
<tr>
<td>Poverty rate (White residents)</td>
<td>0.01</td>
<td>0.00</td>
<td>0.17</td>
</tr>
<tr>
<td>Residents aged 25+ w less than AA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>White</td>
<td>0.28</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Black</td>
<td>0.45</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Latinx</td>
<td>0.46</td>
<td>0.00</td>
<td>0.01</td>
</tr>
<tr>
<td>Asian</td>
<td>0.41</td>
<td>0.00</td>
<td>0.02</td>
</tr>
<tr>
<td>AI/AN/PI/MR/Other</td>
<td>0.03</td>
<td>0.00</td>
<td>0.37</td>
</tr>
<tr>
<td>Veterans</td>
<td>0.10</td>
<td>0.02</td>
<td>0.35</td>
</tr>
</tbody>
</table>

Sources: Author’s calculations from U.S. Census ACS 5yr Estimates 2015-2019
Notes: Underlined values indicate statistically significant p-values using the Conover-Iman post-hoc pairwise comparison test with the Holm adjustment.

Chicago

College neighborhoods in Chicago are dispersed through the study area, with a large number located within the boundaries of the City of Chicago (solid black outline in Figure 5.2). Because there are many non-public competitor colleges (17 main campuses, 15 branch campuses), I can compare neighborhood demographics separately for BACs, for-profit competitors, and nonprofit competitors. Results of the KW test indicate that the rank-sum group means are statistically significantly different from each other on all covariates of interest (Table 5.3). Therefore, the discussion that follows examines the statistically significant differences in rank-sum means as observed using the Conover-Iman post-hoc tests (Table 5.4).

I focus first on measures of income: median income, as well as poverty rates overall and for White and residents of color separately. FP competitor colleges are in tracts with the highest
average income ($102,082) and lowest average poverty rates (8% overall, and 10% and 6% for residents of color and White residents respectively). The inverse is true for broad access college tracts: Here, median income is lowest ($67,572) and poverty rates are highest (17% overall, and 20% and 13% for residents of color and White residents respectively). Rank-sum means for median income are statistically significantly different between all combinations of tract categories in the Conover-Iman post-hoc tests (Table 5.4); rank-sum means for all three poverty rates are statistically significantly different between FP and BAC college tracts. Poverty rates for residents of color and White residents are not statistically significantly different between BAC tracts and NFP college tracts, as well as between NFP tracts and non-college tracts.

Next, I examine differences in race/ethnicity composition. The percentage of White residents is highest in FP college tracts (64%) and lowest in BAC tracts (40%); the difference in rank-sum means for the percentage of White residents is statistically significant in all post-hoc tests except between NFP tracts (average 53% White) and non-college tracts (46%). Although FP and NFP tracts do not have statistically significant differences in rank-sum means for the proportion of the population that identifies as Black, FP tracts are statistically significantly different from both broad access college tracts and non-college tracts. For-profit college tracts have the lowest percentage of Black residents (7%), whereas BAC tracts and non-college tracts have the highest percentages (25% and 23%, respectively). There are no statistically significant differences in rank-sum means for the percentage of Latinx residents, despite a statistically significant KW test for the overall comparison. The average percentage of Asian residents is highest in FP tracts (11%) and comparably low in BAC and non-college tracts (8% and 7%); there is not a statistically significant difference in rank-sum means between FP and NFP tracts.
Despite some statistically significant differences in rank-sum means in post-hoc testing, the average percentage of AI/AN/PI/MR/Other residents is identical in all four categories (2%).

Lastly, I examine the percentage of the population that is a veteran and the percentage of residents aged 25 or older with less than an associate degree. Although there are some statistically significant differences in rank-sum means between sub-group pairings, the observed averages for the percentage of residents that are veterans are near-identical across the sub-groups (4% in BACs, FPs, and non-college; 3% in NFPs). For potential educational demand, all group pairings’ rank-sum means are statistically significantly different from each other, except for FP college tracts and NFP college tracts. The average percentage of residents with less than an associate degree is comparably low in both FP and NFP college tracts (37% and 42%, respectively). This percentage is highest in BAC tracts (59%).

When I examine differences between the neighborhood demographics of broad access public colleges’ main versus branch campuses, as Fisher (2012) observed in the DC area, numerous variables’ sub-group pairings are statistically significantly different in their rank-sum means (Table 5.5). I focus here on variables with a statistically significant MWU test statistic. Median income is approximately $10,500 higher in main campus tracts than in branch campus tracts, and poverty rates are, on average, 5pp lower in main campus tracts (15% versus 20%). Poverty rates for residents of color are lower in main campus tracts (19% versus 22%); there is no statistically significant difference in rank-sum means for White residents’ poverty rates. The percentage of residents with less than an associate degree is lower in main campus tracts than in branch campus tracts (55% versus 65%). Main campus tracts have, on average, a higher percentage of White residents (47% versus 27%) and a lower percentage of Black residents (23% versus 30%) and Latinx residents (21% versus 34%).
Figure 5.2 Map of Neighbor Census Tracts in Chicago (2019)

Sources: U.S. Census 2010 census tract shape files; MSA shape files; UZA shape files; state shape files; U.S. Census ACS 5-year estimates 2015-2019

Notes: Created in ArcGIS. Black outline delineates the City of Chicago. Included tracts are any in the Chicago MSA that are in Illinois and have a center of population within the Chicago UZA.
<table>
<thead>
<tr>
<th></th>
<th>Broad Access College Tracts (n=259)</th>
<th>For-Profit College Tracts (n=161)</th>
<th>Nonprofit College Tracts (n=105)</th>
<th>Non-College Tracts (n=1,502)</th>
<th>K-W Statistic (P-Value)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Land area (mi$^2$)</td>
<td>Mean 1.44, SD 2.97</td>
<td>Mean 1.37, SD 2.69</td>
<td>Mean 0.78, SD 0.97</td>
<td>Mean 1.33, SD 3.12</td>
<td>Statistic 7.55 (0.06)</td>
</tr>
<tr>
<td>Tract population</td>
<td>Mean 4,497, SD 2,192</td>
<td>Mean 5,112, SD 2,399</td>
<td>Mean 5,202, SD 3,258</td>
<td>Mean 4,175, SD 2,005</td>
<td>Statistic 30.86 (0.00)</td>
</tr>
<tr>
<td>Population density</td>
<td>Mean 10,024.21, SD 11,772.30</td>
<td>Mean 14,892.98, SD 17,830.18</td>
<td>Mean 15,192.12, SD 12,788.27</td>
<td>Mean 10,895.80, SD 17,932.61</td>
<td>Statistic 19.62 (0.00)</td>
</tr>
<tr>
<td>Households with zero vehicles</td>
<td>Mean 0.17, SD 0.17</td>
<td>Mean 0.17, SD 0.17</td>
<td>Mean 0.20, SD 0.16</td>
<td>Mean 0.14, SD 0.15</td>
<td>Statistic 17.25 (0.00)</td>
</tr>
<tr>
<td>Median household income</td>
<td>Mean $67,572, SD $34,927</td>
<td>Mean $102,082, SD $31,302</td>
<td>Mean $87,406, SD $36,546</td>
<td>Mean $76,266, SD $39,395</td>
<td>Statistic 115.54 (0.00)</td>
</tr>
<tr>
<td>Poverty rate (all residents)</td>
<td>Mean 0.17, SD 0.13</td>
<td>Mean 0.08, SD 0.05</td>
<td>Mean 0.12, SD 0.08</td>
<td>Mean 0.14, SD 0.12</td>
<td>Statistic 60.69 (0.00)</td>
</tr>
<tr>
<td>Poverty rate (residents of color)</td>
<td>Mean 0.20, SD 0.14</td>
<td>Mean 0.10, SD 0.08</td>
<td>Mean 0.16, SD 0.10</td>
<td>Mean 0.15, SD 0.12</td>
<td>Statistic 54.91 (0.00)</td>
</tr>
<tr>
<td>Poverty rate (White residents)</td>
<td>Mean 0.13, SD 0.17</td>
<td>Mean 0.06, SD 0.04</td>
<td>Mean 0.08, SD 0.06</td>
<td>Mean 0.12, SD 0.18</td>
<td>Statistic 18.53 (0.00)</td>
</tr>
<tr>
<td>Residents aged 25+ w less than AA</td>
<td>Mean 0.59, SD 0.23</td>
<td>Mean 0.37, SD 0.22</td>
<td>Mean 0.42, SD 0.25</td>
<td>Mean 0.55, SD 0.22</td>
<td>Statistic 114.88 (0.00)</td>
</tr>
<tr>
<td>White</td>
<td>Mean 0.40, SD 0.28</td>
<td>Mean 0.64, SD 0.18</td>
<td>Mean 0.53, SD 0.24</td>
<td>Mean 0.46, SD 0.32</td>
<td>Statistic 61.31 (0.00)</td>
</tr>
<tr>
<td>Black</td>
<td>Mean 0.25, SD 0.33</td>
<td>Mean 0.07, SD 0.10</td>
<td>Mean 0.09, SD 0.10</td>
<td>Mean 0.23, SD 0.33</td>
<td>Statistic 19.79 (0.00)</td>
</tr>
<tr>
<td>Latinx</td>
<td>Mean 0.26, SD 0.26</td>
<td>Mean 0.16, SD 0.17</td>
<td>Mean 0.27, SD 0.26</td>
<td>Mean 0.22, SD 0.24</td>
<td>Statistic 10.67 (0.01)</td>
</tr>
<tr>
<td>Asian</td>
<td>Mean 0.08, SD 0.11</td>
<td>Mean 0.11, SD 0.08</td>
<td>Mean 0.09, SD 0.08</td>
<td>Mean 0.07, SD 0.09</td>
<td>Statistic 65.04 (0.00)</td>
</tr>
<tr>
<td>AI/AN/PI/MR/Other</td>
<td>Mean 0.02, SD 0.02</td>
<td>Mean 0.02, SD 0.01</td>
<td>Mean 0.02, SD 0.02</td>
<td>Mean 0.02, SD 0.02</td>
<td>Statistic 15.68 (0.00)</td>
</tr>
<tr>
<td>Veterans</td>
<td>Mean 0.04, SD 0.02</td>
<td>Mean 0.04, SD 0.02</td>
<td>Mean 0.03, SD 0.02</td>
<td>Mean 0.04, SD 0.02</td>
<td>Statistic 38.23 (0.00)</td>
</tr>
</tbody>
</table>

Sources: Author’s calculations from U.S. Census ACS 5yr Estimates 2015-2019

Notes: Population density calculated as tract population divided by land area. Unless expressly noted with a unit of measurement (e.g., mi$^2$, $), all demographic values are proportion variables.
Table 5.4 P-Values from Post-Hoc Pairwise Conover-Iman Tests with Holm Correction for Chicago

<table>
<thead>
<tr>
<th></th>
<th>BAC v. FP</th>
<th>BAC v. NFP</th>
<th>FP v. BAC Non</th>
<th>FP v. NFP Non</th>
<th>NFP v. Non</th>
</tr>
</thead>
<tbody>
<tr>
<td>Land area (mi²)</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>Tract population</td>
<td>0.02</td>
<td>0.17</td>
<td>0.23</td>
<td>0.05</td>
<td>0.00</td>
</tr>
<tr>
<td>Population density</td>
<td>0.10</td>
<td>0.00</td>
<td>0.04</td>
<td>0.13</td>
<td>0.19</td>
</tr>
<tr>
<td>Households with zero vehicles</td>
<td>0.22</td>
<td>0.17</td>
<td>0.08</td>
<td>0.03</td>
<td>0.26</td>
</tr>
<tr>
<td>Median household income</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Poverty rate (all residents)</td>
<td>0.00</td>
<td>0.02</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Poverty rate (residents of color)</td>
<td>0.00</td>
<td>0.06</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Poverty rate (White residents)</td>
<td>0.00</td>
<td>0.26</td>
<td>0.05</td>
<td>0.00</td>
<td>0.04</td>
</tr>
<tr>
<td>Residents aged 25+ w less than AA</td>
<td>0.00</td>
<td>0.00</td>
<td>0.03</td>
<td>0.01</td>
<td>0.00</td>
</tr>
<tr>
<td>White</td>
<td>0.00</td>
<td>0.00</td>
<td>0.01</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Black</td>
<td>0.00</td>
<td>0.18</td>
<td>0.04</td>
<td>0.00</td>
<td>0.01</td>
</tr>
<tr>
<td>Latinx</td>
<td>0.03</td>
<td>0.38</td>
<td>0.04</td>
<td>0.05</td>
<td>0.17</td>
</tr>
<tr>
<td>Asian</td>
<td>0.00</td>
<td>0.00</td>
<td>0.09</td>
<td>0.37</td>
<td>0.00</td>
</tr>
<tr>
<td>AI/AN/PI/MR/Other</td>
<td>0.02</td>
<td>0.06</td>
<td>0.84</td>
<td>0.46</td>
<td>0.00</td>
</tr>
<tr>
<td>Veterans</td>
<td>0.07</td>
<td>0.00</td>
<td>0.05</td>
<td>0.08</td>
<td>0.00</td>
</tr>
</tbody>
</table>

Sources: Author’s calculations from U.S. Census ACS 5yr Estimates 2015-2019
Notes: Underlined values indicate statistically significant p-values using the Conover-Iman post-hoc pairwise comparison test with a Holm adjustment.

Table 5.5 Census Tract Summary Statistics and Mann-Whitney U Test Results (BAC Main vs. Branch Campuses in Chicago; ACS 5-Year Estimates 2015-2019)

<table>
<thead>
<tr>
<th></th>
<th>BAC Main Campus Tracts (n=163)</th>
<th>BAC Branch Campus Tracts (n=96)</th>
<th>MWU Test Statistic (P-Value)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>SD</td>
<td>Mean</td>
</tr>
<tr>
<td>Land area (mi²)</td>
<td>1.79</td>
<td>3.54</td>
<td>0.85</td>
</tr>
<tr>
<td>Tract population</td>
<td>4,744</td>
<td>2,142</td>
<td>4,078</td>
</tr>
<tr>
<td>Population density</td>
<td>9,865.42</td>
<td>13,697.17</td>
<td>10,293.82</td>
</tr>
<tr>
<td>Households with zero vehicles</td>
<td>0.18</td>
<td>0.17</td>
<td>0.17</td>
</tr>
<tr>
<td>Median household income</td>
<td>$71,471</td>
<td>$34,392</td>
<td>$69,953</td>
</tr>
<tr>
<td>Poverty rate (all residents)</td>
<td>0.15</td>
<td>0.12</td>
<td>0.20</td>
</tr>
<tr>
<td>Poverty rate (residents of color)</td>
<td>0.19</td>
<td>0.14</td>
<td>0.22</td>
</tr>
<tr>
<td>Poverty rate (White residents)</td>
<td>0.12</td>
<td>0.16</td>
<td>0.15</td>
</tr>
<tr>
<td>Residents aged 25+ w less than AA</td>
<td>0.55</td>
<td>0.23</td>
<td>0.65</td>
</tr>
<tr>
<td>White</td>
<td>0.47</td>
<td>0.29</td>
<td>0.27</td>
</tr>
<tr>
<td>Black</td>
<td>0.22</td>
<td>0.32</td>
<td>0.30</td>
</tr>
<tr>
<td>Latinx</td>
<td>0.21</td>
<td>0.23</td>
<td>0.34</td>
</tr>
<tr>
<td>Asian</td>
<td>0.08</td>
<td>0.11</td>
<td>0.07</td>
</tr>
<tr>
<td>AI/AN/PI/MR/Other</td>
<td>0.02</td>
<td>0.02</td>
<td>0.02</td>
</tr>
<tr>
<td>Veterans</td>
<td>0.04</td>
<td>0.02</td>
<td>0.04</td>
</tr>
</tbody>
</table>

Sources: Author’s calculations from U.S. Census ACS 5yr Estimates 2015-2019
Notes: Population density calculated as tract population divided by land area. Unless expressly noted with a unit of measurement (e.g., mi², $), all demographic values are proportion variables. *Missing value for 30 tracts where the population of White residents is zero.
Summary of RQ1 Findings

In summary, in both Lansing and Chicago, BAC neighborhoods are lower income and higher poverty than non-public competitor college neighborhoods or non-college neighborhoods. In Lansing, although the percentage of residents of color living in poverty is highest in BAC tracts, there is no difference between BAC census tracts and non-college tracts in the rank-sum means of the poverty rates for this covariate. In contrast, there is a statistically significant difference in the rank-sum means between BAC tracts and either non-public competitor college tracts or non-college tracts in the percentage of White residents living in poverty, suggestive of a concentration of White poverty in BAC tracts, even as these tracts have the lowest average percentage of White residents. In Chicago, the highest-observed poverty rates in BAC tracts are coupled with the lowest-observed poverty rates in FP tracts (there are no for-profit colleges in Lansing). In both study areas, BAC tracts are the most racially diverse (highest percentage of residents of color), though the differences in rank-sum means are not statistically significant between all BAC sub-group pairings in either study area. These findings partially support the hypothesis that less selective college tracts are more racially diverse than non-college tracts. Interestingly, FP neighborhoods in Chicago are the highest income and have the highest proportion of White residents, the latter of which is in keeping with Fisher’s (2012) finding that FP colleges are located in less racially diverse neighborhoods than community colleges.

In the Chicago sub-analysis of neighborhood demographics by broad access colleges’ main versus branch campuses, I find that main campuses are higher income and lower poverty (overall and for residents of color) than branch campuses. This finding is in keeping with previous studies that suggest branch campus locations are chosen specifically to serve a lower-income demographic (Briscoe & De Oliver, 2006; Kenyon, 2011). Unlike Fisher (2012), who finds that main campuses are in neighborhoods with a higher percentage of Black residents, I
find the opposite: Main campuses are located in neighborhoods with a higher percentage of White residents, whereas branch campuses are located in neighborhoods with a higher percentage of Black and Latinx residents. Unlike Fisher (2012), I find no difference in the percentage of Asian residents between broad access college main and branch campus neighborhoods. What this assessment does not answer is whether branch campuses across these institutions have fewer resources, as Briscoe and De Oliver (2006) observed for UTSA.

**RQ2: Evaluation of Most Accessible Institutions by Neighborhood Characteristics**

The next research question examines the most accessible institution by neighborhood characteristics, in pursuit of better understanding whether the type of opportunity accessible to certain neighborhoods varies depending on the characteristics of the neighborhood. Studies find that low-income neighborhoods and/or neighborhoods of color are closer to lower-quality restaurants (Cooksey-Stowers et al., 2017), grocery stores (Block & Kouba, 2006) and parks (Chapman et al., 2021), suggestive of the potential that the colleges nearest to these same neighborhoods likewise have fewer resources and lower student outcomes.

**Lansing**

Figure 5.3 plots which census tracts are categorized as high- versus low-poverty census tracts ($n=34$ and $n=35$, respectively; Panel A), and which are considered high proportion POC versus high proportion White ($n=34$ and $n=34$, respectively; Panel B). Table A.3 and Table A.4 in Appendix A provide additional demographic detail on the characteristics of these census tracts, by group. There is significant overlap in the high poverty and high proportion POC census tracts ($n=24$ categorized as both). Visually, this overlap is evident in the clustering of high poverty and high proportion POC tracts in the central portion of the region. However, due to
sample size constraints, wherein the expected value of some sub-groups’ cell sizes become too small \((n < 5)\), I keep the comparisons that follow separate for poverty and race sub-groupings.

I first examine the type of institution nearest to each tract sub-group, by poverty rate (high poverty, low poverty, all other) and racial composition (high proportion POC, high proportion White, all other). Because, in neither case, the KW test for this high-level comparison is statistically significant, I forego the comparison of average resources and outcomes at the most accessible institution. That I am unable to observe statistically significant differences in the rank-sum means is unsurprising given the small amount of variation in the institutional sample: There are only three less selective colleges in the Lansing study area. Put differently, by design, there is not sufficient institutional variation in the study area to answer RQ2. Therefore, I focus discussion on a descriptive examination of which institution is nearest to each sub-group.

**Figure 5.3 Map of Census Tracts in Key Sub-Groups (Lansing; ACS 5-Year Estimates 2015-2019)**

*Panel A: High vs. Low Poverty Rate Census Tracts*
Panel B: High Proportion POC v. High Proportion White Census Tracts

Sources: U.S. Census 2010 census tract shape files; MSA shape files; UZA shape files; state shape files; U.S. Census ACS 5-year estimates 2015-2019
Notes: Created in ArcGIS.

Acknowledging that there is not sufficient sample size to test whether there is a relationship between tract categories and the nearest institution, I present cross-tabulations of the nearest institution by poverty status (Table 5.6) and racial/ethnic composition (Table 5.7). For poverty status, more than 50% of high-poverty census tracts are nearest to a BAC main campus (29% nearest to Michigan State University [MSU], 24% nearest to LCC’s main campus). In contrast, only 28% of low-poverty tracts are nearest to one of these two institutions. The third most frequently accessible institution to high-poverty tracts is the LCC Center for Workforce Transition, which offers courses in five four-digit CIP codes. The most accessible institution to low-poverty tracts is LCC’s AIS Training Center; this campus, which is located northeast of the

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41 One assumption underlying the chi-square test is that 80% of all cell sizes have an expected value of at least 5. In Lansing, MI, fewer than half of cell sizes meet this criterion.
Lansing/East Lansing downtown region, offered courses in only one four-digit CIP code in fall 2021 (heavy equipment maintenance). Put differently, although residents of low-poverty tracts have LCC campuses nearby, limited campus offerings may make these campuses less desirable for place-bound students. Great Lakes Christian College, the only competitor college, is most-accessible institution to none of the high-poverty tracts, 6% of low poverty tracts, 9% of all other tracts.

Table 5.6 Cross-Tab of Most Accessible Institution for Census Tract Comparison Groups, by Poverty Status (Lansing; 2019)

<table>
<thead>
<tr>
<th>Institution</th>
<th>High Poverty</th>
<th>Low Poverty</th>
<th>All Other</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Great Lakes Christian College</td>
<td>0%</td>
<td>6%</td>
<td>9%</td>
<td>6%</td>
</tr>
<tr>
<td>LCC (AIS Training Center)</td>
<td>12%</td>
<td>40%</td>
<td>17%</td>
<td>22%</td>
</tr>
<tr>
<td>LCC (Aviation Maintenance Center)</td>
<td>0%</td>
<td>3%</td>
<td>13%</td>
<td>7%</td>
</tr>
<tr>
<td>LCC (Center for Workforce Transition)</td>
<td>18%</td>
<td>3%</td>
<td>13%</td>
<td>12%</td>
</tr>
<tr>
<td>LCC Main Campus (Downtown)</td>
<td>24%</td>
<td>14%</td>
<td>24%</td>
<td>22%</td>
</tr>
<tr>
<td>LCC (East Center)</td>
<td>3%</td>
<td>17%</td>
<td>7%</td>
<td>9%</td>
</tr>
<tr>
<td>LCC (West Campus)</td>
<td>15%</td>
<td>14%</td>
<td>7%</td>
<td>11%</td>
</tr>
<tr>
<td>Michigan State University</td>
<td>29%</td>
<td>3%</td>
<td>10%</td>
<td>13%</td>
</tr>
<tr>
<td>Total</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
</tr>
</tbody>
</table>

Sources: Author’s calculations from U.S. Census ACS 5yr Estimates 2015-2019; IPEDS 2019; CDAC O-D Matrix
Notes: Numbers may not add up to 100% due to rounding.

For racial/ethnic composition sub-groups, LCC’s main campus is the most frequently most accessible institution to high proportion POC census tracts (26%). It is tied with LCC’s AIS Training Center for most frequently most accessible institution to high proportion White census tracts (29% each; Table 5.7). The most frequently most accessible campus to all other census tracts is the LCC AIS Training Center (25%). LCC’s Center for Workforce Transition is the most-accessible institution to 21% of high proportion POC tracts, but none of the high proportion White tracts. MSU and LCC’s Aviation Maintenance Center are each the most accessible institution to 12% of high proportion White tracts, whereas LCC’s Aviation Maintenance Center is not the most accessible campus to any high proportion POC census tracts.
Table 5.7 Cross-Tab of Most Accessible Institution for Census Tract Comparison Groups, by Race/Ethnicity Composition (Lansing; 2019)

<table>
<thead>
<tr>
<th>Institution</th>
<th>High POC</th>
<th>High White</th>
<th>All Other</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Great Lakes Christian College</td>
<td>9%</td>
<td>3%</td>
<td>6%</td>
<td>6%</td>
</tr>
<tr>
<td>LCC (AIS Training Center)</td>
<td>6%</td>
<td>29%</td>
<td>25%</td>
<td>22%</td>
</tr>
<tr>
<td>LCC (Aviation Maintenance Center)</td>
<td>0%</td>
<td>12%</td>
<td>8%</td>
<td>7%</td>
</tr>
<tr>
<td>LCC (Center for Workforce Transition)</td>
<td>21%</td>
<td>0%</td>
<td>13%</td>
<td>12%</td>
</tr>
<tr>
<td>LCC Main Campus (Downtown)</td>
<td>26%</td>
<td>29%</td>
<td>15%</td>
<td>22%</td>
</tr>
<tr>
<td>LCC (East Center)</td>
<td>3%</td>
<td>6%</td>
<td>13%</td>
<td>9%</td>
</tr>
<tr>
<td>LCC (West Campus)</td>
<td>21%</td>
<td>9%</td>
<td>7%</td>
<td>11%</td>
</tr>
<tr>
<td>Michigan State University</td>
<td>15%</td>
<td>12%</td>
<td>13%</td>
<td>13%</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
</tr>
</tbody>
</table>

Sources: Author’s calculations from U.S. Census ACS 5yr Estimates 2015-2019; IPEDS 2019; CDAC O-D Matrix
Notes: Numbers may not add up to 100% due to rounding.

Chicago

Whereas in Lansing the small number of institutions yielded too little variation to observe differences in average institutional characteristics across census tract sub-groups, in the Chicago study area, there are 65 campuses and therefore sufficient variation to observe differences in institutional averages. Furthermore, the large number of census tracts in the study area (n=1,885) affords the opportunity to explore the intersection of racial composition and poverty rates. Although I preserve the separation of analyses by poverty rates and racial composition, I include as a supplemental exploration the cross-tabulation of the nearest institutions to tracts where poverty status and racial composition intersect (e.g., high proportion POC and high poverty rates for residents of color). This analysis enables a closer examination of which colleges tend to serve affluent White versus under-resourced POC communities, which is directly relevant to the research question at hand.

High poverty census tracts are disproportionately located within the City of Chicago, whereas low poverty tracts are dispersed throughout the non-Chicago region of the UZA (Figure 5.4, Panel A). High proportion POC census tracts are likewise located within the City of Chicago, with the exception of a cluster of tracts south of the city boundary (Figure 5.4, Panel
B). A small cluster of high-proportion White tracts are located alongside the eastern edge of the City of Chicago, in the Northern part of the city, though most high-proportion White tracts are clustered throughout the non-city portion of the UZA (Figure 5.4, Panel B). For most census tracts in the Chicago study area, a broad access public college (BAC) is the most accessible institution (59%; Table 5.8), followed by a for-profit college (23%). Only 17% have a NFP competitor college as the most-accessible institution. Table A.5 and Table A.6 in Appendix A include information on census tract demographics in each of the sub-groups.

**Figure 5.4 Map of Census Tracts in Key Sub-Groups (Chicago; ACS 5-Year Estimates 2015-2019)**

*Panel A: High vs. Low Poverty Rate Census Tracts*
Panel B: High Proportion POC v. High Proportion White Census Tracts

**Sources:** U.S. Census 2010 census tract shape files; MSA shape files; UZA shape files; state shape files; U.S. Census ACS 5-year estimates 2015-2019

**Notes:** Created in ArcGIS. Black outline delineates the City of Chicago. Included tracts are any in the Chicago MSA that are in Illinois and have a center of population within the Chicago UZA.

**By Poverty Rate.** Turning first to differences in most accessible institution by poverty rate, I examine the sector of the most accessible institution to tracts in each of the poverty sub-categories. A BAC is the most geographically accessible institution for 71% of high-poverty tracts—the highest of any sub-group—and 58% of low-poverty tracts (Table 5.8). Whereas only 6% of high-poverty census tracts are nearest to a for-profit college, 30% of low poverty and 28% of all other census tracts are nearest to this type of institution. Results of a chi-square test indicate that the relationship between poverty rate categorization and sector of the most accessible institution is statistically significant ($\chi^2 = 73.75, p = 0.000$).42

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42 There are seven census tracts in the Chicago study area with more than one less selective college. In six of these tracts, the present colleges are all the same sector (e.g., two for-profit colleges). In the seventh tract, two of the three colleges are for-profits and the third is a broad access public college. An additional origin census tract has two most-
### Table 5.8 Sector of Most Accessible Institution, by Poverty Status (Chicago; 2019)

<table>
<thead>
<tr>
<th></th>
<th>High Poverty - Q4</th>
<th>Low Poverty - Q1</th>
<th>All Other</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>BAC</td>
<td>71%</td>
<td>58%</td>
<td>55%</td>
<td>59%</td>
</tr>
<tr>
<td>For-Profit</td>
<td>6%</td>
<td>30%</td>
<td>28%</td>
<td>23%</td>
</tr>
<tr>
<td>NFP</td>
<td>23%</td>
<td>12%</td>
<td>17%</td>
<td>17%</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>100%</strong></td>
<td><strong>100%</strong></td>
<td><strong>100%</strong></td>
<td><strong>100%</strong></td>
</tr>
</tbody>
</table>

*Sources: Author’s calculations from U.S. Census ACS 5yr Estimates 2015-2019; IPEDS 2019; CDAC O-D Matrix*  
*Notes: Numbers may not add up to 100% due to rounding.*

To further explore whether there are differences in the average quality of the nearest institution by poverty rate sub-groups, I next examine the average resource availability and key outcome measures across sub-groups (Table 5.9), employing a KW test followed by Conover-Iman post-hoc test for each variable. Except for the number of programs offered, all KW tests and the majority of Conover-Iman post-hoc comparison tests are statistically significant. High-poverty tracts are less likely than low-poverty tracts to have a branch campus as the most-accessible institution (47% versus 57%), but no less likely than all other tracts to be nearest a branch campus. Even though branch campuses are more accessible to high-poverty tracts than low-poverty tracts, there are no statistically significant differences in the rank-sum means for the number of program offerings. Put differently, unlike in Briscoe and De Oliver’s (2006) evaluation of differences in UTSA’s main versus branch campuses wherein branch campuses offered fewer courses and majors, in these analyses, main versus branch campus does not serve as a proxy for the breadth of academic offerings.

accessible institutions in different census tracts, one broad access public college and one for-profit. Drive times to the colleges are identical and, though transit travel times differ slightly, the tract does not have any households that lack access to a vehicle, which collapses the accessibility index to the driving-based measure only. Since the chi-square test relies on independence of observations, which would be violated by repeat inclusions of an origin census tract, I take a simplified approach in this and all subsequent chi-square tests: If the tract’s most accessible colleges are of the same sector, I collapse the origin’s most accessible college to one instance of the represented sector. This leaves two instances of differing sectors; I conduct the chi-square test with all four combinations of these institutions as the most accessible (e.g., a for-profit to origin A and a broad access public college to origin B, a for-profit to both origin A and B, etc.). Results are consistently statistically significant; in the text, I present the lowest chi-squared value.
Turning next to institutional resources, observed average per-FTE expenditures are similar between high and low poverty tracts for both instructional spending and student services; in neither case is the difference in rank-sum means statistically significant; Table 5.10). In contrast, the difference in instructional spending between institutions most accessible to high poverty tracts and all other tracts is nearly $750, in favor of high poverty tracts—the largest observe difference in this sub-group analysis. Differences between these two subgroups in the remaining expenditure categories are either not statistically significant in the post-hoc testing (academic support) or the monetary difference is negligible (student services; $32). At the institutions most accessible to low poverty tracts, average per-FTE spending is higher in all three categories, by a maximum observed amount of $526 (instructional).

Full-time retention rates are lower, on average, at the institutions nearest to high poverty tracts as opposed to low poverty or all other tracts (58% in high poverty tracts; 67% and 64% in low poverty and all other tracts, respectively). Although the differences between the averages are not as large for part-time retention rates, the rate remains lower for high poverty tracts than for low poverty and all other tracts (32% in high poverty tracts, as opposed to 47% and 43% in low poverty and all other census tracts, respectively). Graduation rates are low across the board but are lowest at the institutions most accessible to high poverty tracts (25%) and highest at those nearest to low poverty tracts (32%). Mean earnings, measured six and 10 years after initial entry regardless of completion, average the lowest level in high-poverty tracts ($26,906 and $33,391, respectively) and highest level in low poverty tracts ($37,476 and $43,842, respectively), though there is not a statistically significant difference in rank-sum means between low-poverty and all other census tracts in the post-hoc test for six-year mean earnings.
Also included in the list of covariates are the rates of missingness on several variables (full- and part-time retention rate, six- and 10-year mean earnings, three-year student loan repayment rate, and three-year cohort default rate). I include these flags because the patterns of missingness are not random. The one institution without a full-time retention rate does not report this information to IPEDS (Saint Augustine College). Four of the five institutions with missing part-time retention rates report to IPEDS that no students are enrolled part-time; the fifth reports no information on part-time retention despite reporting that 56% of students are enrolled part-time. The two institutions without information on repayment rates and cohort default rates either did not begin participating in the federal student loan program until more recently (Saint Augustine College) or still do not participate as of May 2022 (South Suburban College).

These missing values offer additional context about the characteristics of the nearest less selective college. For example, 21% of high poverty census tracts are nearest to an institution (either Saint Augustine or South Suburban) that did not offer access to federal student loans in 2018, as compared to 1% of low-poverty tracts and 8% of all other tracts. On the one hand, by not participating in the federal student loan program, these institutions ensure that students who enroll cannot leave college with federal student loan debt. On the other hand, students may either opt to rely on private financing (which typically comes with higher interest rates and less generous borrowing terms; Cochrane & Szabo-Kubitz, 2014), enroll in and complete fewer credits (Wiederspan, 2015), or forego enrollment altogether. Even among those institutions that offer federal student loans in aid packages, the average institutional borrowing rate is lower in high-poverty tracts (13%) than in low-poverty or all other tracts (28% and 27%, respectively). That said, when loan programs are available at the nearest institution, the average three-year repayment rate is lower and three-year cohort default rate is higher for high-poverty census tracts.
than for low-poverty or all other census tracts (17% versus 9% and 11%, respectively. Differences in rank-sum means for all sub-group pairings are statistically significant for repayment rates and cohort default rates.
Table 5.9 Average Characteristics and KW Test Results for Most Accessible College, by Poverty Status (Chicago; IPEDS 2019)

<table>
<thead>
<tr>
<th></th>
<th>(1) High-Poverty Tracts (n=487)</th>
<th>(2) Low-Poverty Tracts (n=517)</th>
<th>(3) All Other Tracts (n=1025)</th>
<th>K-W H Statistic (P-Value)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>SD</td>
<td>Mean</td>
<td>SD</td>
</tr>
<tr>
<td>Branch campus&lt;sup&gt;a&lt;/sup&gt;</td>
<td>0.47</td>
<td>0.50</td>
<td>0.57</td>
<td>0.50</td>
</tr>
<tr>
<td># of CIP-4 degrees offered</td>
<td>18.03</td>
<td>18.07</td>
<td>21.08</td>
<td>20.01</td>
</tr>
<tr>
<td>Per-FTE Expenditures</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Instructional</td>
<td>$6,967</td>
<td>$3,660</td>
<td>$6,728</td>
<td>$3,357</td>
</tr>
<tr>
<td>Academic support</td>
<td>$1,665</td>
<td>$1,036</td>
<td>$1,938</td>
<td>$1,218</td>
</tr>
<tr>
<td>Student services</td>
<td>$2,058</td>
<td>$1,056</td>
<td>$2,262</td>
<td>$1,668</td>
</tr>
<tr>
<td>Student Outcomes</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fall-fall retention rate (full-time)</td>
<td>0.58</td>
<td>0.10</td>
<td>0.67</td>
<td>0.11</td>
</tr>
<tr>
<td>Fall-fall retention rate (part-time)</td>
<td>0.32</td>
<td>0.13</td>
<td>0.47</td>
<td>0.15</td>
</tr>
<tr>
<td>150% graduation rate</td>
<td>0.25</td>
<td>0.11</td>
<td>0.32</td>
<td>0.15</td>
</tr>
<tr>
<td>Mean earnings 6yrs post-entry</td>
<td>$26,906</td>
<td>$5,712</td>
<td>$37,476</td>
<td>$12,874</td>
</tr>
<tr>
<td>Mean earnings 10yrs post-entry</td>
<td>$33,391</td>
<td>$7,046</td>
<td>$43,842</td>
<td>$9,038</td>
</tr>
<tr>
<td>Borrowing rate (undergraduates)</td>
<td>0.13</td>
<td>0.21</td>
<td>0.28</td>
<td>0.29</td>
</tr>
<tr>
<td>Borrower 3-year repayment rate</td>
<td>0.30</td>
<td>0.12</td>
<td>0.45</td>
<td>0.12</td>
</tr>
<tr>
<td>Borrower 3-year cohort default rate</td>
<td>0.17</td>
<td>0.06</td>
<td>0.09</td>
<td>0.04</td>
</tr>
<tr>
<td>Missingness Indicators&lt;sup&gt;a&lt;/sup&gt;</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>=1 if missing full-time retention rate</td>
<td>0.17</td>
<td>0.38</td>
<td>0.01</td>
<td>0.10</td>
</tr>
<tr>
<td>=1 if missing part-time retention rate</td>
<td>0.01</td>
<td>0.11</td>
<td>0.02</td>
<td>0.13</td>
</tr>
<tr>
<td>=1 if missing 6yr earnings</td>
<td>0.01</td>
<td>0.10</td>
<td>0.05</td>
<td>0.22</td>
</tr>
<tr>
<td>=1 if missing 10yr earnings</td>
<td>0.01</td>
<td>0.10</td>
<td>0.05</td>
<td>0.22</td>
</tr>
<tr>
<td>=1 if missing 3yr repayment rate</td>
<td>0.21</td>
<td>0.41</td>
<td>0.01</td>
<td>0.11</td>
</tr>
<tr>
<td>=1 if missing 3yr cohort default rate</td>
<td>0.21</td>
<td>0.41</td>
<td>0.01</td>
<td>0.11</td>
</tr>
</tbody>
</table>

Sources: Author’s calculations from U.S. Census ACS 5yr Estimates 2015-2019; IPEDS 2019; CDAC O-D Matrix
Notes: Unless expressly noted with a unit of measurement (e.g., #, $), all demographic values are proportion variables. <sup>a</sup> Denotes a binary variable, in which case a chi-squared comparison test is employed in place of the KW test. Test statict and parenthetical represent the chi-square test statistic and corresponding p-value.
Table 5.10 P-Values from Post-Hoc Pairwise Conover-Iman Tests with Holm Correction for Poverty Sub-Group Comparisons (Chicago)

<table>
<thead>
<tr>
<th></th>
<th>High v. Low-Poverty</th>
<th>High Poverty v. All Other</th>
<th>Low Poverty v. All Other</th>
</tr>
</thead>
<tbody>
<tr>
<td>Branch campus&lt;sup&gt;a&lt;/sup&gt;</td>
<td>0.00</td>
<td>0.76</td>
<td>0.00</td>
</tr>
<tr>
<td># of CIP-4 degrees offered</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>Per-FTE Expenditures</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Instructional</td>
<td>0.47</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Academic support</td>
<td>0.02</td>
<td>0.23</td>
<td>0.00</td>
</tr>
<tr>
<td>Student services</td>
<td>0.05</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Student Outcomes</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fall-fall retention rate (full-time)</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Fall-fall retention rate (part-time)</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>150% graduation rate</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Mean earnings 6yrs post-entry</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Mean earnings 10yrs post-entry</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Borrowing rate (undergraduates)</td>
<td>0.00</td>
<td>0.00</td>
<td>0.17</td>
</tr>
<tr>
<td>Borrower 3-year repayment rate</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Borrower 3-year cohort default rate</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Missingness Indicators&lt;sup&gt;a&lt;/sup&gt;</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>=1 if missing full-time retention rate</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>=1 if missing part-time retention rate</td>
<td>0.51</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>=1 if missing 6yr earnings</td>
<td>0.00</td>
<td>0.00</td>
<td>0.16</td>
</tr>
<tr>
<td>=1 if missing 10yr earnings</td>
<td>0.00</td>
<td>0.00</td>
<td>0.16</td>
</tr>
<tr>
<td>=1 if missing 3yr repayment rate</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>=1 if missing 3yr cohort default rate</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
</tbody>
</table>

Sources: Author’s calculations from U.S. Census ACS 5yr Estimates 2015-2019; IPEDS 2019; CDAC O-D Matrix
Notes: <sup>a</sup> Denotes a binary variable, in which case a chi-squared comparison test is employed in place of the Conover-Iman post-hoc pair-wise comparison test. Test statistic represents the chi-square test statistic and corresponding Holm-adjusted p-value.

By Race/Ethnicity. I next examine the break-down of nearest institution type by the race/ethnicity composition of the census tract. High proportion POC tracts are most frequently closest to a BAC (71%; Table 5.11). In contrast, high proportion White tracts and all other tracts are nearest to a BAC in similar proportions (53% and 57%). Here, as with the poverty rate subgroups, a chi-square test identifies a statistically significant relationship between a census tract’s race/ethnicity categorization and the sector of the most-accessible institution ($\chi^2 = 72.13, p = 0.000$). Therefore, as above, I examine by-subgroup variation in the resources and student outcomes of the nearest institution.
KW tests indicate that the rank-sum means across the three groups are statistically significantly different for all institutional characteristics except the flag for whether the nearest campus is a branch campus (Table 5.12, Column 4). There is a statistically significant difference in the rank-sum means of average instructional expenditures per FTE only among high proportion POC and all other census tracts, though the dollar amount difference is modest: Expenditures are $239 higher in high proportion POC tracts. Average per-FTE expenditures on academic supports are lowest in high proportion POC tracts; the difference in rank-sum means between average per-FTE academic support expenditures in high proportion POC tracts and high proportion White tracts is statistically significant. Although the post-hoc comparison tests identify some statistically significant differences in per-FTE student services expenditures, the observed averages are similar (minimum of $2,030; maximum of $2,214).

Average retention rates, either full- or part-time, are lowest at the institutions nearest to high proportion POC tracts (58% and 32%, respectively). High-proportion White census tracts are nearest to institutions that have, on average, the highest retention rates (66% full-time and 47% part-time). Graduation rates are also lowest at the institutions most-accessible to high proportion POC tracts (25%, versus 33% in high-proportion White tracts). Both six and ten-year mean earnings are lowest, on average, at the institutions nearest to high proportion POC tracts ($26,170 and $32,346, respectively) and highest at the institutions most accessible to high-proportion White tracts ($37,919 and $44,417, respectively). All sub-group pairings’ rank-sum means for these outcomes are statistically significantly different from each other (Table 5.13).

A higher percentage of high proportion POC census tracts are nearest to an institution that does not participate in the Title IV student loan program (23% missing a three-year repayment rate or CDR); only 2% of high proportion White census tracts are nearest to one of
these institutions. Borrowing rates at the institutions that do participate in the federal student loan program are lower at institutions nearest to high proportion POC tracts (12%) than at institutions nearest to high proportion White tracts or all other tracts (29% and 27%, respectively; no statistically significant difference in rank-sum means between these latter two groups). Here again, the average three-year cohort default rate at the set of institutions that do participate in the loan program is twice as high in high proportion POC tracts as it is in high-proportion White tracts (18% versus 9%). Average repayment rates are likewise lower in high proportion POC tracts (28%) than in high proportion White and all other tracts (46% and 42%, respectively).

**Table 5.11 Sector of Most Accessible Institution, by Race/Ethnicity Composition (Chicago; 2019)**

<table>
<thead>
<tr>
<th></th>
<th>High POC</th>
<th>High White</th>
<th>All Other</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>BAC</td>
<td>71%</td>
<td>53%</td>
<td>57%</td>
<td>59%</td>
</tr>
<tr>
<td>For-Profit</td>
<td>6%</td>
<td>34%</td>
<td>26%</td>
<td>23%</td>
</tr>
<tr>
<td>NFP</td>
<td>23%</td>
<td>13%</td>
<td>16%</td>
<td>17%</td>
</tr>
<tr>
<td>Total</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
</tr>
</tbody>
</table>

*Sources: Author’s calculations from U.S. Census ACS 5yr Estimates 2015-2019; IPEDS 2019; CDAC O-D Matrix*

*Notes: Numbers may not add up to 100% due to rounding.*
Table 5.12 Average Characteristics and KW Test Results for Most Accessible College, by Race/Ethnicity Composition  
(Chicago; IPEDS 2019)

<table>
<thead>
<tr>
<th></th>
<th>(1) High POC Tracts (n=487)</th>
<th>(2) High White Tracts (n=530)</th>
<th>(3) All Other Tracts (n=1012)</th>
<th>(4) K-W H Statistic (P-Value)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>SD</td>
<td>Mean</td>
<td>SD</td>
</tr>
<tr>
<td>Branch Campus*</td>
<td>0.46</td>
<td>0.50</td>
<td>0.51</td>
<td>0.50</td>
</tr>
<tr>
<td># of CIP-4 Degrees Offered</td>
<td>15.90</td>
<td>13.59</td>
<td>22.58</td>
<td>20.57</td>
</tr>
<tr>
<td>Per-FTE Expenditures</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Instructional</td>
<td>$6,716</td>
<td>$2,539</td>
<td>$6,422</td>
<td>$3,521</td>
</tr>
<tr>
<td>Academic support</td>
<td>$1,547</td>
<td>$816</td>
<td>$1,966</td>
<td>$1,274</td>
</tr>
<tr>
<td>Student services</td>
<td>$2,094</td>
<td>$1,035</td>
<td>$2,214</td>
<td>$1,766</td>
</tr>
<tr>
<td>Student Outcomes</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fall-fall retention rate (full-time)</td>
<td>0.58</td>
<td>0.11</td>
<td>0.66</td>
<td>0.11</td>
</tr>
<tr>
<td>Fall-fall retention rate (part-time)</td>
<td>0.32</td>
<td>0.13</td>
<td>0.47</td>
<td>0.17</td>
</tr>
<tr>
<td>150% graduation rate</td>
<td>0.25</td>
<td>0.11</td>
<td>0.33</td>
<td>0.16</td>
</tr>
<tr>
<td>Mean earnings 6yrs post-entry</td>
<td>$26,170</td>
<td>$4,963</td>
<td>$37,919</td>
<td>$13,696</td>
</tr>
<tr>
<td>Mean earnings 10yrs post-entry</td>
<td>$32,346</td>
<td>$5,623</td>
<td>$44,417</td>
<td>$9,375</td>
</tr>
<tr>
<td>Borrowing rate (undergraduates)</td>
<td>0.12</td>
<td>0.20</td>
<td>0.29</td>
<td>0.29</td>
</tr>
<tr>
<td>Borrower 3-year repayment rate</td>
<td>0.28</td>
<td>0.11</td>
<td>0.46</td>
<td>0.13</td>
</tr>
<tr>
<td>Borrower 3-year cohort default rate</td>
<td>0.17</td>
<td>0.06</td>
<td>0.09</td>
<td>0.04</td>
</tr>
<tr>
<td>Missingness Indicators*</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>=1 if missing full-time retention rate</td>
<td>0.18</td>
<td>0.38</td>
<td>0.02</td>
<td>0.12</td>
</tr>
<tr>
<td>=1 if missing part-time retention rate</td>
<td>0.03</td>
<td>0.16</td>
<td>0.04</td>
<td>0.20</td>
</tr>
<tr>
<td>=1 if missing 6yr earnings</td>
<td>0.02</td>
<td>0.14</td>
<td>0.04</td>
<td>0.20</td>
</tr>
<tr>
<td>=1 if missing 10yr earnings</td>
<td>0.02</td>
<td>0.14</td>
<td>0.04</td>
<td>0.20</td>
</tr>
<tr>
<td>=1 if missing 3yr repayment rate</td>
<td>0.23</td>
<td>0.42</td>
<td>0.02</td>
<td>0.12</td>
</tr>
<tr>
<td>=1 if missing 3yr cohort default rate</td>
<td>0.23</td>
<td>0.42</td>
<td>0.02</td>
<td>0.12</td>
</tr>
</tbody>
</table>

Sources: Author’s calculations from U.S. Census ACS 5yr Estimates 2015-2019; IPEDS 2019; CDAC O-D Matrix
Notes: Unless expressly noted with a unit of measurement (e.g., #, $), all demographic values are proportion variables. * Denotes a binary variable, in which case a chi-squared comparison test is employed in place of the KW test. Test statistic represents the chi-square test statistic and corresponding p-value.
### Table 5.13 P-Values for Post-Hoc Pairwise Conover-Iman Tests for Race/Ethnicity Sub-Group Comparisons (Chicago)

<table>
<thead>
<tr>
<th></th>
<th>High POC v. High White</th>
<th>High POC v. All Other</th>
<th>High White v. All Other</th>
</tr>
</thead>
<tbody>
<tr>
<td>Branch Campus(^a)</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td># of CIP-4 Degrees Offered</td>
<td>0.01</td>
<td>0.01</td>
<td>0.25</td>
</tr>
<tr>
<td>Per-FTE Expenditures</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Instructional</td>
<td>0.04</td>
<td>0.00</td>
<td>0.12</td>
</tr>
<tr>
<td>Academic Support</td>
<td>0.00</td>
<td>0.32</td>
<td>0.00</td>
</tr>
<tr>
<td>Student Services</td>
<td>0.44</td>
<td>0.01</td>
<td>0.01</td>
</tr>
<tr>
<td>Student Outcomes</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fall-fall retention rate (full-time)</td>
<td>0.00</td>
<td>0.00</td>
<td>0.04</td>
</tr>
<tr>
<td>Fall-fall retention rate (part-time)</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>150% graduation rate</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Mean earnings 6yrs post-entry</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Mean earnings 10yrs post-entry</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Borrowing rate (undergraduates)</td>
<td>0.00</td>
<td>0.00</td>
<td>0.44</td>
</tr>
<tr>
<td>Borrower 3-year repayment rate</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Borrower 3-year cohort default rate</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Missingness Indicators(^a)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>=1 if missing full-time retention rate</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>=1 if missing part-time retention rate</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>=1 if missing 6yr earnings</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>=1 if missing 10yr earnings</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>=1 if missing 3yr repayment rate</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>=1 if missing 3yr cohort default rate</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
</tbody>
</table>

**Notes:**
- Denotes a binary variable, in which case a chi-squared comparison test is employed in place of the Conover-Iman post-hoc pair-wise comparison test. Test statistic represents the chi-square test statistic and corresponding Holm-adjusted p-value.

**Sources:** Author’s calculations from U.S. Census ACS 5yr Estimates 2015-2019; IPEDS 2019; CDAC O-D Matrix

**By Race/Poverty Intersection.** I now briefly examine differences in the sector of the nearest institution by the intersection of racial/ethnic composition and poverty rate. I first identify which census tracts are in the top and bottom quartiles for poverty rates among residents of color and White residents. Then, any census tract that is identified as belonging to either of the racial/ethnic composition groupings (high proportion POC, high proportion White) or either of the corresponding poverty rate groupings (low or high poverty for residents of color; low or high poverty for White residents) is categorized based on its joint membership. Most of the overlap occurs in high proportion White, low White poverty and high proportion POC, high POC poverty.
census tracts ($n=185$ and $n=275$, respectively). In contrast, there is very little overlap between either high proportion White and high White poverty tracts ($n=14$) or high proportion POC and low POC poverty tracts ($n=5$).

There exists a relationship between the census tracts’ combined race/poverty rate categorizations and the sector of the nearest institution ($\chi^2 = 69.31, p = 0.000$; Table 5.14).\(^{43}\)

Focusing on the two groups with the majority of census tracts, 73% of high proportion POC, high POC poverty census tracts are nearest to a BAC, as compared to 53% of high proportion White, low White poverty census tracts. A larger share of high proportion White, low White poverty census tracts are closest to a competitor college, either FP or NFP, than high proportion POC, high POC poverty census tracts. A post-hoc comparison chi-square test of the relationship between the two largest categories of census tracts and whether the nearest institution is a broad access college (i.e., combining FP and NFP competitor colleges) identifies a statistically significant relationship ($\chi^2 = 13.37, p = 0.000$). Put differently, high proportion POC, high POC poverty census tracts are statistically significantly more likely to have a BAC as the most accessible institution, as compared to high proportion White, low White poverty tracts.

\(^{43}\) Due to the small observed and expected cell sizes (less than 5) in the high proportion White, high White poverty rate and high proportion POC, low POC poverty rate categories, I collapse these into the “all other” category when conducting the chi-square test.
Table 5.14 Sector of Most Accessible Institution, by Race/Ethnicity and Poverty Rate Sub-Group (Chicago; 2019)

<table>
<thead>
<tr>
<th></th>
<th>High White, Low Poverty (n=210)</th>
<th>High White, High Poverty (n=22)</th>
<th>High POC, Low Poverty (n=6)</th>
<th>High POC, High Poverty (n=285)</th>
<th>All Other Tracts (n=1506)</th>
<th>Total (n=2029)</th>
</tr>
</thead>
<tbody>
<tr>
<td>BAC</td>
<td>53%</td>
<td>41%</td>
<td>67%</td>
<td>73%</td>
<td>58%</td>
<td>59%</td>
</tr>
<tr>
<td>For-Profit</td>
<td>31%</td>
<td>59%</td>
<td>33%</td>
<td>1%</td>
<td>26%</td>
<td>23%</td>
</tr>
<tr>
<td>NFP</td>
<td>16%</td>
<td>0%</td>
<td>0%</td>
<td>26%</td>
<td>16%</td>
<td>17%</td>
</tr>
<tr>
<td>Total</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
</tr>
</tbody>
</table>

Sources: Author’s calculations from U.S. Census ACS 5yr Estimates 2015-2019; IPEDS 2019; CDAC O-D Matrix
Notes: Numbers may not add up to 100% due to rounding. In 134 census tracts, multiple institutions are tied for most accessible. In these cases, the institutions each appear separately in the count, yielding n sizes in the above table that exceed the number of unique tracts in each sub-group.

Among high proportion White, low poverty census tracts (the second-largest group of tracts), the top five institutions account for just over 30% of all the nearest institutions (Table 5.15, Panel A). In contrast, among high proportion POC, high poverty census tracts, the top five institutions account for nearly 60% of all the nearest institutions (Table 5.15, Panel B); indeed, one institution, City Colleges of Chicago – Kennedy King (CCC-KK), accounts for more than 20% of the nearest institutions. This institution spends more per FTE than the average BAC and FP competitor in the Chicago area. However, student retention rates and mean earnings six and ten years post-entry are lower at CCC-KK than at the average BAC in Chicago. Furthermore, though borrowing rates are approximately equivalent (6% versus 5% at the average BAC in Chicago), three-year repayment rates are lower (23% versus 36%) and cohort default rates are higher (23% versus 14%).
Table 5.15 Top 5 Most Accessible Institutions, by Race/Ethnicity and Poverty Rate Sub-Group (Chicago; IPEDS 2019)

<table>
<thead>
<tr>
<th>Institution (Campus) Name</th>
<th>Freq.</th>
<th>Pct.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A. High White, Low Poverty Census Tracts (n=185)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Oakton Community College (Skokie Campus)</td>
<td>19</td>
<td>9%</td>
</tr>
<tr>
<td>Chamberlain University - Illinois (Main Campus in Addison)</td>
<td>13</td>
<td>6%</td>
</tr>
<tr>
<td>DeVry University (Addison)</td>
<td>13</td>
<td>6%</td>
</tr>
<tr>
<td>William Rainey Harper College</td>
<td>13</td>
<td>6%</td>
</tr>
<tr>
<td>College of Lake County – Southlake (Vernon Hills Campus)</td>
<td>10</td>
<td>5%</td>
</tr>
<tr>
<td><strong>Panel B. High POC, High Poverty Census Tracts (n=275)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>City Colleges of Chicago-Kennedy-King College (Main Campus)</td>
<td>68</td>
<td>24%</td>
</tr>
<tr>
<td>Saint Augustine College (South Satellite)</td>
<td>26</td>
<td>9%</td>
</tr>
<tr>
<td>City Colleges of Chicago- Malcolm X College (West Side Learning Center)</td>
<td>24</td>
<td>8%</td>
</tr>
<tr>
<td>City Colleges of Chicago- Kennedy-King College (Dawson Technical Institute)</td>
<td>23</td>
<td>8%</td>
</tr>
<tr>
<td>City Colleges of Chicago-Olive-Harvey College</td>
<td>20</td>
<td>7%</td>
</tr>
</tbody>
</table>

Sources: Author’s calculations from U.S. Census ACS 5yr Estimates 2015-2019; IPEDS 2019; CDAC O-D Matrix

Summary of RQ2 Findings

The RQ2 findings for the Lansing study area are necessarily limited by the small amount of institutional variation. I am unable to compare average characteristics of the most accessible institution by sub-group but do find that a BAC main campus is more often the most accessible institution to high poverty tracts than low poverty tracts (50% versus 28%; a BAC main campus is equally likely to be the nearest institution to high proportion POC and high proportion White census tracts (41%).

In Chicago, the colleges most geographically accessible to high poverty tracts have lower retention rates, graduation rates, and earnings than the colleges most geographically accessible to low-poverty census tracts. Furthermore, although fewer students at these institutions borrow than at institutions nearest to low poverty or all other census tracts, when students do borrow, the repayment rates are lower and default rates are higher. A similar story unfolds when examined for high proportion POC versus high proportion White census tracts: Even though instructional expenditures are modestly higher in high proportion POC census tracts than in high proportion
White tracts, retention rates, earnings, and student loan repayment rates are lower and cohort default rates are higher. These findings partially support the hypothesis outlined for RQ2, namely that the observed student outcomes at the institutions most accessible to lower income and higher proportion POC neighborhoods are lower than at the institutions most accessible to high income and high proportion White neighborhoods. Although there are some statistically significant spending differences across poverty rate and racial/ethnic composition sub-groups, the dollar amounts are generally small. I explore in more detail the potential causes/origins of these differences in the discussion chapter.

**Chapter Summary**

In both research questions for Part I, my interest was in individual institutions’ geographic context: the demographics of the neighborhoods in close proximity to less selective college campuses; and the average resources and outcomes at the institution nearest to each census tract, evaluated separately by poverty status and racial/ethnic composition. I hypothesized that less selective colleges are more likely to be located in low-income neighborhoods and neighborhoods of color and, indeed, evidence in both study areas supports these hypotheses. Median household income is lower and poverty rates are higher in less selective college tracts. In Lansing, less selective college tracts are more racially diverse, as are BAC tracts in Chicago. That said, FP tracts in Chicago are less racially diverse and have a higher median income than other census tract sub-groups; this evidence runs counter to my general hypotheses but aligns in part with Fisher’s (2012) finding that FP college neighborhoods have the lowest percentages of Black residents. Furthermore, BAC branch campuses are located in lower-income and more racially diverse neighborhoods than BAC main campuses, in alignment with Briscoe and De
Oliver’s (2006) and Kenyon’s (2011) finding that branch campus locations are chosen to serve student populations historically excluded from or underserved by higher education.

The second research question examines a different dimension of accessibility, namely the potential that, when multiple opportunities are present in a region, the opportunity nearest to low-income and racially diverse neighborhoods is lower quality than the opportunity nearest to high-income and high proportion White neighborhoods. For this research question, I identified which less selective college is nearest to each census tract. Then, for the collection of census tracts in each sub-group (e.g., all high poverty census tracts), I compared average expenditures and student outcomes at the tracts’ most-accessible colleges. Although I am unable to evaluate the research question for Lansing, where there are too few less selective colleges, I find in Chicago that student outcomes are lower at the institutions most accessible to high poverty and high proportion POC census tracts than at the institutions most accessible to low poverty and high proportion White census tracts. In the chapters that follow, I pivot my focus to the overall accessibility of broad access public colleges in each of the two study areas in an effort to understand the relationship between college accessibility and neighborhood demographics when all available opportunities of a particular type are incorporated. I begin in the next chapter with a detailed explanation of the construction of the postsecondary accessibility index.
Chapter 6 Development of the Postsecondary Accessibility Index

In this chapter, I detail the development of the postsecondary accessibility index that I employ to evaluate whether and how cumulative accessibility to broad access public colleges varies across the two study areas. The index that I adapt has its origins in the transportation planning field, where scholars have long contemplated how best to operationalize the component parts that together dictate an individual’s geographic access to opportunity (Geurs & van Wee, 2004; see also the literature review in Giannotti et al., 2022). I opt to rely on an index instead of simpler approaches because these approaches have limitations that could, each in their own way, result in the misestimation of accessibility. Contour measures (e.g., co-location with a college) ignore local variation across the designated region, Euclidean distance underestimates distance as measured by roadways, driving distance may underestimate travel time for traffic-heavy regions, and driving time overestimates mobility for transit-reliant individuals.

Gravity measures of accessibility address these limitations in three ways: First, through the incorporation of a decay function, the gravitational pull of an opportunity diminishes as the distance to the opportunity increases (Geurs & van Wee, 2004). This decay function has its origins in urban planners’ theory that, all else being equal, individuals will make fewer trips as the time-costs associated with making a trip increase (Levine et al., 2019). Second, through the incorporation of a desirability measure, I can mediate any given opportunity’s accessibility by its relative attractiveness. Put differently, the destination that is only 10 minutes away may provide inferior services as compared to the option that is 40 minutes away—and therefore be a less likely destination—but this difference is lost when travel time is used as the sole measure of
accessibility. Third, the mode-adjusted version of the index that I construct incorporates travel
time by car and public transit, making it possible to assess whether geographic access varies both
across neighborhoods and within these neighborhoods based on the mode of travel.

Furthermore, I opt to employ a gravity-based model rather than another common
approach, the cumulative opportunity measure, because I am primarily interested in how the
level of accessibility varies across space. Cumulative-based measures of accessibility count the
number of opportunities that are reachable within a given time or distance radius from each focal
area. Dai and Wang (2011) refer to this approach as one focused on “resource availability” that,
as a result, sidesteps the question of variable accessibility across space (p. 660). The smaller the
radius, the fewer the total number of opportunities in the study area are incorporated into the
measure of accessibility. In contrast, a gravity-based accessibility index accounts for the full
range of available opportunities by giving more weight to nearer opportunities but not excluding
further-away opportunities (Levine et al., 2019).

There are also adaptations to the gravity-based index design. The two-step floating
catchment area (2SFCA) model, for example, has been used in studies of access to healthcare
(Cheng et al., 2016), food (Kuai & Zhao, 2017), or daycare (Kim & Wang, 2019). The 2SFCA
model and its ancestors attempt to account for capacity constraints since, in their absence, “the
underlying assumption is that services that fall within the catchment area will be fully available
to residents within that catchment area” (Luo & Wang, 2003, p. 870). With some exceptions, the
post-pandemic narrative surrounding broad access public colleges is one focused on excess
capacity, not constrained capacity (Lanahan, 2021; Moody, 2022; Whitford, 2022). Therefore,
the added complexity of these models is less relevant for my analytic purposes.
The basic equation for a gravity model used in accessibility indices, adapted to the study context, is (Shen, 1998, Zhang, 2005):

\[ A_i = \sum_j f(C_{ij})O_j \]  

(6.1)

where

- \( A_i \) is the postsecondary accessibility for location \( i \)
- \( C_{ij} \) is the time, distance, or cost associated with traveling between location \( i \) and college \( j \)
- \( f(C_{ij}) \) is the impedance function between location \( i \) and college \( j \)
- \( O_j \) is the attractiveness of broad access public college \( j \)

The first component in the accessibility index is \( C_{ij} \), the time, distance, or cost associated with traveling between location \( i \) (the origin point) and institution \( j \) (the destination point). In this study, I rely on travel time as my cost measure. Specifically, \( C_{ij} \) will be measured as the average travel time between the census tract \( i \) (“origin”) and each broad access institution \( j \)’s census tract (“destination”), for all broad access institutions located within the same study area and measured separately for two travel modes, driving and transit.

The impedance function (or “distance-decay factor”), \( f(C_{ij}) \), captures the decay of desirability that urban planners theorize accompanies increased distances between origins and destinations (Levine et al., 2019; Iacono, Krizek & El-Geneidy, 2008). Grengs (2015) refers to the impedance function as a “traveler’s unwillingness to travel long distances,” with larger values suggesting a more rapid decay of willingness to travel long distances (p. 5). The impedance function most commonly takes the following form:

\[ f(C_{ij}) = C_{ij}^{-\beta} \]  

(6.2)

with the value of \( \beta \) reflective of the rate at which an individual’s tolerance for travel decays as distance increases. This decay in willingness to travel is hypothesized to vary across metropolitan areas and depending on the stated purpose of the trip, with high-value trips (e.g.,
job commuting) having higher distance thresholds than lower-value trips (e.g., convenience stores; Mulligan, Partridge, & Carruthers, 2012).

In this study, I use distance-decay factors for work-related trips derived in or used by previous job accessibility studies (see Levine et al., 2011, Shen 1998). This decision represents two adaptations to the approach commonly employed in the literature. The first adaptation is that I opt to rely on decay factors for work-based trips rather than a factor specifically derived for higher education-based trip purposes. I make this decision for two reasons. First, to my knowledge, trip data for commuter students’ travel to and from college do not exist. Several studies derive distance-decay factors for K-12 school-related trips (Iacono et al., 2008; Grengs, 2015; Zhang, 2005), but these distance-decay factors are not likely transferrable to college students’ commuting patterns. Elementary and secondary schools are more numerous than broad access public colleges nationwide (US ED NCES, 2020a; author’s calculations of IPEDS, 2019), and the presence of more K-12 schools in proximity to an individual’s place of residence could lead to a lower travel tolerance than would be the case if there were fewer opportunities available. This lower tolerance would manifest as an increase in the distance-decay factor that, if used to study accessibility to colleges, might result in downward bias in the accessibility index values. Second, the desire to earn a credential or skills that improve labor market prospects motivates place-bound students’ college enrollment (Iloh & Tierney, 2014). In this way, trips to attend college are more like work-based trips—in that they are motivated by future employment prospects—than non-work trips to supermarkets, libraries, or for social visits (Grengs, 2015).

The second adaptation is the decision to rely on existing decay values, universally applied to each of the two study areas. Researchers typically draw on consumer surveys of transportation use (Grengs, 2015) or trip data from transit systems (Boisjoly & El-Geneidy, 2016) to
empirically derive for a single city or metropolitan area population-based values for \( \beta \). In studies that compare accessibility across metropolitan areas, the distance-decay factor is first derived separately for each metropolitan area, then a population-weighted average of these separate distance-decay factors is calculated to employ across all metropolitan areas (Grengs et al., 2010). Relying on previously derived measures prevents the need to derive these measures anew, a process which is itself time-, data-, and skill-intensive. Since final results could be sensitive to the choice of decay factor, I first calculate the index using Levine et al.’s (2011) work-based distance-decay factor derived using data from 38 metropolitan regions (\( \beta = 0.10157 \)).\(^{44}\) I then mimic the robustness check implemented by Wang and Minor (2002), in which I re-estimate the regression analyses using values of \( \beta \) ranging from 0.05 to 0.15.\(^{45}\)

The final component of the gravity model is the desirability factor (\( O_j \)). In applications of the gravity model to the accessibility of job opportunities, \( O_j \) represents the number of job opportunities available in destination zone \( j \) (Bocarejo & Oviedo, 2012; Shen, 1998), where job counts are typically based on the number of jobs available in a given area. When the gravity model is instead used to model the accessibility of nonwork opportunities, this measure captures the perceived attractiveness or desirability of opportunity \( j \) (Grengs, 2015). One example of a non-work operationalization of desirability is the number of retail employees in an area as a proxy for the attractiveness of an area’s shopping opportunities (Grengs, 2015).

In an index of college accessibility, there is no clear theoretical linkage between per-tract counts (of colleges or employees) and perceptions of college desirability. Most tracts have zero

\(^{44}\) The value derived in this study is nearly identical to the value derived in Shen’s (1998) evaluation of job accessibility in Boston, MA (\( \beta = 0.1034 \)).

\(^{45}\) Wang and Minor (2002) derive distance-decay factors for a single city and by mode of transportation (\( \beta = 0.76 \) for drivers; 0.35 for public transit riders). They then test whether regression results change when the larger distance-decay factor is doubled and the smaller is halved. I therefore identify the range to use in my sensitivity check by halving and doubling Levine et al.’s (2011) distance-decay factor; the result is a range of 0.05 to 0.15. It is worth noting that the work-based distance-decay factors derived in Wang and Minor’s (2002) study are higher than the values derived in the other studies included here, especially for driving; it seems possible that these high values may have contributed to the decision to conduct the sensitivity check.
colleges and rarely does a tract with a college have more than one; with this method, colleges would all have a desirability of one, suggestive of little variation in perceived desirability. Similarly, the number of employees at a college is, at best, an indirect proxy for institutional resources, which the academic literature identifies as influential to students’ college enrollment choices (Jacob et al., 2018). The development of the desirability measure in postsecondary education requires more deliberate consideration of how to incorporate factors that are neither too specific to individual students’ preferences nor so general as to have no linkage to the academic literature on college choice. In the sub-section that follows, I detail the steps taken to operationalize desirability using several institution-level covariates that I hypothesize influence a place-bound student’s propensity to enroll at a given campus location.

**Operationalizing Desirability**

The underlying goal of the desirability measure is to coarsely differentiate between otherwise similar opportunities (e.g., broad access public colleges) using institutional characteristics that extend beyond location. The literature on student choice—a full review of which is beyond the scope of this study—demonstrates that students’ college choices, particularly among recent high school graduates, are based on a broad range of factors, including proximity to home (Turley, 2009); price and financial aid availability (Dynarski & Scott-Clayton, 2013); program offerings (Ezarik, 2022); academic reputation (Alter & Reback, 2014); available resources (Jacob et al., 2018); and even reported earnings (Hurwitz & Smith, 2018).

That said, with the desirability index, I seek not to incorporate all factors that might influence individual students’ enrollment choices, nor is it my goal to define a proxy for institutional quality. I instead seek to incorporate key information that is both publicly available and may serve as an early gatekeeper to place-bound students’ decisions about whether and where to
enroll. Rather than rely on a single measure—such as number of jobs or retail employees—I incorporate into my desirability measure two factors that are readily observable and relevant to prospective students’ stated preferences (Cabrera & La Nasa, 2000; Ezarik, 2022; Supiano, 2015): tuition and fees, and undergraduate program offerings by campus location. Detailed below is the theorization and operationalization of each.

**Tuition and Fees.** I include an institutional measure of tuition and fees for undergraduate students since this readily available information about price could disproportionately influence an individual’s assessment of the likely cost of attendance. Specifically, I hypothesize that institutions with lower tuition and fees will be more desirable to the average resident than institutions with higher tuition and fees. The two four-year public universities charge only in-state tuition, but all the public community colleges differentiate pricing based on district residency. Therefore, the tuition and fees value for a given census tract-community college pairing needs to vary based on whether the tract is considered in- or out-of-district. In Michigan, community colleges maintain lists of K-12 school districts that are considered in-district for their institution (for LCC’s K-12 school districts, see Lansing Community College, 2022). In Illinois, the state is divided into 39 community college districts (ICCB, 2020). Since in neither state do district boundaries adhere to tract boundaries, I assign a tract to in-district status if its weighted centroid is within the geographic boundary of the district in question.

The use of tuition and fees is imperfect in at least three ways, each of which likely overestimates the price an individual student might pay, and therefore underestimates an institution’s desirability to an individual student. First, students enrolled part-time would not be charged the full amount. Since I cannot observe the share of students in a census tract who, when deciding whether and where to enroll, intend to enroll as a full- versus part-time student, this
distinction is difficult to incorporate into the desirability measure. Second, tuition may vary by program or by level (e.g., associate degree versus bachelor’s degree), which could lead some institutions to appear more desirable for students interested in certain programs of study or degree offerings. Here again, since student-level preferences are not observable, it is difficult to discern the degree to which these variations would influence overall preferences.

Third, students who are eligible for need- and/or merit-based financial aid may pay a net price that is lower than the published tuition and fees rate. Details on average net price (ANP) by income band are available in the College Scorecard, or a student might estimate their net price for an institution using the institution’s Net Price Calculator. Despite potentially better reflecting what a student could expect to pay, ANP is less useful in the desirability measure due to the inability to disentangle ANP for in- versus out-of-district students. According to IPEDS,

[ANP] is generated by subtracting the average amount of federal, state or local government, or institutional grant and scholarship aid from the total cost of attendance. Total cost of attendance is the sum of published tuition and required fees (lower of in-district or in-state), books and supplies and the weighted average room and board and other expenses (U.S. ED NCES, 2019; emphasis added).

ANP assumes all students’ COA is based on the lower of in-district or in-state tuition, rather than calculating these estimates separately based on residency status. Therefore, its use in the desirability measure would not afford a means of adjusting likely cost based on the geographic boundaries that dictate residency status.

Another way to account for the fact that few students pay the sticker price would be to include a measure that captures the percentage of students who receive need or grant-based aid—in essence, a proxy for the likelihood that a student will receive a discount. A discount could,
based on the college choice literature, sway place-bound students’ choice of where to enroll (Dynarski & Scott-Clayton, 2013). However, many eligible students, including at community colleges that comprise 21 of the 22 BACs in the full sample, do not receive the Pell Grant or other need-based aid even though they are likely eligible (Advisory Committee on Student Financial Assistance, 2008; Kantrowitz, 2011; National College Attainment Network, 2022). Martorell and Friedmann (2018) estimated that 20% of eligible students in California community colleges did not receive the Pell Grant. In this way, the percentage of students who receive financial aid at community colleges is only partially reflective of the actual likelihood that any given student would receive a discount. Given that financial aid receipt is an imperfect proxy for potential aid receipt at the colleges in question, I decide against including such a measure.

Diversity of Program Offerings. The second component of the desirability measure accounts for the breadth of program offerings at a given campus location. Focus groups of students found that students sought out program offerings—on websites like the College Scorecard or CollegeBoard’s Big Future—as part of their filtering process (Supiano, 2015), thereby making it an important consideration in the construction of a desirability measure. I hypothesize that campuses with more program offerings are more desirable to the average place-bound student than campuses with fewer program offerings because of the increased likelihood that a student will have access to their desired program of study at campuses with more program offerings. The Classification of Instruction Programs (CIP) “provides a taxonomic scheme that supports the accurate tracking and reporting of fields of study and program completions activity” (US ED NCES, n.d.), which can be used here as a bridge between the general idea that program of study influences desirability and the specific programs offered at broad access colleges.
For the desirability measure, I count the total number of award and/or degree-granting four-digit CIP codes submitted to IPEDS for each broad access institution.\textsuperscript{46} The reliance on four-digit CIP codes represents a compromise between the use of the full six-digit CIP code, which maximizes detail but requires significant work to manually gather for branch campuses, and the use of the two-digit CIP code, which minimizes manual work but erases meaningful distinctions within CIP codes (e.g., both economics and sociology are subsumed into one two-digit CIP code for the social sciences). Furthermore, this decision is in keeping with a technical review panel’s decision to report key metrics at the four-digit CIP code since, in most cases, the four-digit CIP code closely mirrors the six-digit CIP code with respect to the preservation of information about program of study (RTI Technical Review Panel, 2019).

I create binary variables equal to one if the college offers any degree in each four-digit CIP code, as recorded in the IPEDS Completions file.\textsuperscript{47} I ignore offerings by degree type because my primary goal is to identify the fields of study available to potential students, rather than the specific type of undergraduate degrees offered. I assume that any main campus offers a program in every four-digit CIP code identified using the IPEDS data. In cases where programs are only offered at a branch campus, this approach overestimates the program diversity of the main campus.

Since program offerings at branch campuses may differ from those at the main campus, I next manually identify the program offerings at each branch campus and map these program offerings to the appropriate four-digit CIP code. I do so by locating website information related

\textsuperscript{46} The following eight CIP codes are categorized as not valid for IPEDS reporting because affiliated programs of study are not typically credit-bearing and do not lead to a certificate or degree when completed. Since they are not reported to IPEDS, they are therefore excluded from the list of possible two-digit CIP codes offered at an institution: Reserve officer training corps (28), Basic skills (32), Citizenship activities (33), Health-related knowledge and skills (34), Interpersonal and social skills (35), Leisure and recreational activities (36), Personal awareness and self-improvement (37), High school/secondary diplomas and certificates (53). CIP code 60 (Residency Programs) is available only to post-baccalaureate award levels. See https://nces.ed.gov/ipeds/cipcode/FAQ.aspx?y=55.

\textsuperscript{47} Specifically, I use the information included in the Completions file with the following title: “Number of programs offered and number of programs offered via distance education, by award level: July 1, 2018 to June 30, 2019.”
to program/course offerings at a given location, including only those CIP codes that correspond to undergraduate program or course offerings at or above the associate degree level. Most commonly, this information comes in the form of explicit details (e.g., “the following associate degree programs are offered at this location”) or descriptive write-ups (e.g., “we offer courses in welding and automotive repair at this location”). When not available, I mine Fall 2021 course offerings by location. Because institutions may continue to offer some courses online-only as the pandemic recedes, this approach may underestimate program offerings at branch locations. However, historical course schedules by location are not readily available, preventing the identification of pre-pandemic course offerings.48

**Transforming Covariates for the Desirability Measure.** The unit of measurement for each of the two components—program offerings as well as tuition and fees—differ from each other. Program offerings is a count of the number of four-digit CIP codes offered at any given location; it can range from 1 to 368. In contrast, tuition and fees is a monetary unit of measurement that captures the tuition rate that an institution would charge a resident of a given census tract. If I were to leave both variables in their raw form, the different scales would necessarily result in the numerically high-value covariates for tuition and fees exerting greater influence over the final value of the desirability measure, as well as the final accessibility value, than the lower-value program offering covariate. To avoid increased influence that does not reflect a deliberate weighting of the components, I normalize both variables to be on a scale of zero to one. Furthermore, since providing relative weights to each measure would require information on the specific preferences of place-bound students in each study area, I opt to

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48 At 20 of the 22 broad access colleges in the sample (all community colleges), the three four-digit CIP codes with the most completions account for more than 40% of all completions at the college; Michigan State University and University of Illinois Chicago fall below this threshold with top three CIP codes accounting for 16% and 26% of all completions, respectively. These patterns suggest that, even with numerous degree offerings, most students are concentrated in a small subset of these offerings.
instead weight each of the two measures equally. It is possible that an individual student weights these factors differently and unequally, however the goal of the index is to generate a measure of desirability that captures population-level rather than individual-level considerations of choice.

To normalize the tuition and fees variable to have a value between zero and one, I first identify the least expensive broad access public college in each study area. Then, for each tract-institution pairing, I divide the focal institution’s tuition and fees value by the tuition and fees value of the least-expensive college in the study area. Finally, I take the inverse of this value, which sets the least-expensive institution’s value equal to one, in keeping with the hypothesis that lower tuition and fees is associated with higher desirability. In contrast, the tuition and fees desirability measure at more expensive institutions approaches zero. This ratio-based approach amounts to a calculation of the proportion of tuition and fees at the focal institution that is covered by the tuition and fees amount at the least-expensive college in the study area.

The normalization process for program offerings follows a min-max rescaling procedure: I first identify the broad access college campuses with the least and most program offerings in each study area. Then, for each broad access college campus, I subtract from its program offerings count the program offerings count of the campus with the fewest program offerings. This value is divided by the difference between the most and least number of program offerings at any college campus in that study area. The campus with the most program offerings will have a value of one on this portion of the desirability measure, whereas the value for the campus with the fewest program offerings will equal zero.⁴⁹

⁴⁹ A traditional transportation evaluation of accessibility would refrain from allowing any measure of desirability to be set equal to zero because it is misaligned with the theoretical notion of what makes a given location desirable. Specifically, a value of zero desirability would result in an opportunity’s exclusion from the accessibility index, even though it remains geographically accessible despite its lower level of measured desirability. Although I acknowledge this limitation, I leave the construction as-is since it serves as a means of normalizing to values between zero and one two variables with different underlying units of measurement.
**Final Construction.** The final step involves constructing the desirability sub-component. To do this, I add the two desirability sub-measures together, using the transformed versions of both tuition and fees and program offerings. Using this approach, the maximum value of the desirability measure is two; the minimum value always exceeds zero, since the tuition and fees component never reaches zero. This approach is agnostic in its weighting of the importance of each component, not because the components are assumed equivalent among all place-bound students but because the index is meant to reflect population-level desirability rather than individual-level desirability. A college with a high desirability value would be one with low tuition and fees relative to other colleges in the study area and many program offerings compared to these same colleges. In contrast, a college with low desirability would be one with few program offerings and high tuition and fees, both relative to other colleges in the study area.

The following equation, in which I calculate the mode-weighted accessibility index, modifies the basic gravity model specification (equation 6.1, pg 151) to reflect the study at hand:

$$A_i = \left( \sum_j O_j D_{ij}^{-\beta} \right) * PropCar + \left( \sum_j O_j T_{ij}^{-\beta} \right) * PropNoCar$$ (6.3)

where

- $A_i$ is the postsecondary accessibility for census tract $i$
- $O_j$ is the desirability measure for college $j$, calculated as outlined in the preceding sub-section
- $D_{ij}$ is the driving travel time associated with traveling between the weighted centroids of census tract $i$ and college $j$’s census tract (does not include parking time)
- $PropCar$ is the proportion of households in census tract $i$ that report having access to at least one vehicle
- $T_{ij}$ is the public transit travel time associated with traveling between the weighted centroids of census tract $i$ and college $j$’s census tract
- $PropNoCar$ is equal to 1-$PropCar$ for census tract $i$
- $\beta$ is the distance-decay factor associated with travel for work-based trips (constant across travel modes)

This equation is comprised of two parts, the first multiplying the summation of a census tract’s driving-based accessibility by the proportion of households in the census tract that own at least
one vehicle and the second multiplying the summation of a census tract’s transit-based accessibility by the proportion of households in the census tract without any vehicle. As noted by Grengs (2015), this mode-weighting approach, which assumes that all individuals in a car-owning household benefit from car mobility, likely overestimates the proportion of individuals who are able to commute by car to and from school. Households may have one car shared among multiple individuals (Lucas, 2004), and the reliability of the car as well as the individual’s ability to afford the ancillary costs that accompany a car commute are unknowable in aggregated data.

The final postsecondary accessibility index variable has a bimodal distribution in both study areas (see Figure 8.3 and Figure 8.8 for Lansing and Chicago, respectively). At first blush, this bimodal distribution would be incongruous with expectations to an urban planner familiar with a normally distributed accessibility index. In the study of higher education—and community colleges specifically—the tuition and fees component of desirability is geographically defined by in- versus out-of-district status. Thus, tracts in community college districts with many campuses will have higher accessibility than tracts in regions either without any in-district college campuses or with fewer in-district college campuses.

**Guided Construction of the Index**

To better demonstrate how the accessibility index derives from this equation, I incorporate a running example using two census tracts in the Chicago study area and two broad access colleges in this same area. South Suburban College (SSC) is a two-year public college with one campus, located south of the City of Chicago. Tuition and fees for the 2018-19 academic year were $5,093 (in-district) and $11,033 (out-of-district). Degree programs are offered in a total of 42 of the 368 four-digit CIP Codes. Malcolm X College is a two-year college in the City Colleges of Chicago system, with tuition and fees for the 2018-19 academic year
amounting to $3,504 for in-district students and $9,216 for out-of-district students. The college offered programs in 18 of the 368 2-digit CIP codes.

Census tract A (CT-A; GEOID: 17031241100) is located in the City of Chicago, between I-90 and the Eisenhower Expressway, within the City Colleges of Chicago district. Ten percent of the population in CT-A is Black, and the overall poverty rate is 21%, as compared to 17% and 12% in the broader study area. Census tract B (CT-B; GEOID: 17031827000) is located 26.3 miles away (by driving distance), south of the City of Chicago and in the South Suburban College district. Ninety percent of the population in CT-B is Black, and the overall poverty rate is 38%. The raw and normalized values for each desirability covariate, as well as the composite measure of desirability for each census tract, are included in Table 3.1. Table 3.2 summarizes travel times to each of the two colleges’ census tracts from each of the origin tracts by transit mode, all drawn from the CDAC national O-D matrix. Recall that the CDAC matrix estimates travel time using a departure of 12pm on Monday.

Based on these figures, I can now calculate separate transit and car accessibility indices for each census tract using Levine et al.’s (2011) distance-decay factor derived for work-based trips in 38 metropolitan areas ($\beta = 0.10157$). The value calculated with this approach is then used to answer RQ2, which relies on identifying each tract’s most accessible college (see Chapters 4 and 5). First, for all broad access public colleges and competitor colleges, I calculate each tract-institution pairing’s singular accessibility index value, excluding the desirability measure. To do so, I first adjust all travel times for a given tract-institution pairing using the distance decay factor (travel time raised to the $-\beta$). For the CT-A – SSC pairing, this would result in a driving value of 0.67 and transit value of 0.63. These same values for CT-A – Malcolm X are 0.76 and 0.71, for driving and transit respectively. I then calculate each institution’s mode-adjusted
accessibility value only for CT-A. This involves multiplying the driving value for CT-A – SSC by the proportion of households in CT-A that have access to at least one vehicle (0.73), and the transit value for this same pairing by the proportion of households without access to a vehicle (0.27). I then sum these values. Following this process results in a pairing-specific accessibility value for CT-A – SSC of 0.66; for CT-A – Malcolm X, the pairing-specific accessibility value is 0.75. Were these the only two institutions in the study area, I would identify City Colleges of Chicago – Malcolm X as the institution most-accessible to CT-A. This process allows me to identify the most accessible college to each census tract, based solely on the transportation components of the index (travel time, mode of travel/car reliance within the census tract).

Table 6.1 Raw and Standardized Values for Desirability Covariates, by Institution-Census Tract Pairing

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<thead>
<tr>
<th>Desirability Component</th>
<th>South Suburban College</th>
<th>Malcolm X College</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Raw</td>
<td>Normalized</td>
</tr>
<tr>
<td>Tuition &amp; Fees</td>
<td>$11,033(^a)</td>
<td>0.29</td>
</tr>
<tr>
<td>Program Diversity</td>
<td>42</td>
<td>0.62</td>
</tr>
<tr>
<td>Composite Desirability (Oj)</td>
<td>—</td>
<td>0.91</td>
</tr>
</tbody>
</table>

Panel A: CT-A

Panel B: CT-B

| Tuition & Fees         | $5,093\(^b\) | 0.62       | $9,216\(^b\) | 0.34       |
| Program Diversity      | 42         | 0.62       | 18         | 0.26       |
| Composite Desirability (Oj) | —         | 1.24       | —         | 0.60       |

Sources: IPEDS 2019; CDAC O-D Matrix 2019

Notes: Table provides an example estimation of the accessibility index for two census tracts in the Chicago study area, including the raw and normalized values for the desirability measures (represented by \(Oj\) in Equation 6.3). \(^a\)Out-of-district tuition and fees rate because the tract is not within the boundary of the relevant college’s district. \(^b\)In-district tuition and fees rate because the tract is within the boundary of the relevant college’s district.

Table 6.2 Public Transit and Driving Travel Times to Two Broad Access Colleges in Lansing

<table>
<thead>
<tr>
<th>Departure Day and Time</th>
<th>South Suburban College</th>
<th>Malcolm X College</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Public Transit</td>
<td>Driving</td>
</tr>
<tr>
<td>CT-A</td>
<td>Monday, 12pm</td>
<td>97m</td>
</tr>
<tr>
<td>CT-B</td>
<td>Monday, 12pm</td>
<td>22m</td>
</tr>
</tbody>
</table>

Sources: CDAC O-D Matrix 2019

Notes: All estimates are based on estimated travel times, by mode, between census tracts’ weighted centroids.
I then pivot to the summative calculation of the postsecondary accessibility index for broad access public colleges. The first step is to multiply the distance decay-adjusted travel time (separately for driving and transit) by the value of the tract-institution pairing’s desirability measure. For example, to calculate the tract-institution driving-based accessibility value for CT-A and SSC, I would use the following equation:

\[ A_{CT-A; SSC} = 0.91 \times 50\text{min}^{-0.10157} \]  \hspace{1cm} (6.4)

Here, the desirability measure for the tract-institution pairing is 0.91 (Table 6.1), the driving-based travel time between the two locations is 50 minutes (Table 3.2), and the distance-decay factor that I employ in this study is -0.10157. I then repeat this process to calculate transit accessibility for this pairing (travel time = 97 minutes; Table 6.2). The driving accessibility index value for CT-A – SCC is 0.61; for transit, the value is 0.57. This process is repeated for the CT-A – Malcolm X pairing and results in a tract-institution driving accessibility value of 0.89 and public transit accessibility value of 0.83. Overall transit accessibility, the summation of transit accessibility for CT-A – SCC and CT-A – Malcolm X, is 1.40, versus an overall driving accessibility value of 1.50. The larger value for driving accessibility suggests that postsecondary accessibility is greater for car-reliant than transit-reliant individuals residing in CT-A. ACS 5-year estimates indicate that 73% of households in CT-A report owning a car. Therefore, the mode-weighted postsecondary accessibility index is 1.47 \((1.50 \times 0.73 + 1.40 \times 0.27)\). When I repeat this process for CT-B, I find that the mode-weighted postsecondary accessibility index is 1.39, which indicates that CT-B has overall lower accessibility than CT-A. These final values can then be used to address research questions three and four which, together, comprise Part II of the study. The next chapter outlines the relevant methodological approaches.
Chapter 7 Empirical Approach to Evaluating the Spatial Variation in Broad Access Public College Accessibility

Having developed an index that captures the cumulative accessibility of broad access public colleges within each study area, I now pivot to Part II of the study, in which I use this index to consider tract-level variation in overall accessibility. In this chapter, I provide an overview of the methodological approach I employ to compare the demographics of neighborhoods by their level of accessibility to broad access public colleges. Research questions three and four examine neighborhood demographics at the extremes of accessibility (RQ3) as well as the overall relationship between neighborhood demographics and accessibility (RQ4). The methods employed in RQ3 mirror those employed in the methodology for the first two research questions, whereas in RQ4, I employ a spatial regression model to account for the potential presence and influence of spatial autocorrelation.

Comparison of High Versus Low Accessibility Tracts’ Demographics (RQ3)

In RQ3, I consider whether high accessibility census tracts differ from low accessibility census tracts in their demographic composition. Answering this question involves identifying census tracts with high versus low postsecondary accessibility and then comparing the demographics of census tracts in each of these categories. I allow the bimodal non-overlapping distribution of indices to guide the analysis: In the first stage of analysis, I compare the demographics of lower- versus upper-distribution census tracts; comparisons are conducted using the Mann-Whitney U test since only two groups are being compared.
To understand the demographic consequences of postsecondary accessibility’s bimodal distribution, I next examine the characteristics of high- and low-accessibility census tracts in each of the distributions. For each distribution, I identify the top and bottom quartile census tracts based on their postsecondary accessibility index value. This categorization results in four sub-groups of interest: high accessibility in-district (ID), low accessibility ID, high accessibility out-of-district (OOD), and low accessibility OOD.\textsuperscript{50} I then follow the same testing protocol outlined previously: First, I conduct a non-parametric KW test to identify whether there exist \textit{any} differences between sub-groups in the rank-sum means of covariates.\textsuperscript{51} Then, for those covariates where the KW test reveals a statistically significant difference in the groups’ rank-sum means, I conduct a Conover-Iman post-hoc comparison test. This second stage allows me to identify for which subgroups there are differences in the rank-sum means.

**Spatial Regression Analysis of the Relationship Between Accessibility and Neighborhood Demographics (RQ4)**

With the final research question, I seek to understand the relationship between postsecondary accessibility and census tract demographics, in particular racial/ethnic composition, poverty rate, and level of potential educational demand. To answer this question, I estimate spatial regression analyses separately for the two study areas and, to accommodate the bimodal distribution observed in the accessibility index, the upper and lower distributions within each study area. I make the decision to conduct separate, rather than pooled, analyses for the sub-regions because doing so minimizes the presence and severity of heterogeneity in the residuals and further allows for the coefficients to differ in slope and/or magnitude between the two sub-

\textsuperscript{50} The in- and out-of-district categorizations for the upper and lower distributions, respectively, reflect the presence of a geographical boundary (the community college district boundary) that affects tuition prices and, through the desirability measure in the index, leads to a bi-modal distribution of index values in each of the study areas.

\textsuperscript{51} I reject the Shapiro-Wilk’s null hypothesis of normality of distribution in 22 of the 60 tests in Lansing and 59 of the 60 tests in Chicago. I reject the Levene’s test null hypothesis of equal variance in 10 of the 15 tests in Lansing and 14 of the 15 tests in Chicago.
regions. The result is four separate spatial regression models, which I refer to as follows: Lansing ID, Lansing OOD, Chicago ID, and Chicago OOD. I use the same first-order queen’s contiguity neighbor definition with a row-standardized spatial weights matrix (SWM) that I use in the exploratory spatial data analyses.52 Although there has long been discussion of the potential sensitivity of results to the choice of SWM, LeSage and Pace (2014) provide evidence that, when a spatial regression model is specified correctly, the results should not be sensitive to this choice (see also LeSage, 2014). When I compare diagnostic statistics from the analyses that employ this SWM to alternative \( k \)-nearest neighbor SWM specifications, the preferred SWM has the highest log-likelihood value and, in all but one case, the lowest AIC value (see Table A.1 for relevant test statistics). Because models with different SWMs are not nested, I cannot formally compare the models using a likelihood ratio test.

The question of whether postsecondary accessibility varies depending on census tract demographics is inherently spatial in nature. Neighboring census tracts’ index values and demographics are likely spatially dependent, meaning that the relationship between a focal area and its neighbors is, in part, the result of their location to each other in space (LeSage & Pace, 2009). Put simply, observations that are near each other in space tend to have similar values—a form of spatial spillovers (Anselin, 1989). The consequence of spatial dependence is that observations and, potentially error terms, are not statistically independent, but are instead spatially autocorrelated—an assumption embedded in the standard ordinary least squares (OLS) regression model (Darmofal, 2015; Chi & Zhu, 2020, p. 42).

52 Row-standardized matrices weight a focal area’s neighbors based on its total number of neighbors (e.g., if an area has 8 neighbors, each neighbor is given a weight of 1/8 within the matrix). This approach “make[s] estimated parameters between alternative models more comparable” (Kawabata & Shen, 2007, p. 1766) and is therefore among the most commonly employed approaches (Anselin & Bera, 1998; Dubin, 2009).
In the presence of spatial autocorrelation, the choice of regression model depends on the underlying cause of the spatial autocorrelation. If it can be attributed to spatial diffusion (e.g., a unit’s behavior is the result of its neighbors’ behavior; Darmofal, 2015), then the result is bias in the coefficients. In this case, the appropriate choice is a spatial lag model (SLM), where the dependent variable is spatially lagged, meaning the value of $y$ in the focal tract depends on both the covariate values in that tract and the average value of the dependent variable across the tracts’ neighbors, where neighbors are defined based on the SWM. If the cause is attributional dependence (e.g., neighboring units have similar behavior because “units share characteristics that promote the behavior;” Darmofal, 2015, p. 4), then the standard errors may be biased. Here, the researcher would choose a spatial error model (SEM), where the error terms are spatially lagged, meaning the error term in the estimation of $y$ in the focal tract depends on both its own residual and the average value of the residuals in neighboring tracts. Theorizing on the cause of spatial dependence can be inconclusive; therefore, model selection strategies tend to rely on statistical tests that attempt to isolate the influence of spatial autocorrelation (e.g., does the spatial autocorrelation affect coefficients, error terms, or both).

Elhorst (2010) outlines a process that integrates Anselin’s (2007) specific-to-general decision rule and LeSage and Pace’s (2009, 2010) general-to-specific guidance on model selection (see also Florax & Nijkamp, 2003). He advises the researcher to first estimate a basic OLS regression and conduct Anselin’s (2007) post-hoc Lagrange Multiplier (LM) tests for spatial lag and spatial error. If one or both tests, either in its classic or robust versions, indicate the presence of spatial dependence, the next step is to estimate a Spatial Durbin Model (SDM). Once the SDM is estimated, the researcher can conduct LeSage & Pace’s (2009) LR tests to determine if the model ought to be restricted to a simpler version (either the SLM or SEM).
Unless both the LR test and the initial LM tests on the OLS regression indicate the presence of a single type of spatial dependence (i.e., there is evidence of a spatial lag but not spatial error), the researcher should proceed with the SDM. This maximum likelihood spatial regression model incorporates spatial lags in the dependent variable and select covariates to produce spatially adjusted global coefficient estimates. LeSage and Pace (2009) identify the SDM as the higher-order spatial model that is least sensitive to model misspecification, either in the underlying source of the spatial dependence or via omitted variable bias (see also Elhorst, 2010).\textsuperscript{53}

Adhering to Elhorst’s (2010) procedure, I first estimate a standard OLS regression using the following equation, in matrix notation:\textsuperscript{54}

\[
y = X\beta + B\beta + \epsilon
\]

where \(y\) is an \(n \times 1\) vector of observations of the mode-weighted accessibility index for each census tract in the analysis. \(X\) is an \(n \times k\) matrix of census tract-level variables drawn from the U.S. Census Bureau’s American Community Survey (ACS) five-year estimates, guided by the factors identified in the literature review and conceptual framework as potentially influential to the relationship between overall accessibility and neighborhood demographics.

The covariates included in design matrix \(X\) are: population percentage by race/ethnicity (Black, Latinx, Asian, and American Indian/Alaska Native/Pacific Islander/Multiracial/Other [AI/AN/PI/MR/Other] collapsed into a single group); percentage of tract residents in poverty; and potential educational demand measured as the percentage of the population 25 years and older with less than an associate degree. Since I am most interested in the variations in accessibility among residents of color, I exclude as the reference group the percentage of the

\textsuperscript{53} Although generalized method of moments (GMM) models are likewise available, LeSage and Pace (2009) note that the most significant benefit of a GMM model is the lower computational requirements, a necessity which has since become obsolete.

\textsuperscript{54} I use matrix notation in this equation in alignment with the standard practice of using matrix notation when specifying spatial regression models.
population that identifies as White. For ease of interpretation, I multiply proportion variables by 100 prior to estimation so that coefficients can be interpreted as the estimated change in the dependent variable resulting from a one percentage point (pp) change in the covariate. By example, the beta coefficient on percentage of Black residents can be interpreted as the estimated change in a census tract’s accessibility index that results from a 1pp increase in the percentage of the population that identifies as Black, holding all other covariates at their means.

The existing literature on the geography of college access confirms the importance of both race/ethnicity and income in students’ access to nearby colleges (Briscoe & De Oliver, 2006; Fisher, 2012; González Canché 2018b; Hillman, 2016; Rosenboom & Blagg, 2018). The accessibility literature, as well as the theories that underlie the study’s conceptual framework, identify race/ethnicity and poverty as factors that correlate with lower neighborhood accessibility to services like public libraries (Park, 2012), banks (Hegerty, 2016), and healthcare (Brown et al., 2016; Insaf, n.d.), as well as jobs (Grengs, 2015; Shen, 1998). I therefore hypothesize that the percentage of residents living in poverty, as well as the percentage of residents who identify as Black, Latinx and AI/AN/PI/MR/Other are all associated with lower overall accessibility. Hillman (2016) finds that Asian populations are as likely as White populations to live in a region with broad access public colleges, whereas Fisher (2012) finds that community college branch campuses in the Washington, DC region are more likely to be located in communities with a higher percentage of Asian residents. Therefore, I hypothesize that the relationship to overall accessibility may be higher in census tracts with a higher percentage of Asian residents. Lastly, based on existing evidence (Hillman, 2016) and the proposition borne of the spatial opportunity structures framework, I hypothesize a negative relationship between a tract’s overall accessibility and its percentage of residents aged 25 and older with less than an associate degree.
*Built* is an $n \times k$ matrix of covariates that capture details about the built environment, including the logged population density of the census tract; whether the tract boundaries intersect with or are adjacent to a major highway; whether a broad access college is located in the census tract; a county-level fixed effect; and, in the Chicago OOD model, a community college district fixed effect. Population density captures what Williamson (2008) refers to as “the most obvious feature of traditional urban environments” (p. 909) and accounts for the tendency for more densely populated areas to experience increased accessibility (Levine et al., 2012; Hegerty, 2016). I log population density to ease interpretation; a 1% change in the population density of a census tract is associated with a $\beta$ increase in the postsecondary accessibility index value. The inclusion of a binary variable corresponding to highway adjacency/intersection is to acknowledge that clusters of tracts along highways will likely have higher accessibility values than they would in the absence of the highways (Hu, 2019). I include a binary variable that captures whether a broad access college is located within the tract; being co-located with a college could mean remaining opportunities are further away, or it could suggest that the tract is in a part of the region where opportunities congregate and, therefore, overall accessibility is higher. County- and district-level fixed effects capture unobservable differences in tracts that can be attributed to county or district membership. The two $\beta$ terms are $n \times k$ matrices of coefficients accompanying the $k$ covariates in the $X$ and *Built* design matrices, respectively. $\varepsilon$ is an error term which, in an OLS regression, is assumed to be independent and identically distributed.
Next, I estimate for each of the analyses the SDM using the same set of covariates and the following equation, in matrix notation (LeSage & Pace, 2009; Floch & Le Saout, 2018):

$$y = \alpha \mathbf{1}_n + \rho \mathbf{W} \mathbf{y} + \mathbf{X} \beta + \mathbf{WX} \theta + \mathbf{Built} \beta + \epsilon$$

(7.2)

where \(n\) is the number of census tracts; \(y\) is the \(n \times 1\) vector of dependent variable observations, \(\mathbf{1}_n\) is an \(n \times 1\) vector of ones “associated with the constant term parameter \(\alpha\)” (LeSage & Pace, 2009, p. 46). \(\mathbf{W} \mathbf{y}\) is the spatially lagged dependent variables for weights matrix \(\mathbf{W}\); it is “the endogenous interaction effects among the dependent variables” (Elhorst, 2021, p. 2144). In the presence of \(\mathbf{W} \mathbf{y}\), a census tract’s \(y\) depends on the value of \(y\) averaged across its neighbors.

\(\mathbf{X}\) is an \(n \times 5\) matrix of census tract-level covariates, and \(\mathbf{W}\) is an \(n \times n\) first order queen’s contiguity row-standardized spatial weights matrix. \(\mathbf{Built}\) is an \(n \times k\) design matrix of the built environment covariates; the variables included in this matrix varies depending on the analysis (see Table 6.3). I do not include these covariates in the set of spatially lagged covariates because these variables capture only relationships specific to the geographic region in question. The two \(\beta\) terms are vectors of coefficients that correspond to the census tract covariates and built environment covariates. \(\mathbf{WX}\) is the spatially lagged independent variables for spatial weights matrix \(\mathbf{W}\); it is “the exogenous interaction effects among the independent variables” (Elhorst, 2021, p. 2144). In the presence of \(\mathbf{WX}\), a census tract’s \(y\) depends on the value of its own tract covariates and the values of these same covariates averaged across its neighbors. Both \(\rho\) and \(\theta\) are spatial coefficients that quantify the scale of the spatial lag. \(\epsilon\) is an \(n \times 1\) vector of independent and identically distributed error terms (LeSage & Pace, 2014).

---

55 To estimate the model in R, I use the lagsarlm function in the spdep package (Bivand, 2022). The term \(\alpha \mathbf{1}_n\) is not consistently included in equation specifications for the SDM. LeSage and Pace (2009), Elhorst (2010), and Seldadyo et al. (2010) include this term and its subscript \(n\) even when the remainder of the equation is in matrix notation. Chi and Zhu (2020) and Floch and Le Saout (2018) do not include the term at all. I opt to include the term in the interest of clearly identifying all component parts of the underlying model.
Table 6.1 Covariates Included in Final Regression Analyses

<table>
<thead>
<tr>
<th>Census Tract Demographics</th>
<th>Lansing ID</th>
<th>Lansing OOD</th>
<th>Chicago ID</th>
<th>Chicago OOD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Percent of residents living below the poverty rate</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Percent of residents aged 25+ with less than an AA</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Percent of Black residents</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Percent of Latinx residents</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Percent of Asian residents</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Geographic/Built Environment Covariates</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log(Population Density)</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Highway Intersection/Adjacency</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Tract has a BAC$^b$</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Flag for Lansing/East Lansing City (=1 if in city, else 0)</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>ICCB district fixed effect</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>County FEs</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
</tbody>
</table>

Sources: Author’s model specifications.
Notes: Signifies which covariates are included in each of the four sub-region analyses. $^a$ Variable is spatially lagged.
$^b$All BACs in the Lansing study area are within the in-district sub-region.

Based on Elhorst’s (2010) decision rules, I determine that the SDM is the preferred model for each of the four regression analyses. Table 6.4 below includes, for each of the four analyses, results of the $LMM_{\text{Lag}}$ and $LMM_{\text{Error}}$ tests, classic and robust, as well as the results of the LR test which compares the SDM to the SEM and the SLM. In three of the four analyses, the model selection criteria (Panel A) clearly signal the use of a SDM as opposed to a standard OLS regression. In these three analyses, all or all but one of the LM tests run on the OLS regression residuals are statistically significant and thus signal the potential presence of an underlying spatial process. Furthermore, in these three analyses, when I test whether the SDM should be constrained to a simpler, nested model (either the SEM or the SLM), I am able to reject the null hypothesis of simplifying the model choice for both comparator models.

The exception is the Lansing OOD analyses (Table 6.4, Column 2). The robust $LMM_{\text{Lag}}$ test is statistically significant, which suggests a spatial process that affects the coefficients and thus points to the use of a spatial lag model; when only one test is statistically significant, Elhorst (2010) still recommends proceeding first with the SDM. That said, in neither case can the null
hypothesis of the LR tests be rejected, meaning that the more-complex SDM can be restricted to
the simpler models against which the SDM is being tested. However, it is not possible to
simultaneously restrict the model to both the SEM and the SLM because they would require that
the model be simplified in distinct ways. Were I to use a SEM, I would restrict the model to
include only a spatial lag in the error terms; were I to use a SLM, I would restrict the model to
include only a lag in the covariates. Since the SDM protects against potential bias better than
either of these models, I proceed with the SDM but, as with the other models, present the OLS
and SDM results together.

Table 6.2 Test Statistics for Spatial Regression Model Selection Process

<table>
<thead>
<tr>
<th></th>
<th>(1) Lansing ID</th>
<th>(2) Lansing OOD</th>
<th>(3) Chicago ID</th>
<th>(4) Chicago OOD</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: Model Selection Criterion</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>OLS Model</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$L_{M\text{Lag}}$</td>
<td>32.24 (0.000)</td>
<td>2.04 (0.153)</td>
<td>975.93 (0.000)</td>
<td>589.92 (0.000)</td>
</tr>
<tr>
<td>$L_{M\text{Error}}$</td>
<td>8.19 (0.004)</td>
<td>0.06 (0.807)</td>
<td>1037.4 (0.000)</td>
<td>875.47 (0.000)</td>
</tr>
<tr>
<td>Robust $L_{M\text{Lag}}$</td>
<td>27.68 (0.000)</td>
<td>5.75 (0.017)</td>
<td>35.56 (0.000)</td>
<td>6.37 (0.012)</td>
</tr>
<tr>
<td>Robust $L_{M\text{Error}}$</td>
<td>3.63 (0.057)</td>
<td>3.76 (0.052)</td>
<td>97.04 (0.000)</td>
<td>291.92 (0.000)</td>
</tr>
<tr>
<td><strong>SDM</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>LR Test, SEM</td>
<td>34.26 (0.000)</td>
<td>8.8 (0.185)</td>
<td>18.54 (0.005)</td>
<td>-273.73 (0.000)</td>
</tr>
<tr>
<td>LR Test, SLM</td>
<td>23.20 (0.001)</td>
<td>6.08 (0.415)</td>
<td>134.76 (0.000)</td>
<td>55.20 (0.000)</td>
</tr>
<tr>
<td><strong>Panel B: Residual Diagnostics</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Moran’s I (OLS)</td>
<td>0.19 (0.002)</td>
<td>-0.03 (0.971)</td>
<td>0.65 (0.000)</td>
<td>0.53 (0.000)</td>
</tr>
<tr>
<td>Moran’s I (SDM)</td>
<td>0.04 (0.417)</td>
<td>18.77 (0.281)</td>
<td>-0.08 (0.000)</td>
<td>0.06 (0.000)</td>
</tr>
<tr>
<td>BP Test (SDM)</td>
<td>26.77 (0.044)</td>
<td>-0.16 (0.177)</td>
<td>69.40 (0.000)</td>
<td>45.015 (0.098)</td>
</tr>
</tbody>
</table>

Sources: Author’s calculations using U.S. Census ACS 5-year estimates 2015-2019; IPEDS 2019; CDAC O-D Matrix

Notes: The statistics in Panel A present the diagnostic tests that Elhorst (2010) recommends a researcher consider when deciding which spatial regression model to use. The Lagrange multiplier (LM) test for the presence of omitted spatially lagged variables ($L_{M\text{Lag}}$) or spatially dependent error terms ($L_{M\text{Error}}$). The classic versions assume no spatial dependence of the alternative type (i.e., the $L_{M\text{Lag}}$ test does not account for the potential simultaneous presence of spatially dependent error terms, and vice versa), whereas the robust versions test for the indicated form of spatial dependence in the presence of spatial dependence of the alternative form. The likelihood ratio (LR) tests use the log likelihood values to test whether the more complex version of the model can be simplified to a nested version of the model; the LR test (SEM) tests whether the SDM can instead be simplified to the SEM, in which only the error terms, and not the error terms and covariates, are spatially lagged. In Panel B, I include the global Moran’s I value calculated on the model residuals for both the OLS and the SDM, where a value of zero indicates no spatial autocorrelation, a value of one indicates complete positive spatial autocorrelation, and a value of negative one indicates complete negative spatial autocorrelation. The BP test (Breusch-Pagan test) tests the model against a null hypothesis of homoskedasticity (i.e., equal variance in the error terms). A statistically significant value indicates that the null hypothesis of homoskedasticity can be rejected, and there is detectable heteroskedasticity in the error terms.
Diagnostics were run on the OLS regression and on the final SDM in each of the four analyses to determine whether the presence of spatial autocorrelation in the residuals differs between the two regression models, and whether the residuals in the SDM are heteroskedastic. To evaluate whether spatial autocorrelation is present in the residuals, I estimate the global Moran’s $I$ using the residuals as the covariate of interest. For the three models for which the use of a SDM is clearly indicated (Lansing ID, Chicago ID and OOD), the residual global Moran’s $I$ value is smaller in the SDM than in the OLS (Table 6.4, Panel B, columns 1, 3 and 4). Although the global Moran’s $I$ remains statistically significant in two of these models (Chicago ID and OOD), the magnitudes are substantially smaller. In the Lansing ID analyses, which has the smallest difference in the global Moran’s $I$ values for the two models, the difference is still more than 0.10 (recall that the global Moran’s $I$ cannot exceed 1, and a value of zero reflects the complete absence of spatial autocorrelation). In the Lansing OOD analyses (Column 2), the global Moran’s $I$ value is not statistically significant in either model, further evidence that a spatial model is not obviously indicated.

Next, I employ a spatial version of the Breusch-Pagan test to test for residual heteroskedasticity and find evidence of heteroskedasticity in the Lansing and Chicago ID analyses. In both instances, I can reject the null hypothesis of equal error variances (Table 6.4, Panel B, Columns 1 and 3). The consequence of heteroskedasticity in the residuals is biased standard errors, which in turn inflate the p-values. Inflated p-values can result in mis-specified statistical significance in the regression coefficients. Two analytic evaluations suggest that the heteroskedasticity encountered is limited and, if adjusted for, would not drastically decrease the number of statistically significant relationships observed. First, the heteroskedasticity appears modest based on the Q-Q and residual plots for all four regression models (Figure A.1 and
Figure A.2, respectively). The most problematic Q-Q plot is for the Chicago ID analyses and, even here, the divergence in the tails remains generally modest and points to a long-tailed deviation from a normal distribution (Figure A.1, Panel C). Across the residual plots, there is slight evidence of a fanning pattern only in the residual plot for the Lansing ID analyses (Figure A.2, Panel A). Second, I find that only one coefficient for demographic covariates in the final models would no longer be statistically significant at the 10% level if the standard errors increased by 15% (Table A.2). Even so, I proceed conservatively in my discussion of results, interpreting only those coefficients that are statistically significant at the 5% level or below.

There are also methodological reasons to proceed with the SDM despite the results of the BP tests for the Lansing and Chicago ID analyses. As LeSage and Pace (2009) demonstrate, the SDM is the spatial model least prone to bias in the coefficients. In other words, even if the standard errors are biased, the coefficients are not likely to be affected. Furthermore, Le Gallo et al. (2020) document the challenges associated with diagnosing heteroskedasticity when using tests designed for linear models but adapted to spatial regression models. Specifically, the literature on heteroskedasticity in spatial models “always considers that the null hypothesis is the independence of the regression residuals” (p. 289) when, by design, the residuals in spatial models may be spatially autocorrelated (e.g., the null hypothesis is one of spatial dependence, not independence). Put differently, the test employed may not sufficiently accommodate in its evaluation of heteroskedasticity the spatial nature of the data and therefore adjusting the model based on its results may be premature.

Lastly, when the spatial parameters in the SDM are non-zero, their presence in the model complicates the standard interpretation of the beta coefficients due to the spatial multiplier effect (Darmofal, 2015). By way of example, consider a one percentage point change in covariate X in
focal area \( i \). This change in \( X \) affects \( y_i \) as well as the value of \( X \) in neighboring areas. Since the neighbors’ values of \( y \) are influenced by their \( X \) values and their neighbors’ \( X \) values, the change in \( X \) in focal area \( i \) leads to changes in both the value of \( y_i \) and, indirectly, changes in neighbors’ values of \( y \). To address this interpretation problem, the researcher can conduct an effects analysis to spatially partition impacts into direct (marginal) and indirect (spillover) effects that result from a one-unit change in \( X \) (LeSage & Pace, 2014; Piras & Postiglioni, 2022). Part of this process involves the estimation of measures of dispersion (e.g., confidence intervals), done by repeatedly simulating values from the estimated variance-covariance matrix, then using the median value as the point estimate (LeSage & Pace, 2014; Floch & Le Saout, 2018, p. 170). For each analysis, I use the \textit{impacts} function in the \textit{spdep} R package to conduct 500 simulations in which I estimate direct, indirect, and total effects and accompanying confidence intervals (Bivand, 2022). Though these are referred to as “effects” in the literature, this language choice is arguably inaccurate since the resulting estimates cannot be interpreted as causal in the basic regression framework.
Chapter 8 Results on the Spatial Variation in Broad Access Public College Accessibility

The research questions for Part I examined whether less selective colleges are located in neighborhoods with particular demographics (RQ1) and whether the quality of the nearest less selective college differs between high- and low-poverty tracts, and between high proportion POC and high proportion White tracts (RQ2). In Part II, I focus on a census tract’s overall accessibility to all broad access public colleges (BACs) in a given study area. The analyses rely on each tract’s value for the postsecondary accessibility index introduced in Chapter 3.

As in Chapter 4, I consider Lansing and Chicago separately. I begin by examining the distribution of travel times (by mode) and the distribution of the index. Then, I consider whether the demographics of census tracts with the highest and lowest levels of accessibility differ from each other, hypothesizing that low accessibility tracts will be lower income, have higher poverty rates, and higher percentages of residents who identify as Black, Latinx, and American Indian/Alaska Native/Pacific Islander/Multiracial/Other (AI/AN/PI/MR/Other; RQ3). Lastly, I estimate spatial regression models to discern the magnitude of the relationship between census tract demographics and postsecondary accessibility for all tracts in the study areas (RQ4).

Lansing

Across all census tracts in Lansing, the median travel time to a BAC is 25 minutes by car and nearly 2 hours by public transit. By-mode maps of tract-level median travel times reveal that people living in outlying census tracts must expend substantially more travel time than their counterparts living near the core of the region, regardless of mode (Figure 8.1). Although the overall gradient is similar between driving and public transit—tracts in the central portion of the
region boast the lowest median travel times—the range of travel times is substantially higher on public transit than for driving. By way of example, the maximum observed median drive time is 70 minutes, versus 811 minutes (over 13 hours) on public transit. This high observed time is reflective of the CDAC O-D matrix estimating the time required to walk to the nearest transit stop, with no upper limit placed on walk time; in reality, commute times more than 1-2 hours are not possible for most individuals. I therefore also present median travel times, categorized based on the time frames assessed in the U.S. Census American Community Survey (ACS; Figure 8.2). Here, immediately visible is the variation in median travel times for driving (Panel A)—almost indistinguishable from the preceding plot. In contrast, immediately visible in Panel B is that the median travel time by public transit is more than 2 hours in nearly all the tracts outside the central region. Even with slight variation in local access in the urban core, transit service is not robust across the Lansing study area.

Figure 8.1 Median Travel Time to BAC, by Mode (Continuous Time; Lansing)

Sources: U.S. Census 2010 census tract shape files; MSA shape files; UZA shape files; state shape files; U.S. Census ACS 5-year estimates 2015-2019
Notes: Created in R.
When I plot the distribution of postsecondary accessibility index values (Figure 8.3, mean = 5.13, s.d. = 1.11), I observe the bimodal and non-overlapping distribution that results from differential tuition and fees imposed on tracts depending on whether they are within or outside of the Lansing Community College (LCC) district boundary. Tracts with values in the upper distribution (i.e. higher accessibility) are concentrated in the center city region as well as in parts of the southeast and (less so) west (dark blue tracts in Figure 8.4, Panel A); all of these tracts pay in-district tuition at LCC. Tracts in the lower distribution are in the northeast and southwest regions (light yellow tracts in Figure 7.4, Panel A); these tracts pay in-state tuition at LCC.

The global Moran’s $I$ value indicates a high level of positive spatial autocorrelation in the postsecondary index ($0.7614$, $p = 0.001$), with high-value clusters of the local Moran’s $I$ located in the central city and low-value clusters concentrated in the tracts outside the district (Figure 8.4, Panel B). Based on the bimodal distribution of index values, I calculate the global Moran’s $I$ separately for in- versus out-of-district (ID versus OOD) tracts. I find that, though substantial
spatial autocorrelation remains, the observed levels are lower when calculated separately for the two sub-regions (ID: 0.73882, \( p = 0.001 \); OOD: 0.71552, \( p = 0.001 \))

**Figure 8.3 Histogram of Postsecondary Accessibility Index Values (Lansing; 2019)**

![Histogram of Postsecondary Accessibility Index Values](image)

*Sources.* Author’s calculations of U.S. Census ACS 5-year estimates 2015-2019; CDAC O-D Matrix

*Notes:* Created in Stata. The non-overlapping bimodal distribution of accessibility stems from geographically defined differences in tuition by community college districts and embedded in the index through the desirability measure. For more details, see Chapter 6.

**Figure 8.4 Maps of Postsecondary Accessibility Index and Local Moran’s I Values (Lansing; 2019)**

(a) Covariate  
(b) Local Moran's I

![Maps of Postsecondary Accessibility Index and Local Moran’s I Values](image)

*Sources:* U.S. Census 2010 census tract shape files; Author’s calculations of CDAC O-D Matrix

*Notes:* Created in R.
Table 8.1 below provides summary statistics on neighborhood characteristics by lower versus upper accessibility distribution as shown in Figure 8.3 (Columns 1-4), as well as results of the MWU test (Column 5). Differences in rank-sum means between the two groups are statistically significant for all but two covariates (total population, poverty rate for residents of color). Census tracts in the upper distribution—those within LCC’s boundaries—have a lower median family income ($56,812 versus $63,483) and higher poverty rates (19% versus 10%). A higher average percentage of residents aged 25+ in the lower-distribution census tracts have less than an associate degree (67% versus 54% in upper-distribution tracts), meaning that potential educational demand is higher outside LCC’s district boundary than within it.

The average census tract in both groups is majority White (70% White residents on average, versus 93% White residents on average in the lower distribution tracts). That said, upper-distribution census tracts are more racially diverse overall than census tracts in the lower distribution. An average of only 1% of lower-division residents identify as Black, versus 11% in the upper-division census tracts. Similar patterns hold among Latinx and Asian residents (8% and 6% in upper distribution tracts; 4% and 0% in lower distribution tracts). The average percentage of AI/AN/PI/MR/Other residents is likewise higher in upper distribution than in lower distribution tracts (5% versus 2%).
Table 8.1 Summary Statistics and Results of MWU Test, by Accessibility Distribution (Lansing; ACS 5-Year Estimates 2015-2019)

<table>
<thead>
<tr>
<th></th>
<th>Lower Distribution (n=46)</th>
<th>Upper Distribution (n=93)</th>
<th>(5) MWU Statistic (P-Value)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1) Mean</td>
<td>(2) SD</td>
<td>(3) Mean</td>
</tr>
<tr>
<td>Land area (mi²)</td>
<td>31.9</td>
<td>28.84</td>
<td>7.99</td>
</tr>
<tr>
<td>Tract population</td>
<td>3.942</td>
<td>1.059</td>
<td>3.772</td>
</tr>
<tr>
<td>Population density</td>
<td>721.17</td>
<td>1,091.23</td>
<td>2,858.34</td>
</tr>
<tr>
<td>Households with zero vehicles</td>
<td>0.05</td>
<td>0.04</td>
<td>0.08</td>
</tr>
<tr>
<td>Median household income</td>
<td>$63,483</td>
<td>$15,293</td>
<td>$56,812</td>
</tr>
<tr>
<td>Poverty rate (all residents)</td>
<td>0.10</td>
<td>0.05</td>
<td>0.19</td>
</tr>
<tr>
<td>Poverty rate (residents of color)</td>
<td>0.19</td>
<td>0.13</td>
<td>0.23</td>
</tr>
<tr>
<td>Poverty rate (White residents)</td>
<td>0.09</td>
<td>0.05</td>
<td>0.17</td>
</tr>
<tr>
<td>Residents aged 25+ w less than AA</td>
<td>0.67</td>
<td>0.12</td>
<td>0.54</td>
</tr>
<tr>
<td>White</td>
<td>0.93</td>
<td>0.04</td>
<td>0.70</td>
</tr>
<tr>
<td>Black</td>
<td>0.01</td>
<td>0.01</td>
<td>0.11</td>
</tr>
<tr>
<td>Latinx</td>
<td>0.04</td>
<td>0.02</td>
<td>0.08</td>
</tr>
<tr>
<td>Asian</td>
<td>0.00</td>
<td>0.00</td>
<td>0.06</td>
</tr>
<tr>
<td>AI/AN/PI/MR/Other</td>
<td>0.02</td>
<td>0.02</td>
<td>0.05</td>
</tr>
<tr>
<td>Veterans</td>
<td>0.08</td>
<td>0.02</td>
<td>0.06</td>
</tr>
</tbody>
</table>

Sources: Author’s calculations from U.S. Census ACS 5yr Estimates 2015-2019; CDAC O-D Matrix
Notes: Population density calculated as tract population divided by land area. Unless expressly noted with a unit of measurement (e.g., mi², $), all demographic values are proportion variables.

In this next section, I compare high and low accessibility tracts across the upper and lower distributions. A map of the top and bottom quartile census tracts within each distribution is below (Figure 8.5). Purple census tracts correspond to ID tracts in the top quartile (dark purple) or bottom quartile (light purple) of accessibility; these are all upper distribution census tracts. Dark purple census tracts, which are concentrated in the urban core, have the highest levels of accessibility across all tracts in the region. Dark orange tracts signify high accessibility census tracts in the lower distribution (OOD); these tracts are located just outside the district boundary, reflective of generally similar travel times but higher expected tuition and fees at LCC’s campuses. At the low end of accessibility, light orange tracts signify low accessibility OOD census tracts; these tracts are both furthest from the concentration of BAC campuses in Lansing’s urban core and subject to higher in-state tuition and fees.
Summary statistics and results of the KW test for these four sub-groups of census tracts are presented in Table 8.2; all KW test statistics are statistically significant at the 5% level. P-values for the Conover-Iman post-hoc tests are included in Table 8.3. For parsimony, I focus on a comprehensive comparison across the four groups, noting when comparisons are or are not statistically significantly different from each other in their rank-sum means. First, there are no statistically significant differences between the low accessibility ID group (light purple) and the high accessibility OOD group (dark orange; Table 8.3, Column 3). Put differently, the demographics of high accessibility OOD tracts are indistinguishable from low accessibility ID
tracts. In instances where I discuss either of these groups below, it can therefore be assumed that the two categories of tracts do not differ from each other in rank-sum means.

High accessibility ID census tracts (i.e., the census tracts with the highest accessibility region-wide) have the lowest median income ($43,446) and highest poverty rate (26%) across the four sub-groups. Poverty rates for residents of color and White residents are likewise highest in these tracts (29% for residents of color, 23% for White residents), though rank-sum means for by-race poverty rates in high accessibility ID tracts are not statistically significantly different from rank-sum means in the low accessibility OOD census tracts (Table 8.3, Column 4). Even though the percentage of residents with less than an associate degree is above the regional average in high-accessibility ID tracts (60%, versus 58% region wide), this percentage is highest in high-accessibility OOD tracts (76%; Table 8.2, Column 1).

High accessibility ID tracts are the most racially diverse, with an average of 58% White residents, 17% Black residents, 13% Latinx residents, 4% Asian residents, and 7% AI/AN/PI/MR/Other residents (difference in rank-sum means for Asian residents not statistically significant between high and low accessibility tracts in the upper distribution). The second-most diverse set of tracts is the low accessibility ID tracts (Table 8.2, Column 3), though the rank-sum means for this sub-group are less frequently statistically significantly different from the rank-sum means for the remaining sub-groups. In contrast, high accessibility OOD tracts average the highest percentage of White residents (93%). Although the post-hoc comparison tests are statistically significant for some sub-group pairings on the percentage of residents who are veterans (Table 8.3), the observed values are similar across the four sub-groups (Table 8.2).
## Table 8.2 Summary Statistics and Results of the KW test, by Accessibility Index Categorization (Lansing; ACS 5-Year Estimates 2015-2019)

<table>
<thead>
<tr>
<th></th>
<th>Lower Distribution (OOD)</th>
<th>Upper Distribution (ID)</th>
<th>K-W Statistic (P-Value)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1) Low Accessibility</td>
<td>(2) High Accessibility</td>
<td>(3) Low Accessibility</td>
</tr>
<tr>
<td></td>
<td>(n=12)</td>
<td>(n=11)</td>
<td>(n=24)</td>
</tr>
<tr>
<td>Land area (mi²)</td>
<td>Mean: 30.17, SD: 38.21</td>
<td>Mean: 22.67, SD: 21.28</td>
<td>Mean: 23.68, SD: 23.29</td>
</tr>
<tr>
<td>Tract population</td>
<td>Mean: 3,710, SD: 1,042</td>
<td>Mean: 4,333, SD: 903</td>
<td>Mean: 4,229, SD: 1,006</td>
</tr>
<tr>
<td>Population density</td>
<td>Mean: 1,535.39, SD: 1,742.41</td>
<td>Mean: 550.34, SD: 595.06</td>
<td>Mean: 822.8, SD: 934.36</td>
</tr>
<tr>
<td>Households with zero vehicles</td>
<td>Mean: 0.08, SD: 0.04</td>
<td>Mean: 0.03, SD: 0.02</td>
<td>Mean: 0.05, SD: 0.06</td>
</tr>
<tr>
<td>Median household income</td>
<td>Mean: $50,789, SD: $9,187</td>
<td>Mean: $79,532, SD: $12,677</td>
<td>Mean: $72,867, SD: $19,161</td>
</tr>
<tr>
<td>Poverty rate (all residents)</td>
<td>Mean: 0.13, SD: 0.05</td>
<td>Mean: 0.07, SD: 0.03</td>
<td>Mean: 0.09, SD: 0.04</td>
</tr>
<tr>
<td>Poverty rate (residents of color)</td>
<td>Mean: 0.23, SD: 0.14</td>
<td>Mean: 0.17, SD: 0.14</td>
<td>Mean: 0.12, SD: 0.09</td>
</tr>
<tr>
<td>Poverty rate (White residents)</td>
<td>Mean: 0.12, SD: 0.05</td>
<td>Mean: 0.06, SD: 0.03</td>
<td>Mean: 0.08, SD: 0.05</td>
</tr>
<tr>
<td>Residents aged 25+ w less than AA</td>
<td>Mean: 0.76, SD: 0.08</td>
<td>Mean: 0.54, SD: 0.13</td>
<td>Mean: 0.55, SD: 0.14</td>
</tr>
<tr>
<td>White</td>
<td>Mean: 0.93, SD: 0.03</td>
<td>Mean: 0.91, SD: 0.04</td>
<td>Mean: 0.87, SD: 0.08</td>
</tr>
<tr>
<td>Black</td>
<td>Mean: 0.01, SD: 0.01</td>
<td>Mean: 0.02, SD: 0.02</td>
<td>Mean: 0.03, SD: 0.03</td>
</tr>
<tr>
<td>Latinx</td>
<td>Mean: 0.04, SD: 0.02</td>
<td>Mean: 0.04, SD: 0.02</td>
<td>Mean: 0.04, SD: 0.02</td>
</tr>
<tr>
<td>Asian</td>
<td>Mean: 0.00, SD: 0.00</td>
<td>Mean: 0.01, SD: 0.01</td>
<td>Mean: 0.03, SD: 0.04</td>
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<tr>
<td>AI/AN/PI/MR/Other</td>
<td>Mean: 0.02, SD: 0.02</td>
<td>Mean: 0.02, SD: 0.02</td>
<td>Mean: 0.03, SD: 0.02</td>
</tr>
<tr>
<td>Veterans</td>
<td>Mean: 0.08, SD: 0.01</td>
<td>Mean: 0.07, SD: 0.02</td>
<td>Mean: 0.08, SD: 0.02</td>
</tr>
</tbody>
</table>

**Sources:** Author’s calculations from U.S. Census ACS 5yr Estimates 2015-2019; CDAC O-D Matrix

**Notes:** Population density calculated as tract population divided by land area. Unless expressly noted with a unit of measurement (e.g., mi², $), all demographic values are proportion variables.
Table 8.3 P-Values for Post-Hoc Pairwise Conover Iman Tests, by Accessibility Index Categorization (Lansing)

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Land area (mi²)</td>
<td>0.00</td>
<td>0.00</td>
<td>0.39</td>
<td>0.00</td>
<td>0.28</td>
<td>0.37</td>
</tr>
<tr>
<td>Tract population</td>
<td>0.01</td>
<td>0.01</td>
<td>0.33</td>
<td>0.21</td>
<td>0.26</td>
<td>0.25</td>
</tr>
<tr>
<td>Population density</td>
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<td>0.00</td>
<td>0.40</td>
<td>0.00</td>
<td>0.35</td>
<td>0.47</td>
</tr>
<tr>
<td>Households with zero vehicles</td>
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<td>0.33</td>
<td>0.19</td>
<td>0.01</td>
<td>0.00</td>
</tr>
<tr>
<td>Median household income</td>
<td>0.00</td>
<td>0.00</td>
<td>0.04</td>
<td>0.05</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Poverty rate (all residents)</td>
<td>0.00</td>
<td>0.00</td>
<td>0.16</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Poverty rate (residents of color)</td>
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<td>0.02</td>
<td>0.19</td>
<td>0.21</td>
<td>0.03</td>
<td>0.27</td>
</tr>
<tr>
<td>Poverty rate (White residents)</td>
<td>0.00</td>
<td>0.00</td>
<td>0.18</td>
<td>0.05</td>
<td>0.01</td>
<td>0.00</td>
</tr>
<tr>
<td>Residents aged 25+ w less than AA</td>
<td>0.17</td>
<td>0.12</td>
<td>0.39</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>White</td>
<td>0.00</td>
<td>0.00</td>
<td>0.16</td>
<td>0.00</td>
<td>0.02</td>
<td>0.21</td>
</tr>
<tr>
<td>Black</td>
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<td>0.39</td>
<td>0.00</td>
<td>0.10</td>
<td>0.07</td>
</tr>
<tr>
<td>Latinx</td>
<td>0.00</td>
<td>0.00</td>
<td>0.51</td>
<td>0.00</td>
<td>0.29</td>
<td>0.44</td>
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<tr>
<td>Asian</td>
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<td>0.02</td>
<td>0.03</td>
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<tr>
<td>AI/AN/PI/MR/Other</td>
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<tr>
<td>Veterans</td>
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<td>0.19</td>
<td>0.00</td>
<td>0.17</td>
<td>0.11</td>
</tr>
</tbody>
</table>

Sources: Author’s calculations from U.S. Census ACS 5yr Estimates 2015-2019; CDAC O-D Matrix

Table 8.4 below presents average by-mode travel times separately for in- and out-of-district census tracts, further delineated by quartiles of transit reliance. The median driving time for OOD tracts is approximately twice as high as in ID tracts (45 minutes versus 23 minutes).

Median transit travel times in both ID and OOD tracts are close to or more than two hours (1h44min ID; > 2hrs OOD), a reflection of the limited transit service outside of the urban core which results in the CDAC O-D matrix estimating long walking times to reach a transit stop.

Even acknowledging that transit travel times are lowest for the most transit-reliant ID tracts (approximately one hour), these transit travel times are still four times higher than median drive times for these same tracts (20 minutes). Furthermore, the most transit reliant OOD tracts must commute more than two hours to a BAC. Put differently, although the index adjusts to accommodate variations in tract-level car access in its tract-level estimation, this approach still
obfuscates the substantially lower accessibility experienced by transit-reliant individuals across Lansing. In most cases, individuals will not view these travel times as viable commuting lengths.

Table 8.4 Median Travel Times (in minutes) by Mode, Transit Reliance, and Accessibility Distribution (Lansing; CDAC O-D Matrix 2019)

<table>
<thead>
<tr>
<th></th>
<th>Lower Distribution (OOD)</th>
<th>Upper Distribution (ID)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>N</td>
<td>Median Driving</td>
</tr>
<tr>
<td>Q1 (Least Transit Reliant)</td>
<td>18</td>
<td>43m</td>
</tr>
<tr>
<td>Q2</td>
<td>12</td>
<td>43m</td>
</tr>
<tr>
<td>Q3</td>
<td>12</td>
<td>45m</td>
</tr>
<tr>
<td>Q4 (Most Transit Reliant)</td>
<td>4</td>
<td>59m</td>
</tr>
<tr>
<td>All Tracts</td>
<td>46</td>
<td>45m</td>
</tr>
</tbody>
</table>

Sources: Author’s calculations from U.S. Census ACS 5yr Estimates 2015-2019; CDAC O-D Matrix

In summary, the highest accessibility tracts in Lansing are lower income, have higher poverty rates, and are more racially diverse than lower accessibility tracts. Each of these differences in the demographics of high versus low accessibility census tracts contradicts my hypothesis that low accessibility tracts will be lower income and more racially diverse than high accessibility tracts. Though potential educational demand is high in high accessibility tracts, it is even higher in tracts with the lowest levels of accessibility. This finding is partially in keeping with my hypothesis, since I surmised that low educational attainment would follow from the accumulation of lower accessibility in low-income communities and communities of color. I now use spatial regression analyses to quantify the magnitude and direction of the relationship between these demographic variables and accessibility to broad access public colleges. Based on the bi-modal distribution observed above, I conduct these analyses separately for tracts that are in LCC’s district (Lansing ID) or not (Lansing OOD).

Lansing In-District Regression Results

As discussed in Chapter 3, following Elhorst’s (2010) spatial regression model selection procedure resulted in the use of a Spatial Durbin Model (SDM), based on both the statistically
significant results in the LM tests on the ordinary least squares (OLS) model and the LR tests in which the SDM is compared to the spatial lag model and the spatial error model. Table 8.5 below provides the OLS coefficients alongside the SDM direct, indirect, and total effects (see Table A.7 for raw coefficients from the SDM). The spatial parameter in the SDM is modestly large and statistically significant \((\rho = 0.417, \text{p-value} = 0.000)\), suggestive of an underlying spatial process that, if unaccounted for, could yield biased coefficients in an OLS model. In the discussion that follows, I note instances where there is incongruence in statistical significance between the models or, in cases where both models suggest statistical significance of a covariate’s direct effect, the magnitude or direction of these relationships differ between the models.

Recall that the OLS beta estimates can be interpreted as the change in the index value associated with a one unit change in the covariate of interest, all other covariates being held constant. In contrast, due to the spatial multiplier effect that results from a spatially lagged dependent variable as well as spatially lagged demographic covariates, the results of the SDM are not interpretable as raw coefficients. I therefore partition the coefficients into direct and indirect effects which can be interpreted similar to OLS coefficients. Whereas direct effects can be interpreted like OLS coefficients, indirect effects signify “how other regions’ \(r\)th explanatory variable impact outcomes in the \(i\)th region (LeSage & Pace, 2014, p. 1543). Drawing on the SDM’s direct effects in Table 8.5, a one percentage point increase in a census tract’s percentage of residents with less than an associate degree is associated with a 0.002 unit decrease in the tract’s postsecondary accessibility index value (s.d. of accessibility for ID tracts = 0.18).

I hypothesized that there would be a negative relationship between a tract’s accessibility, measured by my index, and several covariates: poverty rate, potential educational demand (measured by the percentage of residents aged 25 or older with less than an associate degree),
and the percentage of residents who identify as Black, Latinx, or AI/AN/PI/MR/Other. Although
the coefficient for poverty rate is statistically significant and negative at the 10% level in the
OLS model, neither the direct nor indirect effects are statistically significant in the SDM.
Potential educational demand has a statistically significant negative relationship with
accessibility in the SDM ($p < 0.05$), though the magnitude is small: a one percentage point
increase in the percentage of residents in a tract with less than an associate degree is associated
with a 0.002 decrease in the index value. For context, going from the minimum observed rate of
residents with less than an associate degree (9%) to the maximum observed (87%) would
decrease the index by 0.156, or just under one standard deviation.

There are no statistically significant coefficients in either model for the percentage of
Black or Latinx residents in a tract, but there are statistically significant relationships in the SDM
for the percentage of residents who identify as Asian or AI/AN/PI/MR/Other. I observe a
negative relationship between a tract’s accessibility and its percentage of Asian residents (direct
effect: -0.003), even though existing literature suggests this relationship would be positive
(Hillman, 2016; Fisher, 2012). With respect to the percentage of AI/AN/PI/MR/Other residents,
results indicate that both the direct and indirect effects are positive, but the magnitude of the
indirect effect is approximately twice as large (direct effect: 0.009; indirect effect: 0.022). Put
into context, a 23pp increase in the percentage of AI/AN/PI/MR/Other residents in neighboring
tracts (the maximum range observed in the study area) is associated with a 0.51 unit increase in
the accessibility index, or an increase of more than two standard deviations.

A review of the literature revealed the importance of population density when observing
tract-level differences in spatially dependent outcomes (Hegerty, 2016; Williamson, 2008).
When examining the relationship to accessibility, Hegerty (2016) finds a positive relationship
between the two. The same is true in the SDM; there is a positive direct and indirect relationship between a tract’s population density and its accessibility, with a one percentage point change in the focal tract’s population density increasing accessibility by 0.052 \( (p < 0.001) \). A similar increase in population density in neighboring tracts is associated with a 0.034 unit increase in the focal tract’s accessibility (indirect effect; Table 7.5, Column 3). Although being within the city of Lansing has no statistically significant effects, built environment factors (whether there is a BAC in the tract, whether the tract is highway adjacent) have a statistically significant positive relationship to accessibility in both the OLS model and the SDM.

Overall, only one of the hypothesized relationships between accessibility and demographics hold in these analyses: Census tracts with higher potential educational demand have lower accessibility. Three demographic covariates were not statistically significant, even though I hypothesized a statistically significant negative relationship for all three: poverty rates, and the percentage of Black and Latinx residents. Two racial/ethnic covariates were statistically significant but opposite of my hypothesized direction: The relationship between the percentage of Asian residents and accessibility is negative, and the relationship between the percentage of AI/AN/PI/MR/Other residents, either in the focal tract or in neighboring tracts, is associated with a positive change in accessibility. Even though the point estimates on the direct and indirect effects for the percentage of AI/AN/PI/MR/Other residents are small, the distribution of index values is narrow and the range of observed values on tracts’ demographics are large. The result is that large swings in accessibility are possible between tracts with few versus many residents who identify as AI/AN/PI/MR/Other, with tracts with a higher percentage of AI/AN/PI/MR/Other residents experiencing higher accessibility.
Table 8.5 Regression Results for Lansing ID Analysis (DV = Accessibility Index)

<table>
<thead>
<tr>
<th></th>
<th>OLS (1)</th>
<th>SDM (2)</th>
<th>(2) Direct Effects (SEs)</th>
<th>(3) Indirect Effects (SEs)</th>
<th>(4) Total Effects (SEs)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Coefficients (SEs)</strong></td>
<td><strong>Coefficients (SEs)</strong></td>
<td><strong>Coefficients (SEs)</strong></td>
<td><strong>Coefficients (SEs)</strong></td>
<td><strong>Coefficients (SEs)</strong></td>
<td><strong>Coefficients (SEs)</strong></td>
</tr>
<tr>
<td>Intercept</td>
<td>5.260***</td>
<td>0.000</td>
<td>0.002</td>
<td>0.002</td>
<td></td>
</tr>
<tr>
<td>(0.110)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td></td>
</tr>
<tr>
<td>Pct. Poverty</td>
<td>-0.002†</td>
<td>0.000</td>
<td>0.002</td>
<td>0.002</td>
<td></td>
</tr>
<tr>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.003)</td>
<td></td>
</tr>
<tr>
<td>Educ. Attain.</td>
<td>-0.001</td>
<td>-0.002*</td>
<td>0.002</td>
<td>0.002</td>
<td></td>
</tr>
<tr>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.003)</td>
<td></td>
</tr>
<tr>
<td>Pct. Black</td>
<td>0.002</td>
<td>-0.001</td>
<td>0.002</td>
<td>0.001</td>
<td></td>
</tr>
<tr>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.002)</td>
<td>(0.003)</td>
<td>(0.003)</td>
<td></td>
</tr>
<tr>
<td>Pct. Latinx</td>
<td>0.002</td>
<td>0.000</td>
<td>0.009</td>
<td>0.009</td>
<td></td>
</tr>
<tr>
<td>(0.003)</td>
<td>(0.002)</td>
<td>(0.008)</td>
<td>(0.009)</td>
<td>(0.009)</td>
<td></td>
</tr>
<tr>
<td>Pct. Asian</td>
<td>-0.003†</td>
<td>-0.003**</td>
<td>0.006</td>
<td>0.003</td>
<td></td>
</tr>
<tr>
<td>(0.002)</td>
<td>(0.001)</td>
<td>(0.004)</td>
<td>(0.005)</td>
<td>(0.005)</td>
<td></td>
</tr>
<tr>
<td>Pct. AI/AN/PI/MR/Other</td>
<td>0.011**</td>
<td>0.009**</td>
<td>0.022*</td>
<td>0.031**</td>
<td></td>
</tr>
<tr>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.009)</td>
<td>(0.011)</td>
<td>(0.011)</td>
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<tr>
<td>log(popdentity)</td>
<td>0.084***</td>
<td>0.052***</td>
<td>0.034*</td>
<td>0.086***</td>
<td></td>
</tr>
<tr>
<td>(0.014)</td>
<td>(0.011)</td>
<td>(0.015)</td>
<td>(0.022)</td>
<td>(0.022)</td>
<td></td>
</tr>
<tr>
<td>Flag – Tract has BAC</td>
<td>0.076†</td>
<td>0.083**</td>
<td>0.054†</td>
<td>0.137*</td>
<td></td>
</tr>
<tr>
<td>(0.044)</td>
<td>(0.030)</td>
<td>(0.034)</td>
<td>(0.059)</td>
<td>(0.059)</td>
<td></td>
</tr>
<tr>
<td>Flag – Highway Adjacency</td>
<td>0.061**</td>
<td>0.040*</td>
<td>0.026†</td>
<td>0.066*</td>
<td></td>
</tr>
<tr>
<td>(0.023)</td>
<td>(0.016)</td>
<td>(0.016)</td>
<td>(0.030)</td>
<td>(0.030)</td>
<td></td>
</tr>
<tr>
<td>Flag – In Lansing/East Lansing City</td>
<td>0.046</td>
<td>-0.052</td>
<td>-0.033</td>
<td>-0.085</td>
<td></td>
</tr>
<tr>
<td>(0.035)</td>
<td>(0.031)</td>
<td>(0.026)</td>
<td>(0.054)</td>
<td>(0.054)</td>
<td></td>
</tr>
<tr>
<td><strong>Spatial Parameter (ρ)</strong></td>
<td><strong>0.417</strong>*</td>
<td><strong>0.417</strong>*</td>
<td><strong>0.417</strong>*</td>
<td><strong>0.417</strong>*</td>
<td></td>
</tr>
<tr>
<td><strong>N</strong></td>
<td>92</td>
<td>92</td>
<td>92</td>
<td>92</td>
<td></td>
</tr>
</tbody>
</table>

**Sources:** Author’s calculations from U.S. Census ACS 5yr Estimates 2015-2019; CDAC O-D Matrix
**Notes:** Outcome is postsecondary accessibility index, estimated at the tract level using the protocol outlined in Chapter 6. Sample includes all tracts with weighted centroids within the boundary of a K12 district classified as in-district at Lansing Community College. Direct, indirect, and total effects not estimated for the intercept in the SDM. Raw coefficient values in Table A.7. † p<0.10, *p<0.05, **p<0.01, ***p<0.001. aAdjusted R2 bNagelkerke pseudo R2
**Lansing Out-of-District Regression Results**

Unlike in the Lansing ID analyses, where Elhorst’s (2010) process clearly points to the use of a SDM, the decision is less clear for the Lansing OOD analyses. Notably, the spatial parameter in the SDM is approximately half the size of the spatial parameter in the Lansing ID analyses (0.210), and is not statistically significant, indicative of minimal, if any, underlying spatial processes. Therefore, rather than preference one model over the other, I present and discuss the results of both models, noting any inconsistencies.

Among demographic covariates, I observe a statistically significant negative relationship between accessibility and potential educational demand (Table 8.6). The coefficient for the potential educational demand covariate is of similar magnitude and direction in the OLS model and SDM direct effects, though the statistical significance level is higher in the OLS model ($p < 0.01$ versus $p < 0.05$, respectively). In the OLS model, a one percentage point change in the percentage of residents with less than an associate degree is associated with a 0.004 unit decrease in the tract’s accessibility. Moving from the lowest observed level of associate degree receipt (32%) to the highest level (87%) is associated with a 0.22 unit decrease in the index value, or just under two standard deviations (s.d. = 0.12).

There is no statistically significant relationship between accessibility and the percentage of residents who identify as Black in either model. Similarly, there is no statistically significant relationship for the percentage of residents who identify as Latinx in the OLS model or in the direct effects for the SDM model. That said, there is a statistically significant indirect effect for the percentage of residents who identify as Latinx: A one percentage point increase in the percentage of Latinx residents in neighboring tracts is associated with a 0.018 unit decrease in accessibility in the focal census tract. Even though there is no statistically significant relationship
in the OLS model between accessibility and the percentage of residents who identify as Asian, there is a statistically significant and negative direct effect in the SDM (0.033, \( p < 0.05 \)).

The coefficient on highway adjacency is statistically significant in the OLS model, as well as in the SDM direct effects (\( p < 0.01 \) in both cases), and the coefficients are of similar direction and magnitude (0.101 in OLS; 0.098 in SDM direct effects). Being in a census tract that is adjacent to or intersects a highway is associated with a 0.10 unit increase in accessibility (OLS model). To place this magnitude in context, it would take a 25pp increase in the percentage of residents with less than an associate degree to observe an increase in accessibility equivalent to the increase associated with highway adjacency.

Here, as in the Lansing ID analyses, only one theorized demographic relationship is observed: a negative relationship between accessibility and potential educational demand. I find no statistically significant relationship between accessibility and the poverty rate or the percentage of residents who identify as Black, Latinx, or AI/AN/PI/MR/Other. The negative relationship between the percentage of Asian residents and accessibility is identical in magnitude to the relationship observed in the Lansing ID analyses but is directionally oppositional to the positive relationship that I hypothesized.
Table 8.6 Regression Results for Lansing OOD Analysis (DV = Accessibility Index)

<table>
<thead>
<tr>
<th></th>
<th>OLS</th>
<th>Direct Effects (SEs)</th>
<th>Indirect Effects (SEs)</th>
<th>Total Effects (SEs)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>3.826***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.097)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pct. Poverty</td>
<td>-0.002</td>
<td>-0.004</td>
<td>-0.005</td>
<td>-0.009</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.004)</td>
<td>(0.009)</td>
<td>(0.011)</td>
</tr>
<tr>
<td>Educ. Attain.</td>
<td>-0.004**</td>
<td>-0.003*</td>
<td>0.000</td>
<td>-0.003</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.003)</td>
<td>(0.003)</td>
</tr>
<tr>
<td>Pct. Black</td>
<td>0.007</td>
<td>0.008</td>
<td>-0.001</td>
<td>0.007</td>
</tr>
<tr>
<td></td>
<td>(0.008)</td>
<td>(0.008)</td>
<td>(0.021)</td>
<td>(0.026)</td>
</tr>
<tr>
<td>Pct. Latinx</td>
<td>0.000</td>
<td>-0.001</td>
<td>-0.018*</td>
<td>-0.019*</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.003)</td>
<td>(0.009)</td>
<td>(0.010)</td>
</tr>
<tr>
<td>Pct. Asian</td>
<td>-0.026</td>
<td>-0.033*</td>
<td>-0.018</td>
<td>-0.051</td>
</tr>
<tr>
<td></td>
<td>(0.018)</td>
<td>(0.017)</td>
<td>(0.056)</td>
<td>(0.062)</td>
</tr>
<tr>
<td>Pct. AI/AN/PI/MR/Other</td>
<td>-0.004</td>
<td>-0.002</td>
<td>0.007</td>
<td>0.005</td>
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<td></td>
<td>(0.005)</td>
<td>(0.006)</td>
<td>(0.018)</td>
<td>(0.021)</td>
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<td>log(popdensity)</td>
<td>0.006</td>
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<td>0.016</td>
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<td>(0.009)</td>
<td>(0.012)</td>
<td>(0.005)</td>
<td>(0.015)</td>
</tr>
<tr>
<td>Flag – Highway Adjacency</td>
<td>0.101***</td>
<td>0.098***</td>
<td>0.025</td>
<td>0.123***</td>
</tr>
<tr>
<td></td>
<td>(0.017)</td>
<td>(0.018)</td>
<td>(0.026)</td>
<td>(0.034)</td>
</tr>
<tr>
<td>County FEs</td>
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<td>✓</td>
<td>✓</td>
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<tr>
<td>Spatial Parameter (ρ)</td>
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<td></td>
<td></td>
<td>0.210</td>
</tr>
<tr>
<td>N</td>
<td>46</td>
<td>46</td>
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</table>

**Diagnostics**

<p>| | | | | |</p>
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<th></th>
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<td>LM_Lag</td>
<td>2.041 (0.15)</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>LM_Error</td>
<td>0.059 (0.810)</td>
<td></td>
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<tr>
<td>Robust LM_Lag</td>
<td>5.745 (0.017)</td>
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<td>Robust LM_Error</td>
<td>3.764 (0.052)</td>
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<td>Likelihood</td>
<td>75.84662</td>
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<td>AIC</td>
<td>-127.69</td>
<td>-122.62</td>
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<td>Moran’s I (Residuals)</td>
<td>-0.026</td>
<td>-0.158</td>
<td></td>
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<tr>
<td>R²</td>
<td>0.80a</td>
<td>0.870b</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Sources:** Author’s calculations from U.S. Census ACS 5yr Estimates 2015-2019; CDAC O-D Matrix

**Notes:** Outcome is the postsecondary accessibility index, estimated at the tract level using the protocol outlined in Chapter 6. Sample includes all census tracts with weighted centroids outside the boundary of a K12 school district classified as qualifying for in-district tuition status at Lansing Community College. † p<0.10, *p<0.05, **p<0.01, ***p<0.001. Direct, indirect, and total effects not estimated for the intercept in the SDM. Raw coefficient values in Table A.7. Both models include county fixed effects. aAdjusted R² bNagelkerke pseudo R²
**Chicago**

In the Chicago study area, the median travel time to a BAC across all census tracts is 48 minutes by driving and nearly two hours by public transit. When I map tract-level median travel times separately for driving and public transit, visible in the drive times are the general locations of arterial highways between the suburbs and city center (Figure 8.6, Panel A). Median travel times to BACs are substantially higher on public transit: In a third of tracts, the median travel time is between 2 and 3 hours, and in 4% of tracts the median travel time exceeds four hours (turquoise/blue tracts in Figure 5.5, Panel B). In Figure 8.7, I plot median travel time using U.S. Census ACS categories. The visual pattern for driving remains similar, if not less granular (Panel A), whereas the visual pattern for public transit reinforces the high median travel times that transit-reliant residents across Chicago would experience. Even in the portion of the study area corresponding to the City of Chicago, median travel times are between one and two hours. In the geographically dominant outer region, median travel times universally exceed two hours.

**Figure 8.6 Median Travel Time to BAC, by Mode (Continuous Time; Chicago)**

(a) Driving

(b) Public Transit

*Sources:* U.S. Census 2010 census tract shape files; Author’s calculations of U.S. Census ACS 5-year estimates 2015-2019; CDAC O-D Matrix; IPEDS 2019

*Notes:* Created in R.
Across the study area, cumulative postsecondary accessibility varies from 12.9 to 18.4 (mean = 15.4, s.d. = 1.9), though here again the index follows a non-overlapping bimodal distribution based on tracts’ residency status for the City Colleges of Chicago district (Figure 8.8). Tracts inside the district boundary experience higher accessibility than tracts in neighboring community college districts (see Figure 8.9 below). Accessibility region-wide is strongly positively spatially autocorrelated (0.948, \( p = 0.001 \)). When the global Moran’s \( I \) is calculated separately for tracts that are in- versus out-of-district in the City Colleges of Chicago system, positive spatial autocorrelation remains, but at a lower level than observed across the entire study area (ID: Moran’s \( I = 0.735, p = 0.001 \); OOD: Moran’s \( I = 0.791, p = 0.001 \)). An evaluation of the local Moran’s \( I \) identifies a dense high-accessibility cluster in the City of Chicago, with low-accessibility clusters scattered throughout the western periphery (Figure 8.9, Panel B).
Figure 8.8 Histogram of Postsecondary Accessibility Index Values (Chicago; 2019)

Sources: Author’s calculations of U.S. Census ACS 5-year estimates 2015-2019; CDAC O-D Matrix
Notes: Created in Stata. The non-overlapping bimodal distribution of accessibility stems from geographically defined differences in tuition by community college districts and embedded in the index through the desirability measure. For more details, see Chapter 6.

Figure 8.9 Maps of Postsecondary Accessibility Index and Local Moran’s I Values (Chicago; 2019)

Sources: U.S. Census 2010 census tract shape files; Author’s calculations of U.S. Census ACS 5-year estimates 2015-2019; CDAC O-D Matrix; IPEDS 2019
Notes: Created in R.
Next, I unpack whether demographics differ between CCC district tracts (ID) and tracts outside the CCC boundary (OOD; Table 8.7). I find that OOD tracts are higher income and less racially diverse, which runs counter to my hypothesis that higher income and Whiter neighborhoods will experience higher accessibility to public colleges. Median income is approximately $27,000 higher and average poverty rates more than 10pp lower in OOD tracts than in ID tracts. Although the rank-sum means for the percentage of residents with less than an associate degree differ between the two distributions (Table 8.7, Column 5), the observed difference in values is modest: 53% potential educational demand in OOD tracts, 58% in ID tracts. OOD tracts have a higher percentage of White residents and lower percentage of Black residents than ID tracts (58% White, 12% Black versus 31% White, 35% Black). The average percentage of Asian residents is nearly identical between ID and OOD tracts (8% ID, 6% OOD).

Table 8.7 Census Tract Characteristics and Results of the MWU Test by Accessibility Distribution (Chicago; ACS 5-Year Estimates 2015-2019)

<table>
<thead>
<tr>
<th></th>
<th>Lower Distribution</th>
<th>Upper Distribution</th>
<th>(5) MWU Statistic (P-Value)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>OOD Tracts (n=1,090)</td>
<td>ID Tracts (n=795)</td>
<td></td>
</tr>
<tr>
<td>Land area (mi²)</td>
<td>2.08 (3.73)</td>
<td>0.28 (0.35)</td>
<td>33.68 (0.00)</td>
</tr>
<tr>
<td>Tract population</td>
<td>4,810 (1,982)</td>
<td>3,434 (1,867)</td>
<td>16.5 (0.00)</td>
</tr>
<tr>
<td>Population density</td>
<td>4,659.55 (3,692.29)</td>
<td>19,200.97 (23,055.03)</td>
<td>-31.2 (0.00)</td>
</tr>
<tr>
<td>Households with zero vehicles</td>
<td>0.06 (0.06)</td>
<td>0.26 (0.15)</td>
<td>-31.73 (0.00)</td>
</tr>
<tr>
<td>Median household income</td>
<td>$87,586 (37,983)</td>
<td>$60,541 (34,442)</td>
<td>16.93 (0.00)</td>
</tr>
<tr>
<td>Poverty rate (all residents)</td>
<td>0.09 (0.08)</td>
<td>0.20 (0.13)</td>
<td>-20.78 (0.00)</td>
</tr>
<tr>
<td>Poverty rate (residents of color)</td>
<td>0.11 (0.09)</td>
<td>0.22 (0.13)</td>
<td>-18.9 (0.00)</td>
</tr>
<tr>
<td>Poverty rate (White residents)</td>
<td>0.07 (0.09)</td>
<td>0.18 (0.24)</td>
<td>-10.86 (0.00)</td>
</tr>
<tr>
<td>Residents aged 25+ w less than AA</td>
<td>0.53 (0.20)</td>
<td>0.58 (0.25)</td>
<td>-5.84 (0.00)</td>
</tr>
<tr>
<td>White</td>
<td>0.58 (0.27)</td>
<td>0.31 (0.30)</td>
<td>18.57 (0.00)</td>
</tr>
<tr>
<td>Black</td>
<td>0.12 (0.21)</td>
<td>0.35 (0.39)</td>
<td>-11.27 (0.00)</td>
</tr>
<tr>
<td>Latinx</td>
<td>0.20 (0.21)</td>
<td>0.26 (0.28)</td>
<td>-0.21 (0.84)</td>
</tr>
<tr>
<td>Asian</td>
<td>0.08 (0.09)</td>
<td>0.06 (0.10)</td>
<td>8.21 (0.00)</td>
</tr>
<tr>
<td>AI/AN/PI/MR/Other</td>
<td>0.02 (0.02)</td>
<td>0.02 (0.02)</td>
<td>3.06 (0.00)</td>
</tr>
<tr>
<td>Veterans</td>
<td>0.05 (0.02)</td>
<td>0.03 (0.02)</td>
<td>16.3 (0.00)</td>
</tr>
</tbody>
</table>

Sources: Author’s calculations from U.S. Census ACS 5yr Estimates 2015-2019; CDAC O-D Matrix
Notes: Population density calculated as tract population divided by land area. Unless expressly noted with a unit of measurement (e.g., mi², $), all demographic values are proportion variables
Because observing average demographics by in-district status masks internal variation, I identify the highest and lowest accessibility tracts within each sub-group (Figure 8.10; City Colleges of Chicago district boundary outlined in black). As in the Lansing analyses, dark purple signifies high accessibility ID tracts (i.e., highest accessibility within the region) and light purple corresponds to low accessibility ID tracts. The highest accessibility tracts fan outward from the central portion of the city, northwest along Interstate 90 and due west along Interstate 55. Most low accessibility ID tracts are in the southernmost or northeastern-most areas.

Orange corresponds to OOD census tracts; dark orange indicates an OOD census tract with high accessibility, whereas light orange signifies an OOD tract with low accessibility (i.e., lowest accessibility region-wide). OOD high accessibility tracts cluster in a region just outside the CCC boundary, between I-90 and I-294; a more northern region of OOD high accessibility tracts straddles I-90 on the east and state route 12 to the west. The large clusters of dark orange on the western edge of the study area span I-90 and I-80. The lowest accessibility tracts are in the southernmost region, as well as in pockets along the western edge.

I conduct a KW test with Conover-Iman post-hoc tests to compare the demographics of these four tract sub-groups (Table 5.8 and Table 5.9, respectively). For parsimony, I highlight only those instances where the rank-sum means using the Conover-Iman test are statistically significantly different from each other. Beginning first with median income, all sub-group pairings are statistically significantly different from each other in their rank-sum means, except for high accessibility ID and low accessibility OOD tracts. High accessibility OOD tracts have the highest median income ($96,872; Table 8.8, Column 2), whereas low accessibility ID tracts have the lowest observed median income ($38,852; Table 8.8, Column 3). Overall and racial sub-group poverty rates are highest in low accessibility ID tracts (29% overall, 30% for residents
of color and 27% for White residents; Table 8.8, Column 3) and lowest in high accessibility OOD tracts (8% overall, 10% for residents of color and 7% for White residents; Table 8.8, Column 2). Poverty rates in the remaining two sub-groups—lowest and highest accessibility (Table 8.8, Columns 1 and 4, respectively)—are comparable in magnitude for overall rates (11% and 14% overall) and among White residents (10% and 9%). Among residents of color, poverty rates are higher in the high accessibility tracts (17% versus 13%). Low accessibility ID tracts have the highest average percentage of residents with less than an associate degree (64%, Table 5.8, Column 3). High accessibility ID and OOD tracts have the lowest levels of potential educational demand (46% and 50%, Table 8.8, Columns 4 and 2; Conover-Iman rank-sum means are not statistically significantly different, Table 8.9, Column 2).

**Figure 8.10 Map of High and Low Accessibility Tracts, by Accessibility Distribution (Chicago; 2019)**

*Sources:* U.S. Census 2010 census tract shape files; Author’s calculations of U.S. Census ACS 5-year estimates 2015-2019; CDAC O-D Matrix; IPEDS 2019

*Notes:* Created in ArcGIS.
Racial demographics also differ across these four sub-groups. High accessibility OOD tracts have the highest average percentage of White residents (60%; Table 8.8, Column 2) and lowest percentage of Black residents (6%), whereas low accessibility ID tracts have the lowest percentage of White residents (20%) and highest percentage of Black residents (58%). The percentage of Asian residents is comparably high in high accessibility ID and OOD tracts (10%), and the rank-sum means in post-hoc testing are not statistically significantly different from each other (Table 8.9, Column 2). The average percentage of Latinx residents ranges from 15% for low accessibility ID and OOD tracts to 30% for high accessibility ID tracts (all post-hoc tests are statistically significant). The rank-sum means for the percentage of AI/AN/PI/MR/Other residents are not statistically significantly different in any sub-group pairings (Table 8.9), and the percentages are near identical across all four groups (2% in three sub-groups, 3% in one sub-group). The observed differences in the percentage of veterans are modest across the four groups (range from 3% to 5%), even though all sub-group pairings differ in their rank-sum means.

Median drive time across the quartiles of transit reliance are similar within the two distributions (56 minutes in OOD tracts, 49 minutes in ID tracts; Table 8.10), but median transit travel time is near or in excess of two hours in both ID and OOD tracts (1 hour 42 minutes and more than 2 hours, respectively), a consequence of lower transit access in these areas. In both ID and OOD tracts, transit travel times are lowest in the tracts with the highest percentages of households without vehicle access, but these median travel times remain near or above two hours, which would require four hours round-trip, assuming no further delays. Transit reliant individuals in these tracts would have to commute approximately three times as long to the median BAC than car-owning residents in the same tracts. The most likely outcome is that transit-reliant individuals would forego enrollment if it required this time commitment.
Table 8.8 Census Tract Characteristics and Results of the KW Test by Accessibility Index Categorization (Chicago; ACS 5-Year Estimates 2015-2019)

<table>
<thead>
<tr>
<th></th>
<th>Lower Distribution (OOD)</th>
<th>Upper Distribution (ID)</th>
<th>(5) K-W Statistic (P-Value)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1) Low Accessibility</td>
<td>(2) High Accessibility</td>
<td>(3) Low Accessibility</td>
</tr>
<tr>
<td></td>
<td>(n=273)</td>
<td>(n=272)</td>
<td>(n=199)</td>
</tr>
<tr>
<td><strong>Land area (mi^2)</strong></td>
<td>2.29 ± 3.20</td>
<td>2.45 ± 5.30</td>
<td>0.29 ± 0.56</td>
</tr>
<tr>
<td><strong>Tract population</strong></td>
<td>4700 ± 1791</td>
<td>5210 ± 2653</td>
<td>3388 ± 1806</td>
</tr>
<tr>
<td><strong>Population density</strong></td>
<td>3793.72 ± 2533.58</td>
<td>4382.45 ± 3292.55</td>
<td>24120.48 ± 41992.37</td>
</tr>
<tr>
<td><strong>Households with zero vehicles</strong></td>
<td>0.07 ± 0.07</td>
<td>0.04 ± 0.04</td>
<td>0.40 ± 0.15</td>
</tr>
<tr>
<td><strong>Median household income</strong></td>
<td>$80,048 ± $34,213</td>
<td>$96,872 ± $42,869</td>
<td>$38,852 ± $18,942</td>
</tr>
<tr>
<td><strong>Poverty rate (all residents)</strong></td>
<td>0.11 ± 0.10</td>
<td>0.08 ± 0.06</td>
<td>0.29 ± 0.14</td>
</tr>
<tr>
<td><strong>Poverty rate (residents of color)</strong></td>
<td>0.13 ± 0.11</td>
<td>0.10 ± 0.09</td>
<td>0.30 ± 0.14</td>
</tr>
<tr>
<td><strong>Residents aged 25+ w less than AA</strong></td>
<td>0.09 ± 0.12</td>
<td>0.07 ± 0.07</td>
<td>0.27 ± 0.29</td>
</tr>
<tr>
<td><strong>White</strong></td>
<td>0.51 ± 0.29</td>
<td>0.60 ± 0.25</td>
<td>0.20 ± 0.26</td>
</tr>
<tr>
<td><strong>Black</strong></td>
<td>0.25 ± 0.31</td>
<td>0.06 ± 0.11</td>
<td>0.58 ± 0.38</td>
</tr>
<tr>
<td><strong>Latinx</strong></td>
<td>0.15 ± 0.14</td>
<td>0.22 ± 0.22</td>
<td>0.15 ± 0.19</td>
</tr>
<tr>
<td><strong>Asian</strong></td>
<td>0.07 ± 0.10</td>
<td>0.10 ± 0.10</td>
<td>0.04 ± 0.07</td>
</tr>
<tr>
<td><strong>AI/AN/PI/MR/Other</strong></td>
<td>0.02 ± 0.02</td>
<td>0.02 ± 0.02</td>
<td>0.02 ± 0.02</td>
</tr>
<tr>
<td><strong>Veterans</strong></td>
<td>0.05 ± 0.02</td>
<td>0.04 ± 0.02</td>
<td>0.04 ± 0.03</td>
</tr>
</tbody>
</table>

**Sources:** Author’s calculations from U.S. Census ACS 5yr Estimates 2015-2019; CDAC O-D Matrix

**Notes:** Population density calculated as tract population divided by land area. Unless expressly noted with a unit of measurement (e.g., mi^2, $), all demographic values are proportion variables.
Table 8.9 P-Values for Post-Hoc Pairwise Conover-Iman Post-Hoc Comparison Tests, by Accessibility Index Categorization (Chicago; 2019)

<table>
<thead>
<tr>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Land area (mi²)</td>
<td>0.23</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
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<tr>
<td>Tract population</td>
<td>0.49</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Population density</td>
<td>0.28</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Households with zero vehicles</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Median household income</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.09</td>
<td>0.00</td>
</tr>
<tr>
<td>Poverty rate (all residents)</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Poverty rate (residents of color)</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Poverty rate (White residents)</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.04</td>
<td>0.00</td>
</tr>
<tr>
<td>Residents aged 25+ w less than AA White</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Black</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Latinx</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.02</td>
</tr>
<tr>
<td>Asian</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>AI/AN/PI/MR/Other</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Veterans</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
</tbody>
</table>

Sources: Author’s calculations from U.S. Census ACS 5yr Estimates 2015-2019; CDAC O-D Matrix

Table 8.10 Median Travel Times (in minutes) by Mode, Transit Reliance, and Accessibility Distribution (Chicago; CDAC O-D Matrix 2019)

<table>
<thead>
<tr>
<th>Lower Distribution</th>
<th>Upper Distribution</th>
</tr>
</thead>
<tbody>
<tr>
<td>N</td>
<td>Median Driving</td>
</tr>
<tr>
<td>Q1 (Least Transit ~)</td>
<td>462</td>
</tr>
<tr>
<td>Q2</td>
<td>396</td>
</tr>
<tr>
<td>Q3</td>
<td>205</td>
</tr>
<tr>
<td>Q4 (Most Transit R~)</td>
<td>27</td>
</tr>
<tr>
<td>All Tracts</td>
<td>1090</td>
</tr>
<tr>
<td>N</td>
<td>Median Driving</td>
</tr>
<tr>
<td>Q1 (Least Transit ~)</td>
<td>10</td>
</tr>
<tr>
<td>Q2</td>
<td>75</td>
</tr>
<tr>
<td>Q3</td>
<td>266</td>
</tr>
<tr>
<td>Q4 (Most Transit R~)</td>
<td>444</td>
</tr>
<tr>
<td>All Tracts</td>
<td>795</td>
</tr>
</tbody>
</table>

Sources: Author’s calculations from U.S. Census ACS 5yr Estimates 2015-2019; CDAC O-D Matrix

Were the only point of comparison the upper versus lower distributions of accessibility, then my hypothesis that low accessibility tracts are lower income and more racially diverse would not align with the findings for the Chicago study area. Tracts in the upper distribution for accessibility have lower median household incomes, higher poverty rates, and are more racially diverse. However, when I instead compare the demographics of high and low accessibility...
census tracts within these distributions, I discover a more nuanced story: Low accessibility ID tracts are lower income and more racially diverse than high accessibility ID tracts; the same pattern holds for OOD tracts. In the next section, I seek to quantify the magnitude and direction of the relationship between accessibility and census tract demographics using a spatial regression model. Here, as in Lansing, I conduct the analyses separately for ID versus OOD tracts.

**Chicago In-District Regression Results**

The use of the SDM is indicated by Elhorst’s (2010) selection process, in which the results of the LM tests on the OLS model and the LR tests comparing the SDM to simpler spatial models both suggest the presence of an underlying spatial process. Furthermore, the spatial parameter ($\rho$) for the SDM is large and highly significant (0.859, $p = 0.000$; Table 8.11). Therefore, I present the results of the OLS model but discuss only those of the SDM. I find that two demographic variables are statistically significant and directionally aligned with my hypotheses: poverty rate, and the percentage of residents with less than an associate degree. A 1pp increase in a census tract’s poverty rate is associated with a 0.006 unit decrease in accessibility ($p < 0.001$), meaning that a 48pp increase in the poverty rate corresponds to a one standard deviation decrease in accessibility (s.d. = 0.29). Poverty rates among in-district tracts range from zero percent to 75%, so census tracts with the highest poverty rates could—based on this coefficient—experience accessibility that is 1.5 standard deviations lower than zero poverty tracts. The direct effect coefficient for potential educational demand is similar in size to the coefficient for poverty rate (0.007, $p < 0.001$). Because educational demand ranges from 3.4% to 96%, high educational demand tracts could experience accessibility that is more than two standard deviations lower than accessibility in tracts with low educational demand.
The percentage of residents who identify as Black and Asian have statistically significant direct effects at the 10% level, and both in the hypothesized direction: A 1pp increase in the percentage of Black residents decreases accessibility by 0.004 units, and a 1pp increase in the percentage of Asian residents increases accessibility by 0.001 units. However, both covariates are statistically significant at the 10% level and it is therefore possible that this statistical significance would not remain were the standard errors adjusted for heteroskedasticity. Although the percentage of Latinx and AI/AN/PI/MR/Other residents have statistically significant coefficients in the OLS model, there are no statistically significant coefficients in the SDM for either the percentage of Latinx or AI/AN/PI/MR/Other residents.

Next, I examine the relationship between built environment factors and accessibility. Looking first at population density, although there is a statistically significant negative relationship in the OLS model, there are no statistically significant effects observed in the SDM. One potential explanation for this difference in results is that the spatial modeling in the SDM captured a spatial process that, in an OLS regression, would instead be captured through the population density variable. Lastly, the direct and indirect effects for the coefficient on highway adjacency are highly significant and positive, though the indirect effect is more than four times as large. When a neighboring census tract is highway adjacent, a focal census tract’s accessibility increases by 0.304, approximately one standard deviation. In contrast, when a focal tract is itself highway adjacent, the direct effect is only 0.068. One possible explanation for the larger indirect effect is that operationalizing highway access as adjacency and/or intersection does not adequately capture highway access points (e.g., there are not exit ramps in each tract that has highway adjacency). Another interpretation is that highways fracture accessibility, which means highway adjacency would minimize, not improve, accessibility for the fractured tracts.
All told, the findings for the Chicago ID analyses confirm that some, but not all, of the differences in demographics between low and high accessibility tracts in the sub-region are global relationships present within the entire sub-region. Both poverty and potential educational demand are negatively related to accessibility in the SDM, meaning that broad access public colleges are less accessible to lower-income residents and residents with less than an associate degree in the City of Chicago. Even though the two statistically significant relationships between accessibility and racial/ethnic composition of the census tract are directionally aligned with my hypotheses—accessibility is lower in tracts with a higher percentage of Black residents and higher in tracts with a higher percentage of Asian residents—these covariates are only statistically significant at the 10% level, rendering them sensitive to any subsequent adjustments to the standard errors for heteroskedasticity. I do not observe any statistically significant indirect effects across the demographic covariates.
Table 8.11 Regression Results for Chicago ID Analysis (DV = Accessibility Index)

<table>
<thead>
<tr>
<th></th>
<th>OLS</th>
<th>Direct Effects (SEs)</th>
<th>Indirect Effects (SEs)</th>
<th>Total Effects (SEs)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficients (SEs)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td>18.336***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.152</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pct. Poverty</td>
<td>-0.006***</td>
<td>-0.006***</td>
<td>-0.025</td>
<td>-0.030</td>
</tr>
<tr>
<td></td>
<td>0.001</td>
<td>0.001</td>
<td>0.005</td>
<td>0.006</td>
</tr>
<tr>
<td>Educ. Attain.</td>
<td>-0.004***</td>
<td>-0.007***</td>
<td>-0.001</td>
<td>-0.007</td>
</tr>
<tr>
<td></td>
<td>0.001</td>
<td>0.001</td>
<td>0.004</td>
<td>0.004</td>
</tr>
<tr>
<td>Pct. Black</td>
<td>0.000</td>
<td>-0.004†</td>
<td>-0.001</td>
<td>-0.005</td>
</tr>
<tr>
<td></td>
<td>0.001</td>
<td>0.001</td>
<td>0.003</td>
<td>0.003</td>
</tr>
<tr>
<td>Pct. Latinx</td>
<td>0.003***</td>
<td>-0.001</td>
<td>0.003</td>
<td>0.002</td>
</tr>
<tr>
<td></td>
<td>0.001</td>
<td>0.001</td>
<td>0.003</td>
<td>0.003</td>
</tr>
<tr>
<td>Pct. Asian</td>
<td>0.003**</td>
<td>0.001†</td>
<td>0.004</td>
<td>0.005</td>
</tr>
<tr>
<td></td>
<td>0.001</td>
<td>0.001</td>
<td>0.006</td>
<td>0.006</td>
</tr>
<tr>
<td>Pct. AI/AN/PI/MR/Other</td>
<td>-0.008†</td>
<td>0.002</td>
<td>0.002</td>
<td>0.004</td>
</tr>
<tr>
<td></td>
<td>0.005</td>
<td>0.003</td>
<td>0.034</td>
<td>-0.014</td>
</tr>
<tr>
<td>log(popdensity)</td>
<td>-0.053***</td>
<td>-0.001</td>
<td>-0.013</td>
<td>-0.014</td>
</tr>
<tr>
<td></td>
<td>0.015</td>
<td>0.011</td>
<td>0.050</td>
<td>0.060</td>
</tr>
<tr>
<td>Flag – Tract has BAC</td>
<td>-0.007</td>
<td>-0.035</td>
<td>-0.157</td>
<td>-0.192</td>
</tr>
<tr>
<td></td>
<td>0.068</td>
<td>0.046</td>
<td>0.217</td>
<td>0.262</td>
</tr>
<tr>
<td>Flag – Highway Adjacency</td>
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<td>0.304*</td>
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<td>0.099</td>
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<tr>
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<td>795</td>
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<tr>
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<td></td>
<td></td>
</tr>
<tr>
<td>LM_{lag}</td>
<td>975.93 (0.000)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>LM_{error}</td>
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<td></td>
</tr>
<tr>
<td>Robust LM_{lag}</td>
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<td></td>
</tr>
<tr>
<td>Robust LM_{error}</td>
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<td></td>
<td></td>
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<tr>
<td>Likelihood</td>
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<td></td>
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<tr>
<td>AIC</td>
<td>-59.93</td>
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<td></td>
</tr>
<tr>
<td>Moran’s I (Residuals)</td>
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<td>-0.08***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>R²</td>
<td>0.35a</td>
<td>0.78b</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Sources: Author’s calculations from U.S. Census ACS 5yr Estimates 2015-2019; CDAC O-D Matrix
Notes: Outcome is the postsecondary accessibility index, estimated at the tract level using the protocol outlined in Chapter 6. Sample includes all census tracts with weighted centroids within the boundary of the City Colleges of Chicago district. †p<0.10, *p<0.05, **p<0.01, ***p<0.001. Direct, indirect, and total effects not estimated for the intercept in the SDM. Raw coefficient values in Table A.8. aAdjusted R² bNagelkerke pseudo R²
Chicago Out-of-District Regression Results

Now, I turn to the portion of the Chicago study area that is outside the CCC district boundary. Here, as with the Chicago ID analyses, when I follow Elhorst’s (2010) protocol, I identify the SDM as the preferred regression model. In alignment with that recommendation, the spatial parameter ($\rho$) is large and statistically significant ($\rho = 0.608, p < 0.001$), indicative of an underlying spatial process. Therefore, as above, I focus my discussion on the results of the SDM but include in Table 8.12 the results of the OLS model.

An increase in a census tract’s poverty rate or its percentage of residents with less than an associate degree is associated with lower accessibility, as theorized in the conceptual framework. A one percentage point increase in a tract’s poverty rate is associated with a 0.003 unit decrease in accessibility. Holding all else constant, the tract in the region with the highest poverty rate (50%) would be expected to have accessibility that is approximately half a standard deviation lower than the tract with the lowest poverty rate (0%; s.d. for accessibility = 0.28). There are also statistically significant direct and indirect effects observed in the SDM for the percentage of residents with less than an associate degree, though the coefficients are of opposing directions. A one percentage point increase in the focal tract is associated with a 0.001 unit decrease in accessibility whereas a one percentage point increase in neighboring tracts is associated with a 0.003 unit increase in accessibility. The opposing directions point to the need for additional work that theorizes on the underlying mechanisms through which this relationship manifests differently depending on whether the unit of change is occurring in a tract or its neighbors.

All the four racial/ethnic composition variables have statistically significant direct and/or indirect effects in the SDM. The percentage of a tract’s residents who identify as Black is associated with a small decrease in accessibility for that tract (0.001, $p < 0.05$); the indirect effect is slightly larger and positive (0.002, $p < 0.05$). The direct effect between accessibility and the
percentage of residents who identify as Latinx is positive but small (0.001, \( p < 0.05 \)) whereas the indirect effect is negative and four times as large (0.004; \( p < 0.01 \)). Although there is not a statistically significant direct effect for the percentage of Asian residents, the indirect effect is positive and statistically significant at the 1% level (0.006), in keeping with the hypothesized direction. The direct and indirect effects between accessibility and the percentage of AI/AN/PI/MR/Other residents are both negative (direct: -0.005, \( p < 0.05 \); indirect: -0.048, \( p < 0.001 \)). The coefficient for the indirect effect is nearly 10 times as large as the coefficient for the direct effect, suggestive of a stronger relationship between accessibility and neighboring tracts’ percentage of residents who identify as AI/AN/PI/MR/Other.

Next, I turn to the built environment covariates. Population density is statistically significant and positive in both the OLS model and the SDM, as is co-location with a BAC. A one percentage point change in a tract’s population density is associated with a 0.028 unit increase in accessibility; the same change in neighboring tracts is associated with a 0.037 unit increase in the focal census tract’s accessibility. A tract’s co-location with a BAC is associated with a 0.057 unit increase in accessibility; when a neighboring tract is instead the tract with a BAC, accessibility is 0.076 units higher than when there is no BAC in a neighboring tract. Highway adjacency likewise has a strong positive direct and indirect relationship to accessibility in the SDM (direct effect: 0.069, \( p < 0.001 \); indirect effect: 0.092, \( p < 0.001 \)).

The Chicago OOD analyses provide supporting evidence for my hypotheses across nearly all the covariates. Poverty rates, potential educational demand, the percentage of Black residents, and the percentage of residents who identify as AI/AN/PI/MR/Other are all associated with decreases in accessibility, as captured by the direct effects in the SDM. Furthermore, these relationships align with the distributional patterns I observed when limiting my examination to
the highest and lowest accessibility tracts in the sub-region. Low accessibility OOD tracts in Chicago are lower income, higher poverty, have higher potential educational demand, and are more racially diverse than high accessibility OOD tracts. Counter to my hypothesis is the finding that the percentage of residents who identify as Latinx is higher in high accessibility OOD tracts and, in the SDM, positively associated with a tract’s accessibility. Although I observe a positive indirect effect for the percent of Asian residents, I do not find evidence in the direct effects for my hypothesis that accessibility is positively associated with the percentage of Asian residents.
Table 8.12 Regression Results for Chicago OOD Analysis (DV = Accessibility Index)

<table>
<thead>
<tr>
<th></th>
<th>OLS Coefficients (SEs)</th>
<th>Direct Effects (SEs)</th>
<th>Indirect Effects (SEs)</th>
<th>Total Effects (SEs)</th>
</tr>
</thead>
<tbody>
<tr>
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<td>-0.004</td>
<td></td>
</tr>
<tr>
<td><strong>Pct. Poverty</strong></td>
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<td>-0.003***</td>
<td>-0.001</td>
<td>-0.004</td>
</tr>
<tr>
<td><strong>Educ. Attain.</strong></td>
<td>0.000</td>
<td>-0.001**</td>
<td>0.003</td>
<td>0.002</td>
</tr>
<tr>
<td><strong>Pct. Black</strong></td>
<td>-0.001†</td>
<td>-0.001*</td>
<td>0.002*</td>
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</tr>
<tr>
<td><strong>Pct. Latinx</strong></td>
<td>0.000</td>
<td>0.001</td>
<td>0.001</td>
<td>0.001</td>
</tr>
<tr>
<td><strong>Pct. Asian</strong></td>
<td>0.001†</td>
<td>-0.001</td>
<td>0.006**</td>
<td>0.005**</td>
</tr>
<tr>
<td><strong>Pct. AI/AN/PI/MR/Other</strong></td>
<td>-0.004†</td>
<td>-0.005*</td>
<td>-0.048***</td>
<td>-0.052***</td>
</tr>
<tr>
<td><strong>log(popdensity)</strong></td>
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<td>0.028***</td>
<td>0.037***</td>
<td>0.065***</td>
</tr>
<tr>
<td><strong>Flag – Tract has BAC</strong></td>
<td>0.081*</td>
<td>0.057*</td>
<td>0.076*</td>
<td>0.133*</td>
</tr>
<tr>
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<td>0.112***</td>
<td>0.069***</td>
<td>0.092***</td>
<td>0.161***</td>
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<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td><strong>Spatial Parameter (ρ)</strong></td>
<td>0.608***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>N</strong></td>
<td>1090</td>
<td>1090</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Diagnostics**
- $L_M^{\text{Lag}}$: 589.92 (0.000)
- $L_M^{\text{Error}}$: 875.47 (0.000)
- Robust $L_M^{\text{Lag}}$: 6.37 (0.012)
- Robust $L_M^{\text{Error}}$: 291.92 (0.000)
- Likelihood: 635.08  898.68
- AIC: -1210.15 -1723.40
- Moran’s I (Residuals): 0.53***  0.06***
- $R^2$: 0.762a  0.857b

**Sources:** Author’s calculations from U.S. Census ACS 5yr Estimates 2015-2019; CDAC O-D Matrix
**Notes:** Outcome is the postsecondary accessibility index, estimated at the tract level using the protocol outlined in Chapter 6. Sample includes all census tracts with weighted centroids outside the boundary of the City Colleges of Chicago district. † p<0.10, *p<0.05, **p<0.01, ***p<0.001. Direct, indirect, and total effects not estimated for the intercept in the SDM. Raw coefficient values in Table A.8. aAdjusted $R^2$ bNagelkerke pseudo $R^2$
Robustness Checks for Spatial Regression Analyses

A central component to the postsecondary accessibility index (i.e., the dependent variable in the above regressions) is the choice of distance decay factor—the $\beta$ in equation 6.3. Recall that the distance decay factor is a value by which the travel time to a given destination erodes. The consequence to the index value is that accessibility decreases exponentially as travel time increases. For the index used in the above analyses, I opt for a value of $\beta$ (0.10157) derived by Levine et al. (2011) using a gravity model and individual-level trip data in sixteen metropolitan areas. Since I do not derive the distance decay factor using study area-specific information, I test the sensitivity of my regression results to the choice of distance decay factor. To do so, I re-estimate the accessibility index using values of $\beta$ ranging from 0.05 to 0.15, increasing in 0.01 intervals.\textsuperscript{56} I then re-estimate the SDM and its corresponding direct, indirect, and total effects using the procedure outlined in Chapter 3.

To easily visualize the similarity in the direct and indirect effects—both in magnitude and statistical significance—I plot for each covariate the effect estimate and its confidence interval (CI). These plots are available in Appendix A, Figure A.5 – Figure A.12. In summary, although there are slight variations in statistical significance across the models, the CIs for the direct and indirect effects in the robustness check models overlap with the CIs for the preferred models in all but two cases. In these cases, the CIs for the preferred model overlap with all robustness check CIs except the model in which I use a distance decay factor of 0.05 (the lowest used). This overlap indicates that, even if the values of the coefficients differ across models, the estimates

\textsuperscript{56} When using a distance decay factor of 0.05, a 60-minute trip receives a value of 0.81 ($60^{-0.05}$); with a distance decay factor of 0.15, that same trip receives a value of 0.54. This value is then multiplied by the desirability measure, meaning that the same trip with a smaller distance decay factor is estimated as more accessible than it would be with a larger distance decay factor. The range I rely on here draws from the approach taken by Wang and Minor (2002), in which the authors test the sensitivity of the regression results when the distance-decay factor ranges from half its preferred value to double its preferred value.
are not statistically significantly different from each other. Based on these results, I maintain the preference for the Levine et al. (2011) distance decay factor of 0.10157.

**Chapter Summary**

In this chapter, I sought to better understand whether and how accessibility to broad access public colleges varied depending on census tract demographics. I hypothesized that accessibility would be lower in census tracts with higher poverty rates, more residents with less than an associate degree, and higher percentages of residents who identify as Black, Latinx, or AI/AN/PI/MR/Other. Based on existing evidence in the literature, I hypothesized a positive relationship between accessibility and the percentage of residents who identify as Asian. To answer the research questions, I compared accessibility and neighborhood demographics in two ways: First, I compared for each study area the demographics of neighborhoods with the highest and lowest levels of accessibility. Second, I quantified the relationship between tract-level demographics and accessibility using spatial regression models.

In Lansing, I find that low accessibility tracts—those outside of the LCC district—are higher income, less racially diverse, and have more residents aged 25 and older with less than an associate degree. The first two of these relationships run counter to my stated hypotheses regarding the demographics of low accessibility tracts. When I examine the demographics of high- versus low-accessibility tracts separately by in- versus out-of-district status, I find that the high accessibility tracts inside the LCC boundary remain the lowest income and most racially diverse. Indeed, even low accessibility tracts within the LCC boundary are more racially diverse than tracts outside of the LCC boundary. That said, the least accessible tracts in the study area—low accessibility out-of-district tracts—have the highest percentage of residents with less than an associate degree. This is in keeping with my prediction that educational attainment would be
lower in low accessibility tracts, though these tracts are predominantly White, rather than in low-income communities and communities of color as I initially hypothesized.

The spatial regression results for Lansing provide reinforcing evidence that there is a negative relationship between potential educational demand in a tract and its level of accessibility to broad access public colleges. The coefficient on educational demand is negative and statistically significant in both the ID and OOD analyses. Despite the differences in poverty rates that I observe between high and low accessibility tracts, there is no discernible global relationship between poverty rate and accessibility in either regression model. Likewise, the higher percentage of Black residents in high accessibility ID tracts relative to low accessibility ID tracts does not translate to a positive global relationship in the regression. In both the in- and out-of-district analyses, the relationship between accessibility and the percent of Asian residents is negative, even though the rank-sum means for the percentage of Asian residents were not statistically significantly different from each other when comparing high versus low ID tracts (Table 8.3, Column 1) and high versus low OOD tracts (Table 8.3, Column 6). The positive relationship between accessibility and percent of AI/AN/PI/MR/Other residents in the Lansing ID analyses is aligned with the differences observed between high and low accessibility ID tracts (Table 8.2), but not aligned with my hypothesized negative relationship.

In Chicago, were I to conclude my examination of differences in accessibility with the comparison of demographics between tracts that are within versus outside of the CCC district boundary, I would find that in-district (also higher accessibility) tracts are lower income, more racially diverse, and have a larger share of residents with less than an associate degree—all findings that are incongruous with my hypotheses. When I instead examine demographics separately for high and low accessibility tracts within the in- and out-of-district regions, I find
demographic differences in alignment with my hypotheses: high accessibility ID tracts are higher income, less racially diverse, and have lower potential educational demand than low accessibility ID tracts. The same pattern holds when I compare high versus low accessibility OOD tracts. Although ID tracts benefit from increased accessibility as compared to OOD tracts—due to being eligible for in-district tuition at all the City Colleges of Chicago campuses—there are still within-district differences in the demographics of high and low accessibility tracts.

The regression analyses for Chicago provide additional evidence that, for both in- and out-of-district tracts, poverty rates and potential educational demand are negatively associated with accessibility. Statistically significant differences in racial/ethnic composition between high and low accessibility ID and OOD tracts are less visible in the regression results. Even though the average percentage of Black residents in low accessibility ID tracts is 46pp higher than the average in high accessibility ID tracts, the negative direct effect between accessibility and the percentage of Black residents is imprecisely measured in the ID analyses ($p < 0.10$). In the OOD tracts, this same negative relationship reaches a higher statistical significance threshold ($p < 0.05$) and would amount to one third of a standard deviation difference in accessibility between the OOD tracts with the highest and lowest percentages of Black residents. Among the remaining race/ethnicity covariates, I observe a statistically significant positive direct effect and negative indirect effect for percentage of Latinx residents in the OOD model, a positive direct effect for percentage of Asian residents in the ID analyses and positive indirect effect in the OOD analyses, and negative direct and indirect effects for the percentage of AI/AN/PI/MR/Other in the OOD analyses. For only one of these findings—the positive direct effect for percentage of Latinx residents in the OOD model—is the observed relationship misaligned with my hypotheses.
Chapter 9 Practitioner Toolkit

The preceding analyses make clear that the circumstances of geographic accessibility are unique to the local context: a city, its colleges, the individuals who enroll (or not) at local institutions. The best that case studies such as these can demonstrate is the variability, the near-impossible generalizability of one region’s circumstances to another. And yet, the contours of a story appear, from the literature review in Chapter 2 to the results in Chapters 5 and 8: Place matters, and the capacity to move from home to school and back again influences whether and how individuals pursue postsecondary education. College leaders recognize the indirect influence of steady transportation on students’ continuity in their investments (Arnett, 2020; Mangan & Schmalz, 2019; Smith, 2016; Wood, 2022).

The challenge is in coupling academic findings with college leaders’ ongoing efforts to remove barriers to college access and success. Put differently, the preceding exploratory research demonstrates how geographic access varies within two regions but does little for the college practitioner seeking to understand geographic access for their institution’s students. For this reason, I developed a toolkit prototype that institutional practitioners can employ to make concrete the narrative of geographic accessibility for their student population.

At its simplest, the toolkit report provides institutional practitioners with a descriptive assessment of students’ geographic accessibility. If an institution is in the process of evaluating whether and where to open additional campuses, the toolkit could be deployed during site selection to determine whether potential locations are accessible to currently enrolled students. An application of this nature is essentially a policy simulation, in which practitioners can
evaluate how a potential change in the built environment differentially affects accessibility (see, for example, Moreno-Monroy et al., 2017). Adaptations of the code would enable practitioners to evaluate accessibility relative to enrollment, identifying regions with high potential enrollment demand but few currently enrolled students.

This toolkit is in the spirit of two existing efforts that comprehensively document variation in accessibility across and within geographic regions. First, TransitCenter’s Equity Dashboard evaluates public transit and driving commute times (Klumpenhouwer et al., 2021) to key opportunities such as jobs and, relevant to this study, colleges and universities. Although the Equity Dashboard evaluates accessibility at the block group level, it does so only in a small number of cities and calculates a composite measure of accessibility to a given opportunity based on all colleges located in that city (e.g., includes more selective institutions, instead of just the broad access public colleges that are the focus of this toolkit).

Second, the Seldin/Haring-Smith Foundation’s Public Transit Map identified, for all community colleges, the distance to the nearest bus stop (Crespi et al., 2021). The map is a powerful starting point for demonstrating the limited public transit access to community colleges nationwide, but leaves uncontextualized how bus stop locations translate into commute times for individuals who enroll at (or who consider enrolling at) these same community colleges. College practitioners can take the findings of their report as a starting point: How far away is the nearest bus stop (measured by straight line), and what bus lines service this stop? To fully ground the work in the institutional context requires linking information on bus stop locations to more exhaustive data on students’ relative locations, modes of transit, and mode-specific travel times.

The toolkit prototype developed as part of this study is designed with institutional practitioners in mind. The collection of files that comprise the toolkit include an instructions
document, Stata do-files, and an auto-populating report template that institutional researchers can use to investigate transit accessibility for their student populations. Because the accessibility index used elsewhere in the study is inherently more difficult to interpret than a straight-forward mobility measure such as commute time (Geurs & van Wee 2004; Handy & Niemeier, 1997), I design the toolkit based on driving and public transit travel times. In the remainder of this chapter, I briefly explain key files included in the toolkit. Appendices B-D includes the text of the instructional guide, all three do-files, and an example report using the Markdown template.

**Data Requirements**

The toolkit requires several datasets, most notably a dataset that includes estimated travel times by driving and public transit between each block group in an institution’s region and the institution itself. HERE, a third-party mapping service, offers API integration with a user-written Stata command, *georoute*, that allows any user with a HERE API key to estimate travel time by mode between any set of origins and destinations. There are several downsides to relying on a user-written program and the HERE API. First, since *georoute* is not maintained by HERE employees, the continued integration of its API with *georoute* depends on whether the Stata program is updated to accommodate changes in the HERE API. Second, a toolkit user must both create a HERE account and, if the number of necessary transactions exceeds the maximum number of free transactions in a month, the user must incur a small fee to do so.

The available options for estimating public transit commute times are more limited than the options for estimating driving time; the two primary alternatives are either similarly costly (Google Distance Matrix API) and/or require the user to work in Python or R (Google Distance Matrix API; OpenStreetMap and OpenTripPlanner, the latter of which is open source and

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57 Stata is statistical software, and do-files refer to text files that contain user-written commands to manipulate and analyze data that has been brought into the Stata environment.
therefore does not require that the user incur a cost). Furthermore, with any of these services, there is the potential for future changes to render inoperable static code written to integrate with any of these routing services. Therefore, in the interest of maintaining the simplicity of this prototype and demonstrating its potential if formally developed, I opt for the Stata-accessible approach of integrating with the HERE API.

Also necessary are several U.S. Census datasets, including block group shape files, block group weighted centroids, and tract-level information on car ownership. These data files are publicly available, and download links and instructions are included in the instruction guide. The final component is an institutional dataset formatted to integrate with the do-files and thus the report template. Although I provide detail on the format required for this dataset, including variable names and value labels, the user is responsible for its construction. Likewise, because the toolkit calculates accessibility between block groups and the institution, the user must accurately identify students’ census block groups using student-level address records.

Instructional Guide

The instructional guide is a step-by-step “how to” for institutions interested in assessing transit accessibility for their student population (Appendix B). In this guide, I provide detail about how to modify the accompanying do-files to successfully execute on the user’s computer, the student-level data required for the analysis (i.e., how to structure the dataset, variable names and definitions, variable values), and details on using the HERE API to calculate travel times. Specifically, the institutional researcher will need to construct a dataset that includes one observation per student and identifies for each student the census block group (i.e., GEOID) that corresponds to their place of residence.
Stata Do-Files

Included in the toolkit are three do-files that intake U.S. Census and institutional data, calculate travel times using the HERE API for the collection of census block groups in the institution’s region, and compile a report with summary information on average travel times by key measures (time of day, student demographics, student outcomes; Appendix C). The first of these do-files imports and properly formats U.S. Census data files (block group shape files, block group weighted centroids, and tract-level information on car ownership). The second do-file uniquely identifies all block groups represented in the institution dataset, calculates travel times between block group weighted centroid coordinates and the institution’s coordinates, and cleans the resulting output to be merged onto the institution’s dataset. The third do-file merges the student-level institution dataset with travel time information, generates key graphs, and compiles the report using the markdown file report template.

Report Template

The toolkit relies on Stata’s integration with Markdown to automatically populate a report on student accessibility by mode, demographics, and key outcome measures. Information highlighted in the report includes: average travel time by car and by public transit at three times of day (morning, afternoon, and evening); average morning commute duration by race/ethnicity, Pell receipt, and enrollment intensity; full- and part-time retention rates and graduation rates by commute time (estimated separately for driving and public transit); maps of travel time by census block group; and travel time by population percentile.

User-Driven Template Add-Ons

The toolkit in its base form centers the relationship between travel time and student outcomes, differentiated by key demographics where possible. However, commuting

[58] Markdown is “a lightweight markup language” that is used to format text documents (Cone, 2022).
encompasses numerous costs that are not accounted for in an assessment of time. With respect to driving, parking availability on college campuses is a frequent point of contention in discussions of campus life (Rivard, 2014) or, even recently, in federal law (Seltzer, 2018). Parking permit fees—in addition to the costs associated with gas, car insurance premiums, and car maintenance—add to the financial burden of car commuting and vary depending on the geographic region. Detroit, for example, has notoriously high car insurance premiums, making car ownership more costly than it is elsewhere (The Economist, 2018). For public transit, individuals must purchase tickets or passes, both of which come with per-ride, monthly, or by-semester costs. How much students can expect to spend on either form of commuting depends on each college’s regional context. I encourage institutional practitioners to quantify these by-mode commuting costs to build a comprehensive picture of the time and financial resources required of commuter students. In service of this goal, I include a section in the report template where users of the toolkit can, if they choose, incorporate this information directly into the report.

**Sample Report Output**

In this section, I demonstrate the toolkit’s functionality by using fictional student-level data to produce a report for Imaginary Community College (ICC) in Lansing (see Appendix D for complete report output). In the charts that I explore, there are no discernible relationships between travel time and student outcomes. This is to be expected, since the data are generated based on a set of institutional and regional demographic parameters. That said, examining these

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59 To create the fictional data, I generated new observations that, when aggregated, reflected the racial/ethnic and Pell Grant recipient demographic profile of a less selective college in the region. I then assigned fictional outcome values (full- versus part-time status, retention, graduation in 150% time) to each fictional student, again based on publicly available institutional data. A student’s place of residence is set to the block group level, and assignment to the block group is based on the proportion of individuals in a block group who identify as the same race/ethnicity of the fictional student. This student-level data and its underlying variables are formatted to align with the specifications outlined in the instructional guide, and the final dataset is run through the toolkit’s three do-files.
key charts provides context for how institutional practitioners might interpret the toolkit’s findings and translate these findings into next steps.

The first two charts provide a baseline assessment of geographic accessibility across the current student population. Figure 9.1 presents the by-mode average travel times by race/ethnicity population sub-groups (see Appendix D for this chart by enrollment intensity and Pell receipt). In almost all instances, the institutional researcher should expect to observe travel times that are longer by public transit than driving. That said, unlike the CDAC data used elsewhere in the dissertation, the HERE API does not return a result if a transit stop is more than 1.2 miles (2000 meters) from either the origin or destination. Therefore, these public transit commute times represent the duration of travel for students whose block groups are serviced by the region’s public transit agencies. A large disparity in these within-mode average travel times across racial/ethnic sub-groups is a preliminary indication that certain populations experience disproportionately high travel times when commuting to campus.

**Figure 9.1 Average Commute Times by Race/Ethnicity (Toolkit Example)**

![Average Commute Times by Race/Ethnicity](image)

*Sources:* Fictional dataset derived using U.S. Census ACS 5yr Estimates 2015-2019; IPEDS 2019; HERE API

*Notes:* Created in Stata.
Figure 9.2 moves beyond average commute times presented in the above graph to instead document the cumulative distribution of travel times by racial/ethnic subgroups and mode of travel. Although the report template includes this figure only by race/ethnicity, the institutional researcher could adapt the code to include other populations of interest (e.g., gender identity, Pell status). Focusing on the population of Black students at ICC (maroon line), the slope of the line increases rapidly, then levels off at the 90th percentile around the 20 minute mark. In contrast, the bright red line for Native Hawaiian/Pacific Islander does not reach the 90th percentile until more than 40 minutes. Whereas 90% of Black students can travel by car to ICC in 20 minutes or less, approximately a quarter of Native Hawaiian/Pacific Islander students cannot reach ICC by car in less than 45 minutes.

An institutional researcher examining this chart can observe the student populations for whom commute times are not a barrier versus those for whom long commute times are the norm and thus may affect academic outcomes. These findings can help institutional leaders determine whether solutions that address transportation barriers are best implemented universally (e.g., available to all students) or targeted at certain populations for whom long commute times are a documented problem. Targeting interventions at populations with low accessibility has the potential to improve outcomes for many students, whereas universal approaches or approaches directed toward student populations with generally high accessibility may be less cost efficient.
Whereas the above charts examine accessibility by student racial demographics, in Figure 9.3, the report pivots to descriptive charts that document the relationship between commute times and student outcomes. These bar charts, which report the retention rate by commute time for driving (presented below) and public transit (see full report output in Appendix D), are not causal and they are not accompanied by any formal tests of statistical significance. That said, institutional researchers can use these charts to identify worrying patterns in retention rates based on intervals of commute times. Were these charts to reveal large differences in retention rates between short versus long commutes—for instance, if part-time retention rates dropped precipitously between the 20-30min commute band and the 30-40min commute band—it could suggest that there is a commute duration threshold after which the length of the commute negatively affects students’ academic outcomes. In this case, the next step would be identifying the students for whom retention appears correlated with commute time and gathering additional data to identify the mechanisms through which commute time affects retention (time, finances,
psychological stress). Once the mechanisms are identified, institutional leaders can begin to identify and implement strategies that address these mechanisms.

**Figure 9.3 Retention Rates by Mode-Specific Commute Intervals (Driving; Toolkit Example)**

*Panel A: Full-Time Students*  
*Panel B: Part-Time Students*

Sources: Fictional dataset derived using U.S. Census ACS 5yr Estimates 2015-2019; IPEDS 2019; HERE API

Notes: Created in Stata

Lastly, I include below two maps that plot for each block group the average commute time by mode (Figure 9.4). These maps foremost convey how travel times vary across the college’s service area. For instance, in the map below, what I observe is that outlying block groups have very far to go by car (Panel A, dark green), but so too do close-in block groups with public transit service (Panel B, dark purple). Institutional leaders examining these maps might consider how to best support students who enroll from the outer edges of the service area or, more to the point, whether there are individuals in these regions for whom the potential commute time is a barrier to initial enrollment. Long commutes or, for most of the region, the total absence of public transit service could likewise limit initial enrollment or affect retention among those who enroll. An institutional researcher can examine this map to understand the degree of overlap between the public transit service area and the institution’s service area. In instances where these
areas do not overlap or overlap only partially, the misalignment could have enrollment and retention consequences for transit-reliant students.

**Figure 9.4 Map of Tract-Level Average Commute Times by Mode (Toolkit Example)**

*Panel A: Driving Times*  
*Panel B: Public Transit Times*

*Sources:* Fictional dataset derived using U.S. Census ACS 5yr Estimates 2015-2019; IPEDS 2019; HERE API  
*Notes:* Created in Stata.

This toolkit is merely a prototype. Subsequent iterations could better incorporate students’ perspectives on what makes transportation a barrier—perhaps by combining these descriptive assessments with survey data collected from currently enrolled students. A survey administered to students could include questions about mode of travel, reliability of this mode of travel, or activities included in any trip-chaining such as the frequency with which a student must travel between campuses or between a job and campus. Furthermore, direct input from campus and community leaders would ensure that the toolkit provides information that is immediately useful to the people in positions to translate key findings into targeted student success strategies. Collaborating with institutional researchers would ensure that the process of adapting student level-data into the format required for the toolkit is clearly described and easily implemented.
Chapter 10 Discussion

Although proximity to college has long been identified as a factor influential to individuals’ enrollment decisions (Card, 1993; Rouse, 1995; Turley, 2009), only in more recent decades have scholars begun to evaluate the geographic access of higher education within and across communities (Briscoe & De Oliver, 2006; Dache-Gerbino, 2014; Fisher, 2012; Hillman, 2016; Krause, 2017). This new cohort of scholars, myself included, find that the built environment is unavoidably linked with the past and present of college access. At the national level, Hillman’s (2016) cross-region assessment of geographic access demonstrates that regional demographics correlate with the number of colleges in the region, with Latinx commuting zones and those with low educational attainment having access to fewer colleges.

Whereas Hillman (2016) examines the question nationally, case studies of local access to higher education re-affirm what urban planning scholars have long documented: Access to opportunity, even among communities in the same region, varies predictably and unequally along demographic axes (Grengs, 2010, 2012). Briscoe and De Oliver (2006) discover in their case study of the University of Texas – San Antonio’s (UTSA) branch campus opening that neighborhood demographics can motivate an institution’s choice to locate in one neighborhood over another. Dache’s studies identify college deserts and oases in Rochester (Dache-Gerbino, 2018); provide evidence of Latina students’ tendency to enroll close to home, thereby favoring institutions with lower outcomes (Dache-Gerbino et al., 2018); and demonstrate that riding the bus to college is not just time-consuming but involves constant exposure to criminalizing
messaging and poorly maintained bus stops (Dache, 2022). Fisher (2012) and Krause (2017) find differential access within metropolitan areas by race/ethnicity and income, respectively.

In this study, I pursued a new approach for unpacking how the built environment influences geographic access to less selective colleges for low-income communities and communities of color. I examined the demographics of college neighborhoods; observed which colleges were most accessible to tracts with populations historically excluded from or underserved by higher education; and evaluated tract-level accessibility to broad access public colleges using an index design drawn from the urban planning literature. Unlike single-dimension measures of accessibility, such as driving distance or driving time, this index allows for tract-level adjustments to accessibility estimates based on willingness to travel, car access within the tract, and mode-specific travel times (Levine et al., 2019). These adjustments yield a comprehensive measure of accessibility, especially for transit-reliant communities that are disproportionately low-income and high proportion people of color (POC; Blumenberg & Pierce, 2012; Rapheal et al., 2001).

This summative chapter seeks to bring the underlying narratives into focus. I summarize key findings, explore the historical context of the two study areas to better situate these findings, and outline the study’s contributions alongside suggestions for future research. I identify the implications for policy and practice and, where possible, use the toolkit prototype outlined in Chapter 6 as the starting point for these actionable steps. Throughout, I remain attentive to the conceptual tenets of critical race spatial analysis (CRSA) by centering in my discussion the potential linkages between what I observe in the geography of college access in present day and the spatial processes that, over time, resulted in this unequal distribution of access.
Research Findings

The purpose of this study was to document the presence and severity of differential geographic access to less selective colleges within metropolitan areas and, in doing so, highlight whether there are structural differences in accessibility for low-income and racially minoritized populations as compared to high-income and White populations. Using a collection of quantitative research methods, including descriptive test statistics and spatial regression analyses, I evaluated the demographics of less selective college neighborhoods; compared average outcomes at the colleges nearest to low- versus high-income and high proportion White versus high proportion POC tracts; and quantified the magnitude of the relationship between accessibility to less selective public colleges and tract demographics. Here, I explore five key findings as they relate to the purpose of the study and the underlying research questions.

Finding #1: Socio-economic and racial diversity is more pronounced in less selective public college neighborhoods, but outcomes at the less selective colleges nearest to high poverty and high proportion POC neighborhoods are the lowest observed

In both Lansing and Chicago, less selective public college neighborhoods are higher poverty than non-college tracts (RQ1), a 12 and 3 percentage point (pp) difference in Lansing and Chicago respectively. These neighborhoods are also, on average, less White than non-college tracts, by 23pp and 7pp in Lansing and Chicago. A comparison of main versus branch campus neighborhood demographics among the less selective public colleges in Chicago found further stratification of neighborhood demographics: Main campus neighborhood tracts are higher income, lower poverty, and Whiter than branch campus neighborhood tracts. These findings corroborate Fisher’s (2012) finding that community college branch campuses decrease the distance to the nearest community college for predominantly Black and Latinx census tracts and align with Briscoe and De Oliver’s (2006) case study finding that UTSA deliberately chose a lower-income, high proportion POC neighborhood in San Antonio for its branch campus.
Moreover, when I considered the location of all high-poverty or high proportion POC tracts in Chicago (not just those in a college neighborhood), I find that 71% of both the high poverty and high proportion POC tracts are nearest to a less selective public college, as opposed to a less selective for-profit or nonprofit college. The findings presented here, when combined with evidence from previous literature, suggest that less selective public colleges are geographically accessible to local communities of low-income and racially minoritized populations.

High accessibility is not, however, where the story ends. When I considered student outcomes at the less selective colleges nearest to high poverty and high proportion POC tracts—71% of which are public—I found that average retention and graduation rates, mean six- and ten-year earnings, and student loan repayment rates are all lower at the institutions nearest to these census tracts than to low poverty or predominantly White census tracts (RQ2). These findings suggest a problematic alignment between geographic accessibility for populations historically excluded from or underserved by higher education and the potential for success at nearby colleges. A single broad access public college on Chicago’s Southside—Kennedy-King College, where less than a quarter of students graduate within three years—is most accessible to a quarter of high poverty, high proportion POC census tracts in Chicago. Put differently, higher education is another axis along which spatial processes contribute to the systemic accrual of lower quality opportunities near or in low-income communities and communities of color.

When an institution serves a primarily local population of students, its student outcomes cannot be divorced from the systemic spatial injustices experienced by these local communities. Galster and Sharkey’s (2017) spatial opportunity structure framework theorizes that individuals are shaped by their built environment, where spatial confinement directly alters the potential payoff of a particular opportunity and indirectly modifies their accumulation of skills and
capacities over time. In the case of postsecondary accessibility, the underinvestment in low-income and high proportion POC neighborhoods along other axes—such as K-12 education (Weathers & Sosina, 2022) and public services access (Trounstine, 2018)—contributes to individuals’ educational backgrounds prior to enrollment, their experiences when enrolled, and potentially the wages they can demand after departing higher education. Community-level underinvestment may also affect resources at the colleges themselves, with public colleges in these neighborhoods receiving fewer resources than similar colleges in wealthier communities. This form of underinvestment could further constrain institutional capacity to retain and graduate students.

**Finding #2: For-profit colleges are accessible to low poverty and predominantly White census tracts, whether measured by proximity or mobility**

Whereas less selective public colleges are located in neighborhoods that are lower income and more racially diverse as compared to the rest of the study area, the same is not true of for-profit colleges in Chicago (there are no for-profit colleges in the Lansing sample). For-profit college neighborhoods are the highest income, have the lowest poverty rates, and have the highest proportion of White residents (RQ1). Over 60% of residents in the average tract surrounding a for-profit college identify as White (as compared to 53% in the next-lowest subgroup, nonprofit colleges). The difference in poverty rates is 2pp between for-profit college tracts and nonprofit college tracts and 8pp between for-profit versus public college tracts.

When I accounted for travel time and transit reliance (RQ2), I found that a for-profit college is the most accessible type of institution for 30% of low poverty and 34% of high proportion White tracts, as compared to 6% of high poverty and high proportion POC tracts. In other words, for-profit colleges are more likely to be accessible to affluent White tracts than to high-poverty POC tracts. That said, for-profit colleges’ student demographics do not align with
the demographics of the colleges’ neighborhoods: For-profit colleges enroll a lower percentage of White students than either nonprofit or public colleges (24%, versus 32% and 34% respectively; see Table 3.8), despite being in neighborhoods where the average census tract is 64% White (Table 5.3). This incongruity of demographics is evident in K-12 school choice settings: Urban New Jersey charter schools in White neighborhoods still predominantly enroll students of color (Gulosino & d’Entremont, 2011).

Although I hypothesized that differences in neighborhood demographics may arise based on a college’s sector, I did not hypothesize about the composition of these differences because the existing literature is inconsistent. Fisher’s (2012) findings accord with my own: For-profit colleges in Washington, DC locate nearer to tracts with more Asian and White residents. In contrast, the Student Borrower Protection Center’s (2021) report on for-profit colleges’ neighborhood demographics finds that for-profit colleges in Chicago are disproportionately located in high proportion Black and Latinx zip codes. Not only is this finding incongruent with my own, but the magnitude of the differences are substantial: The study’s authors find that, among Chicago zip codes in the top decile for the percentage of Black or Latinx residents, 41% and 53% have at least one for-profit college. When I replicate these figures using my tract-level data for Chicago, I find that none of the census tracts in the top decile for the percentage of Black, Latinx or White residents have a for-profit college.

Why might these findings differ so drastically? A likely explanation is that two differences between research designs render the findings incomparable. First, I include only Title IV eligible, degree granting institutions, whereas the Student Borrower Protection Center’s (2021) study includes any for-profit college that participates in Title IV or that is eligible to receive GI bill benefits from the Department of Veterans Affairs. The exclusion criteria I employ
risk being academic in nature—reasonable in the context of observing how access varies to a specific set of institutions but unnecessarily restrictive in any consideration that seeks to incorporate the full range of higher education opportunities marketed to place-bound individuals. The demographic differences that I observe in for-profit colleges’ neighborhoods could reflect locational decisions of a specific type of for-profit college (e.g., the subset of degree-granting Title IV eligible for-profit colleges), rather than the sector overall.

The second difference relates to the identification of college neighborhoods. Whereas the Student Borrower Protection Center (2021) study aggregates census tract demographics to the zip code level, I identify college neighborhoods using an empirical approach that is informed by the literature on individuals’ perceptions of neighborhood boundaries. Both zip codes and census tracts are governmental boundaries that are abstracted from residents’ qualitative descriptions of where their neighborhoods start and end. For instance, in her study of a gentrifying Philadelphia neighborhood, Hwang (2016) finds that White respondents were more likely than the neighborhood’s residents of color to exclude from their neighborhood definition areas of lower socio-economic status or higher crime. One possibility is that the White, higher-income residents in the for-profit college neighborhoods I construct do not consider the area around the for-profit college as within their neighborhood’s boundary. Both quantitative measures are likely imperfect, however measurement error becomes more pronounced when aggregating census tracts into zip codes since census tracts are not wholly contained within zip codes (Grubesic, 2008). In contrast, I test my neighborhood definition against alternative definitions and find the results are generally robust to my preferred approach.

Although not a perfect corollary, K-12 studies of charter school locations further contextualize these results. Many charter schools appear to “identify locational opportunities that
provide access to students with preferred socioeconomic and demographic characteristics to enhance the schools’ market position” (Gulosino & Lubienski, 2011, p. 11). In Chicago and Ohio, their locations avoid the highest-poverty neighborhoods (LaFleur, 2016; Saultz & Yaluma, 2017). In Michigan, the schools locate in higher-income areas (Koller & Welsch, 2017). In DC, for-profit charter schools serve a student population that is less disadvantaged than the population served by the public schools (Lacireno-Paquet et al., 2002). Burdick-Will (2017) hypothesizes that, for charter schools that cannot set admission criteria, “selective location may be their primary way of influencing the characteristics of their student body” (p. 60-61). The same may be true of less selective for-profit colleges entering new local markets. If locational decisions are deliberate, it would suggest that for-profit colleges behave competitively in their local markets for higher education—a point I return to later in this chapter.

Finding #3: Community colleges’ district boundaries create sharp spatial differences in cumulative accessibility to broad access public colleges

In my conceptual framework, I posited that cumulative accessibility to broad access public colleges would be highest in census tracts with higher incomes, lower poverty rates and a higher percentage of White residents. This pattern was apparent in Hillman’s (2016) evaluation of cross-region access to higher education; a 1% increase in the number of White or Asian residents in a commuting zone is associated with a larger increase in the estimated number of colleges in that same region than a 1% increase in the percentage of Black, Latinx, or American Indian residents. Krause (2017) found that, in four of the six metropolitan areas he studies, areas with high accessibility to public colleges were also higher income. In my study, histograms and maps of tract-level accessibility values revealed a bimodal distribution of accessibility at the edges of community college districts. In both cases, comparing in- versus out-of-district
demographics resulted in findings that were incongruent with the existing literature: in-district tracts were lower income, higher poverty, and more racially diverse than out-of-district tracts.

The boundaries of these districts became embedded in the distribution of accessibility through the desirability measure. Residents of in-district tracts pay less when the college in question is in-district, which increases the desirability value; the more colleges for which a tract is considered in-district, the higher that tract’s overall accessibility to broad access colleges. In Lansing, tracts that are in-district to LCC have higher accessibility; in Chicago, tracts within the City Colleges of Chicago (CCC) district have higher accessibility. This process amounts to a sub-division of both study areas into two geographic regions—tracts near/in the population center of the study area and outlying census tracts further from the areas with the highest population density. Observing more racial diversity in the higher-density in-district tracts is not surprising. Densely populated areas remain more racially diverse and have higher poverty rates than the less population-dense suburbs (Parker et al., 2018), even as suburban demographics diversify (Kneebone, 2020). That said, these cross-region analyses, where I compare in-district tracts to out-of-district tracts, mask within-region variation in accessibility—a concrete example of the Modifiable Areal Unit Problem’s scale effect (see Chapter 3 for more on MAUP).

This incongruous finding regarding the demographics of in- versus out-of-district tracts still merits consideration, since the geographic boundaries of community college districts are, in Soja’s (2010) language, an exogenous decision that could beget spatial injustices. When geographical boundaries are drawn in a way that systematically benefits a single population, the boundaries are said to be gerrymandered (Tapp, 2019). This concept is most commonly applied to congressional districts, however Baker et al. (2021) find preliminary evidence of gerrymandering in Texas community college districts. Notably, some districts have “larger
shares of White residents and smaller shares of either Black or Latinx residents when comparing districts to local environments” (p. 26). In contrast, a Center for American Progress (CAP) policy report on community college demographics in Michigan finds that White students are underrepresented and Black and Latinx students are overrepresented at many of the state’s community colleges, when compared to the racial demographics of the district (Custer, 2020).

Because I do not explicitly seek to measure gerrymandering using the methodological tools employed by Baker et al. (2021), I cannot conclusively identify it as a mechanism that underlies my findings. That said, how these boundaries interact with college enrollment patterns is likely a result of both exogenous and endogenous factors. First, community college districts do result in differential prices charged to individuals on either side of the boundary, and students outside community college district boundaries enroll in higher education at lower rates as a result (Acton, 2021; Denning, 2017; McFarlin et al., 2017). In this way, the boundaries are exogenous decisions that influence residents’ spatial access to opportunity. Second, individual geographies of privilege could motivate the observed spatial patterns in at least two ways: The residential decision could be a Tiebout-style choice (Richards, 2014) in which families with financial resources practice school choice by purchasing a potentially more expensive home in their desired district. Alternatively, families without an in-district option may not be as price sensitive as individuals within the district and therefore do not have a price-based incentive to relocate.

Neither Custer (2020) nor Baker et al. (2021) examine Chicago’s districts, though this is an area worthy of investigation. With one exception, district boundaries in Illinois were established by the 1970s (Heartland Community College, n.d.; Scott, 2008). The long-term stability of the boundaries likely means that any demographic differences across Chicago-area

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60 In the K-12 literature, there is mixed evidence that school districts are gerrymandered (Richards & Stroub, 2015; Saporito & Van Riper, 2016; see also Baker et al., 2021 for a detailed discussion of differences in methodology).
community college districts are not the result of modern attempts to exclude/include certain populations within a district, but instead an indirect consequence of historical spatial processes that contributed to residential segregation and the placement of college campuses. That said, there are measurable differences between average outcomes in the CCC system and community colleges in surrounding districts: Retention rates for full-time students are more than 10pp lower in the CCC system than across non-CCC community colleges in the area, and three-year graduation rates are 18pp lower. If the difference in price between in- versus out-of-district tuition results in Chicago’s low-income residents or residents of color opting for a college with lower outcomes when a higher-performing college is down the road, then these boundaries could be considered spatial processes that constrain historically underserved students’ capacity to select a similarly accessible but higher-performing college.

Finding #4: The accessibility benefits of living within the City of Chicago are not enough to counter lower levels of accessibility in low-income and high proportion POC tracts

The cross-district differences I observe in the cumulative accessibility to broad access public colleges mask within-district variation in this same accessibility measure for the Chicago study area. Previous studies provide compelling evidence that higher income and high proportion White neighborhoods benefit from within-region variation in accessibility to opportunities such as parks (Barbosa et al., 2007; Chapman et al., 2021), libraries (Park, 2012), and banks (Hegerty, 2016). The Chicago findings are in accord with these patterns, though only when the relationship between cumulative accessibility and demographics is considered separately for in- versus out-of-district tracts. In the City of Chicago (i.e. in-district), high accessibility tracts are higher income and less racially diverse than low accessibility tracts in the same region. Outside the city boundary, high accessibility tracts are once again higher income and less racially diverse than low accessibility tracts in the same region. In both regression analyses, higher poverty rates and a
higher percentage of residents who identify as Black are associated with lower accessibility, though the statistical significance on the coefficient for percentage of Black residents would likely disappear were the standard errors adjusted to accommodate remaining heteroskedasticity.

Comparing these findings to the existing geography of postsecondary opportunity literature is complicated by differences in type of college considered and the operationalization of accessibility. Fisher (2012) calculates average distance to each focal college in her sample (community colleges and for-profit colleges), Dache-Gerbino (2018) examines a contour measure of the number of colleges, regardless of sector, radiating outward from Rochester’s urban core. Krause (2017) combines a measure of proximity to each college with a by-tract median commute time threshold and examines the results across all colleges and by college sector. I use a gravity-based mode-adjusted accessibility index to calculate each tract’s cumulative accessibility to broad access public colleges.

In each case, however, there is partial alignment between their story of accessibility and what I observe in Chicago: Dache-Gerbino (2018) observes that the college closest to the urban college desert (where low-income Black and Latinx residents live) is a community college branch campus; I find that, for more than 50% of high-poverty or high proportion POC tracts, the nearest college is a community college. Fisher (2012) finds that incorporating community college branch campuses shrinks the distance to the nearest community college campus for tracts with high numbers of Black and Latinx residents; I find that community college branch campus neighborhoods are lower-income and higher proportion POC than main campus neighborhoods—which are themselves lower-income and higher proportion POC than for-profit, nonprofit, and non-college neighborhoods. Krause (2017) finds that, in four of the six regions he evaluates, low-income tracts have lower accessibility to public colleges than high-income tracts.
In alignment with Krause’s (2017) finding, I observe a negative relationship between poverty and cumulative accessibility to broad access colleges in both my in- and out-of-district regression analyses for Chicago.

Perhaps more interesting is the alignment of my cumulative accessibility findings and the findings in Chicago-based evaluations of accessibility to non-educational opportunities. Liu and co-authors evaluated accessibility to jobs (Liu & Kwan, 2020), urban green space (Liu et al., 2021a), healthcare (Liu et al., 2021b), and Covid-19 vaccination sites (Liu et al., 2022)—all for the Chicago area. All four studies employed a gravity-based measure of accessibility, and all four studies examined the spatial patterns of accessibility with respect to race/ethnicity and income. Although the ACS sample years differ—these studies almost exclusively rely on 2018 one-year estimates, and I rely on 2015-2019 five-year estimates—the spatial distribution of tract-level demographics aligns with what I observe in my study. And, indeed, in all four cases—including two which employ OLS regression analyses (Liu et al., 2021a, 2021b)—the relationships between accessibility and demographics parallel what I observe for broad access public colleges: Low-income and majority Black or Latinx tracts have lower accessibility to the four types of opportunities the scholars evaluate. That said, the relative accessibility for tracts within versus outside the City of Chicago differs across opportunities. Overall job accessibility is higher inside the city than outside of it (Liu & Kwan, 2020), but healthcare and Covid-19 vaccination site accessibility are lower inside the city (Liu et al., 2021b; Liu et al., 2022). Unequal geographic access to broad access public colleges in Chicago is part of a replicable regional narrative of unequal access to opportunity by race/ethnicity and income.

The findings in Lansing diverge from the patterns observed in Chicago and in the accessibility literature. I found that the highest accessibility tracts in Lansing were the lowest
income, had the highest poverty rates, and were the most racially diverse tracts in the entire study area. In contrast, high accessibility tracts outside the LCC boundary were the highest income and had the highest percentage of White residents in the region. Evaluating these relationships in a regression framework revealed few statistically significant relationships between demographics and accessibility—perhaps due to small sample sizes and a tight distribution in the dependent variable. In the in-district analysis, a one standard deviation increase in either the percentage of Asian residents or the percentage of AI/AN/PI/MR/Other residents would amount to a less than one-fifth standard deviation decrease or increase, respectively, in accessibility. Put differently, in- and out-of-district tracts differ from each other demographically, but within-region variation in demographics are either not associated with changes in accessibility or only modestly so.

Interestingly, the direction of the relationships between accessibility and the percentage of Asian or AI/AN/PI/MR/Other residents are opposing in the Lansing and Chicago analyses. In the Lansing ID and OOD analyses, the relationships between accessibility and the percentage of Asian residents are negative, whereas in the Chicago ID and OOD analyses, the relationships are positive. Vice versa for the percentage of AI/AN/PI/MR/Other residents: The relationship is positive in the Lansing ID analyses, but negative in the Chicago OOD analyses. Returning to the ESDA maps presented in Chapter 3 provides a partial answer. In the Lansing ID analyses, census tracts with the highest percentage of Asian residents are on the western edge of the urban core that corresponds to East Lansing (Figure 3.2, Panel K). This is also where the MSU campus is located, which means these tracts are most accessible to the broad access college in the region with the highest tuition and fees and on the other side of town from the western cluster of LCC campuses (Figure 3.1). Taken together, the consequence is a negative relationship between accessibility and the percentage of residents in a tract who identify as Asian. (In the Lansing
OOD sub-region, a maximum of 2% of a tract identifies as Asian, rendering this relationship statistically significant but relevant to a small number of residents.) In Chicago, there are several clusters of tracts with high percentages of Asian residents that overlap with high accessibility tracts (compare Figure 3.4, Panel K to Figure 8.10), likely influencing the positive relationship. Similar spatial patterns emerge when examining campus locations and overall accessibility to the percentage of tract residents that identify as AI/AN/PI/MR/Other in both study areas.

The divergent results in the two study areas could be due to, among other differences beyond those considered in this study, true underlying regional differences in the built environment (including campus locations), differences in the spatial distribution of populations within the study area, or some combination of both. The Lansing study area includes rural tracts in outlying counties, whereas the Chicago study area is constrained to tracts that satisfy the conditions required for urbanized area eligibility. That said, the consequences of these patterns are not inherently better or worse in either setting. In Lansing, the few available options leaves historically underserved students in a near-desert of broad access public colleges whereas in Chicago, the seeming abundance of opportunity could be construed as a false choice when contextualized by the low outcomes observed at these same institutions. Perhaps the most notable lesson in these differences is that extrapolation of these findings to other study areas must be done carefully to avoid misattributing the underlying cause.

Finding #5: Accessibility is lower in areas with more potential educational demand

Finally, I sought to understand whether there is overlap between tracts with low accessibility and tracts with low educational attainment/high potential educational demand (RQ4). Based on Hillman’s (2016) findings that areas with more four-year colleges have higher levels of educational attainment and Dache-Gerbino’s (2018) finding that college oases have a
higher percentage of residents with at least a bachelor’s degree, I hypothesized that areas with lower educational attainment will experience lower accessibility to broad access public colleges. My findings partially support this hypothesis. In Lansing, tracts with the lowest overall accessibility had the highest percentage of residents with less than an associate degree (e.g., lower educational attainment). That said, these tracts were predominantly White and I initially hypothesized that this relationship would occur in low-income communities and communities of color. Put differently, low potential educational demand in Lansing is not coupled with the demographic markers that signify low accessibility in many studies of geographic access in urban areas. In Chicago, although in-district tracts collectively averaged a higher percentage of residents with less than an associate degree, educational attainment was still lowest in low accessibility ID or OOD tracts. The results of all four spatial regressions confirmed that an increase in the percentage of residents with less than an associate degree is associated with a decrease in accessibility.

There are both individual and structural contributors to any observed relationship between accessibility and educational attainment. As Hillman (2016) acknowledges after finding similar results across regions, “[p]eople move to areas that have colleges, but areas that have colleges can also produce higher educational attainment levels” (p. 1009). If the convenience effect—an individual-level mechanism—motivates enrollment decisions for place-bound students, then lower accessibility may either decrease the likelihood of college enrollment at the outset or increase enrollment at an institution with low graduation rates. If the latter, then low community-level educational attainment can be thought of as a down-stream consequence of constrained accessibility to postsecondary education (Galster & Sharkey, 2017). After enough time, a community’s spatial isolation from any college or its limited access to a lower-quality
college could manifest as a negative relationship between potential educational demand and accessibility, as observed here. Russell and Andrews (2022) find that counties chosen for university campus locations have higher bachelor’s degree attainment rates than the “losing” counties, even decades after the decisions were made—suggestive of a direct and positive relationship between the presence of colleges and college attainment.

The Need for Historical Context to Situate Place-Based Findings

Chicago and Lansing are indisputably different regions: One is a metropolitan area with under 500,000 residents, the other is an urbanized area with more than 15 times as many residents in a similar land area. Lansing is 78% White, whereas in Chicago more than 50% of residents identify as AI/AN/PI/MR/Other. These geographic and demographic differences are neither a surprise nor an accident. I sought a marginal education desert (Lansing) to test the hypothesis that regional access to colleges is a sufficient proxy for local access; I chose a large urban area rich in postsecondary educational opportunities and with robust transit service (Chicago) to observe whether local accessibility varies even when opportunities abound. And yet, even acknowledging these differences, my quantitative research design leaves no space for surfacing the historical factors that contribute to the differing accessibility patterns that I observe. In this section, I seek to remedy this shortcoming by examining high-level shifts in demographics alongside the (in)stability of campus locations.

I focus on two factors in the historical explorations that follow: the geographic placement of less selective college campuses, and changes in the demographic composition of each study area. First, there are at least three avenues through which colleges become embedded in a neighborhood: (1) the college’s location precedes modern-day demographics; (2) neighborhood demographics precede and possibly motivate the college’s location (Briscoe & De Oliver, 2006);
or (3) a college changes location in response to shifts in demographics (Dache-Gerbino, 2017). Second, the demographic composition of urban areas has shifted several times in the preceding century. Nationwide, the suburban fringe is more racially and economically diverse than it was prior to the 1970s (Frey, 2011), even as individual suburban neighborhoods have become more segregated by race and income (Kneebone, 2020). Population totals in some large cities have rebounded since White flight in the 1950s and 1960s (Harshberger & Perry, 2019). The return of White residents to urban areas (Baum-Snow & Hartley, 2020; Frey, 2015) has displaced POC populations from a small number of urban neighborhoods, though the trend has occurred unevenly both across cities and within cities (Richardson et al., 2020).

**Lansing: Shifting Demographics Contribute to Increased Accessibility for Black Residents**

The population center of the Lansing study area is two neighboring cities, Lansing and East Lansing. Here, I focus on Lansing and two colleges’ campuses, the main campus for Lansing Community College (LCC) and Great Lakes Christian College’s (GLCC) former downtown site. The Black population in Lansing grew sizably in the 1940s, though redlining and racial covenants segregated Black residents in certain neighborhoods (Aerni-Flessner & Marks-Wilts, 2021). Most of these residents lived in a redlined region south of downtown and north of the Grand River. Shortly after the 1940s increase in the size of the Black population, two of the region’s three present-day less selective colleges opened Lansing campuses: LCC’s main campus opened in downtown Lansing in 1957, and GLCC relocated its rural campus to a small building just north of downtown Lansing in 1958 (Harrison, 2021). GLCC’s campus was outside any formally redlined region, whereas LCC’s original building bordered a redlined neighborhood (the campus now extends into this historically redlined area).
By the time redlining was formally outlawed through the Fair Housing Act of 1968, construction of Interstate 496 was nearly complete (Historical Society of Greater Lansing, n.d.). This “urban renewal” project cut directly through the heavily populated Black neighborhood south of downtown. More than six hundred homes in the neighborhood were demolished (Historical Society of Greater Lansing, n.d.), and remaining residents who lived south of the interstate were marooned by the interstate to the north and the river to the south and east. The interstate displaced Lansing’s Black residents at a time when the total number of Black residents was on the rise, the result of which was over-crowding and housing shortages in historically Black neighborhoods throughout the 1960s and 1970s (Isaacs-Thomas, 2019). Since the 1970s, the Black, Latinx, and Asian populations in Lansing have continued to increase (author’s calculations of U.S. Census data), and gentrification in the region has been limited. Richardson et al. (2020) identified only two gentrified tracts in the urban core, measured based on changes in median income, college attainment, and median home values between 2012 and 2017: one in the southeastern portion of East Lansing (not graded by HOLC) and one across the river from downtown Lansing (a historically redlined neighborhood).

Locations of both GLCC’s original downtown campus and LCC’s main campus predate urban renewal efforts and the accompanying spatial shifts in the region’s racial demographics.61 Whereas LCC continues to operate its main campus—opting to open branch campuses in other neighborhoods—GLCC relocated in 1970 to the less densely populated Delta Township (which is also Whiter and has a higher median household income than the study area overall). Further exploration would be necessary to deduce the motivations for this relocation, however one possibility is that the city’s shifting demographics were a partial catalyst and the institution’s

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61 The neighborhood surrounding MSU’s campus—which also predates these demographic shifts—has become Whiter and higher income since the 1980s (Foote, 2017).
small size made the move feasible (163 undergraduate students in 2019). Regardless of whether demographics were the catalyst, the sequencing of events parallels what Dache-Gerbino (2017) documents in Rochester: A neighborhood-level demographic shift occurred just prior to the 1968 relocation of the area’s only community college (Dache-Gerbino, 2017).

In present day, residents of LCC’s main campus neighborhood are disproportionately residents of color when compared to the study area: On average, nearly 50% of residents in the neighborhood’s census tracts identify as Black or Latinx, as compared to 22% of residents across the region. This is perhaps due in part to its original location on the boundary of a red-lined neighborhood. Historical artifacts could contextualize the college’s decision to locate on this boundary. One possibility is that the proximity to the state capitol in combination with lower property values made the decision pragmatic if not racialized. Regardless of the original motivations, the stability of LCC’s main campus location alongside the continued racial diversification of downtown Lansing yield increased accessibility for the lower-income and POC populations residing in the urban core.

Chicago: The Campuses of “Urban Renewal”

The demographic trends of early 20th century Chicago were dominated by the arrival of immigrants from Europe and Black families departing the American south during the Great Migration (Sharkey-O’Malley, 2016). After World War II, the city experienced the White flight that is emblematic of the era—the city declined from 86% to 50% White between 1950 and 1980, amounting to a decrease of nearly 2 million White residents (Chicago Commission on Human Resources, 1961; Great Cities Institute, 2019). At the same time, urban renewal projects in the city displaced an estimated 23,000 families, most of whom were households of color (Digital Scholarship Lab, n.d.). A single highway project—the construction of Eisenhower
Expressway—displaced an estimated 13,000 residents in Chicago’s Near West Side (Loerzel, n.d.). Since the 1980s, the city has experienced what Saunders (2019) calls a reverse Great Migration: The number of Black residents is declining while the number of White and Latinx residents is increasing. The city has also experienced income gentrification since 2012 (Richardson et al., 2020) and rising housing costs risk displacing residents in urban neighborhoods where low income and predominantly Black populations have long resided (Chapple et al., 2021).

I focus on the locational histories of two campuses in the CCC system: Malcolm X College and Kennedy-King College. Both colleges’ first dedicated campuses were razed lands in historically redlined neighborhoods, acquired as part of the city’s urban renewal projects. In practice, the nature of these purchases meant that the benefits of expanded educational opportunities came with costs incurred by the neighborhoods’ displaced families. Malcolm X College (formerly Crane Junior College and Herzl Junior College) first opened in 1911 in Chicago’s Near West Side (Malcolm X College, n.d.). At the time, the neighborhood was lower income and a mix of Black, Mexican, Italian, Greek, and Jewish residents (Sharkey-O’Malley, 2016). Kennedy-King College (formerly Woodrow Wilson Junior College) opened in 1935 as part of the city’s early expansion of junior colleges (Krebs, 1999); at the time, its southside neighborhood was majority White but adjacent to some of the city’s earliest predominantly Black neighborhoods (author’s analysis of data provided by Paral, n.d.).

Malcolm X College went through a closure and several re-locations between its founding and the college’s purchase of its final campus site in 1966. I focus here on the move to its present-day campus just half a mile from its original home in Crane High School. In 1966, after several failed attempts, the college procured “approximately twenty acres of urban renewal
property” (Smith, 1980, p. 203). This urban renewal land, like the original location at Crane HS, was just north of the recently completed Eisenhower Expressway and thus embedded in a community that had experienced significant displacement of its residents and businesses (Loerzel, n.d.). The campus was an active center for the Black Panther party in the late 1960s and early 1970s and, in 1969, students in what was then a predominantly Black, low-income neighborhood rallied for the college to change its name to Malcolm X College (Perkins, 2001).

When the newly developed City Colleges of Chicago system bought land in the late 1960s to build a permanent campus for Kennedy-King College (then Wilson Junior College), leaders chose another urban renewal site. This decision meant the cost of acquisition “was covered by federal funding and was, therefore, only nominal for the college” (Smith, 1980, p. 203). In 2007, after nearly four decades at its original site, the college moved to a new facility one mile away, in an area targeted for transit-oriented development (Camiros, Ltd., 2008). The old site sat vacant for two years, during which vandals broke in, glass was left shattered in open spaces, and the college was forced to hire security guards and dogs to prevent trespassing (Lourgos, 2009). Put differently, the local neighborhood was incurring the costs of the college’s decision to leave the former campus vacant but not demolished. Demolition occurred in 2009 and, though the college originally alluded to readying the site for retail development (Bey, 2010), it remains vacant as of 2022.

In keeping with the city-wide decline in the size of the Black population over recent decades, both colleges’ neighborhoods have experienced decreases in the number of Black residents since the 1980s (Great Cities Institute, 2019). Malcolm X College’s home tract remains high poverty (44% overall, 55% poverty rate among residents of color) and high proportion POC (75%) but is not in the top quartile for either. Even though the college was predominantly Black
when the land for its current campus was purchased, now the percentage of Black and Latinx students are almost equivalent (38% Black, 44% Latinx). Kennedy-King College’s two most recent campuses are in clusters of census tracts that I categorize as high proportion POC, high poverty—it’s current home tract is more than 97% Black and more than three-quarters of the college’s students identify as Black (79%). Although these figures suggest continued alignment between the college’s neighborhood demographics and the students enrolled, both the college and its Englewood neighborhood are losing residents. Enrollment at Kennedy-King College was 60% lower in 2018-19 as compared to 2009-10, and the area’s total population declined more than 20% between 2010 and 2020 (Ramos, 2021). These rapid declines in population will create new revenue pressures for both the college and the local community and will reinforce spatial injustices that lead to lower resources in lower income communities and communities of color.

**Contributions of the Study and Future Research Directions**

In this section, I call attention to the study’s methodological and theoretical contributions and identify avenues for future research. Methodological contributions include the adaptation of an urban planning accessibility measure, the use of spatial statistical methods, and the development of a practitioner toolkit. As it relates to theory building, the findings of the study suggest a need for more deliberate theorizing on geography as one component of a multidimensional concept of access, the expansion of theoretical work on local higher education market competition, and the continued development of frameworks that support investigations of spatial processes resulting from the historical presence of community college districts.

**Methodological Contributions**

This study has three central methodological contributions. First, I introduce into higher education research the gravity-based accessibility index, which has been in use by urban and
transit planning scholars since the 1940s (Geurs & van Wee, 2004). Measuring accessibility using more familiar measures—such as proximity (e.g., Euclidean or network distance) or mobility (e.g., driving or transit time)—is valuable insofar as the results are easily understood. However, when the goal is evaluating differences in cumulative accessibility—what is a census tract’s overall accessibility to broad access public colleges?—these measures cannot capture three component parts of geographic access: distance decay, desirability, and mode-based mobility. Aggregate travel patterns demonstrate that the relationship between distance/time to an opportunity and willingness to travel is both negative and non-linear (Handy & Niemeier, 1997). The average individual becomes less willing to travel as the distance or travel time to the opportunity increases. With the gravity-based accessibility index, I can directly account for this non-linear relationship using a distance decay factor that decreases the relative accessibility of further away opportunities.

The incorporation of the desirability measure serves as a coarse means of differentiating between opportunities, with more desirable opportunities contributing more to a tract’s cumulative accessibility. Influential though it is, geographic access is not the only factor that shapes a place-bound student’s choice of where to enroll in college. The desirability measure is an avenue for incorporating into a geographic measure these non-geographic factors. I include program offerings and tuition and fees in the desirability measure I construct; however, this is merely a first attempt. Non-education accessibility indices typically attempt to capture a quantitative count of a type of opportunity within each areal unit of the study area. For instance, how many jobs exist in each areal unit (Shen, 1998)? This approach assumes that most areal units have multiple opportunities however, in my study, there are few opportunities relative to the number of areal units. Therefore, I must instead rely on opportunity-level rather than areal
unit-level differences in offerings to construct the desirability measure. This is inherently more subjective and, though what I have done represents a robust first attempt, subsequent work in this area could identify more comprehensive avenues for capturing relative desirability.

By adjusting the value of the index based on the estimated percentage of a tract’s population without access to a vehicle, I acknowledge that public transit service is vastly inferior to driving with respect to the time commitment required and this would result in a different level of accessibility for transit- and car-reliant individuals in the same tract. Recall that the median travel time to a BAC in most census tracts in both Lansing and Chicago is more than two hours. Transit-reliant students in most neighborhoods must either endure the long commute, cobble together funds to purchase and maintain a personal vehicle or forego commuting altogether. The price paid is time, money or deferred educational opportunity. Purchasing a car may solve the mobility problem in the short term, but it places a steep financial burden on transit-reliant populations, many of whom are low income and therefore already financially constrained. These costs could lead to emotional stress that in turn negatively affects academic performance.

Second, I join González Canché (2018a) in his assertion that inherently spatial questions require spatial methods. In my exploratory spatial data analyses, I observe high levels of spatial autocorrelation between census tract demographics in both study areas. In the presence of spatial autocorrelation, the demographics of a census tract influence and are influenced by the demographics of neighboring census tracts. The consequence of unaddressed spatial autocorrelation when employing an OLS regression is biased coefficients, standard errors, or both. By employing a spatial regression model, I was able to incorporate this spatial correlation into the regression analyses and thus minimize bias in my estimates.
Third, in developing the practitioner toolkit, I provide an actionable adaptation of academic research into a practitioner setting. Throughout this study, I make the case that accessibility matters because it is a likely contributor to whether place-bound individuals enroll and, once enrolled, whether they persist. If accessibility influences enrollment and persistence in this way, then identifying tract-level variation in accessibility using publicly available data (as I do in Chapters 4 and 5) identifies the existence of a problem but leaves unexplored how to quantify that problem for individual colleges. Improvements and adaptations to the toolkit can ensure that its output accommodates an institution’s specific needs; my hope is that these changes are feasible for an institutional researcher with access to student-level data and a modest level of experience coding in Stata.

**Theoretical Contributions**

As Soja (2010) argues, spatial injustices result from social processes that manifest in the built environment. Policies and practices are not race- or class-neutral, and the consequences of these policies accumulate into spatial injustices that further strain historically marginalized populations. The cross-sectional research design limits my ability to link descriptive findings to historical spatial processes, and the purpose of the study was not to formally test any component of the conceptual frameworks that I draw upon. Even so, I identify three theoretical implications that draw from the findings highlighted above; if incorporated into future work, these implications would serve as an avenue for more holistically identifying the causes and consequences of spatial differences in college access.

First, when I measure accessibility as only geographic access (RQ2), I find that public colleges are the most accessible type of institution for high poverty and high proportion POC tracts, but outcomes at these same colleges are the lowest observed. This finding points to the
need for conceptualizing spatial opportunity as a measure of access that includes, but is not limited to, geography. As a starting point, I draw on Dache-Gerbino’s (2018) typology of college oases/deserts and Penchansky and Thomas’ (1981) delineation of five domains that they argue combine to produce a composite measure of access. First, in her Critical Geographic College Access framework, Dache-Gerbino (2018) examines “how a county and city are divided across racialized spaces and the spatial relationships these areas have to where colleges and universities are located” (p. 99). In her analysis, she identifies several college oases in Rochester’s suburban areas, which are White and higher income, and a college desert in the urban core, which is Black/Latinx and lower income. The author points to the correlation between demographics and college opportunity categorization as evidence of the need to develop a typology of within-region geographic access that can guide future studies in this domain.

I agree and argue that such a typology must consider how geographic access intersects with other access domains. Here, I turn to Penchansky and Thomas’ (1981) framework for creating a “taxonomic definition of access, one that disaggregates the broad and ambiguous concept into a set of dimensions that can be given specific definitions” (p. 128). The authors identify five dimensions as it relates to healthcare access: accessibility (where is the service relative to an individual), availability (is there enough of the service to go around), acceptability (are the characteristics of the service in alignment with an individual’s preferences), affordability (can individuals afford it), and adequacy (are individuals able to easily use the service). To this list, Saurman (2016) adds awareness (is information about the service readily available to target customers). Although specific adaptations would be required to translate the authors’ framework into higher education, the parallels are immediately obvious: Accessibility captures the geographic access on which I focus, whereas acceptability could encompass quality indicators as
well as academic or non-academic goodness of fit. Adequacy could capture class times, especially relevant for working students, and awareness captures efforts to provide students with information about college choices and financial aid during the college choice process.

I propose integrating their access framework with Dache-Gerbino’s (2018) typology of college deserts/oases within local communities. Returning to my findings, Chicago appears to be a college oasis—there are 64 less selective college campuses in the study area and the median census tract is within 3 miles of the nearest less selective college. Yet the low outcomes that I observe suggests that the oasis classification is insufficient; high poverty and high proportion POC tracts that have high access to colleges with low outcomes may be better characterized as low-performing college oases. Integrating multiple domains of access into the desert/oasis typology can better capture the diversity of college landscapes that exist across the U.S. and the racialized geographies that contribute to their construction and maintenance. As evidenced in Chicago, these landscapes extend beyond the urban/suburban divide that Dache-Gerbino (2018) observes. Place-bound students likely grapple with the intersection of and trade-offs between accessibility, acceptability, and affordability in their own college choices; so too can theories of geographic access to postsecondary education.

Second, I find that for-profit colleges are maximally accessible to higher income and predominantly White census tracts in Chicago, but I do little in my conceptual framework to unpack why for-profit colleges might prefer a neighborhood with this demographic profile. The theoretical motivations for these decisions could be explored using market theory as the foundation. Empirical studies demonstrate that for-profit colleges are in competition with public colleges (Armona et al., 2017; Cellini, 2009; Cellini et al., 2016; Darolia, 2013; Deming et al., 2016; Goodman & Henriques, 2015), and that they enter and exit the market strategically.
(Armona et al., 2017; Cellini, 2009, 2010). In other words, for-profit colleges behave competitively, and locational decisions may therefore reflect a deliberate competitive strategy.

Yet, the for-profit colleges in my sample are not predominantly White or high income, so is the competitive strategy unsuccessful or more nuanced than a base desire to enroll higher income, White students? Burdick-Will (2017) finds that geographic enrollment patterns for K-12 students in Chicago differ depending on the characteristics of the origin neighborhood: Students who live in poorer neighborhoods travel to schools across the city whereas “students from safe and affluent neighborhoods attend many fewer schools, are less likely to make long distance trips, and are more likely to attend school with a large proportion of their neighbors” (p. 37). Put differently, affluent students remain local, but low-income students travel. To the for-profit college, a campus in an affluent neighborhood captures both high-income students who will not travel and low-income ones who will. This pattern, alongside studies that demonstrate charter schools avoid high-poverty neighborhoods (Koller & Welsch, 2017; LaFleur, 2016; Saultz & Yaluma, 2017) and seek out less racially diverse neighborhoods (Gulosino & d’Entremont, 2011) makes plausible the hypothesis that for-profit colleges locate strategically, and that these decisions are motivated by race and income demographics.

This study cannot affirm that college locations are reflective of institutional leaders’ competitive strategies, in part because local higher education markets are undertheorized. Indeed, much of the formal theorizing on market competition focuses on selective colleges with excess demand (Hoxby, 1997, 2009; Rothschild & White, 1993, 1995; Winston, 1999). Theorizing on local higher education markets—especially as it relates to colleges’ locational decisions—is a worthy endeavor for at least three reasons: First, undergraduate enrollment across higher

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62 A related question, which I cannot answer in this study, is whether the affluent students in these neighborhoods view the for-profit college as a viable college choice.
education has declined for several years in a row, including by 4.7% in the past year (Moody, 2022); when enrollment declines, so too does revenue. When revenue declines, colleges may turn to competitive behaviors to recapture lost enrollment. Second, the demographic pattern that I observe in Chicago—and which Dache-Gerbino (2014) observes in Rochester—suggests that colleges’ locational strategies are racialized. However, without deliberate theorizing and subsequent empirical evaluations, I can only conjecture. Third, this theorizing paves the way for investigations into the short- and long-term consequences of competitive strategies on revenue, student demographics, and outcomes for place-bound students who rely on local colleges.

The third theoretical contribution relates to community college district boundaries. I found that community college districts create sharp changes in cumulative accessibility. I did not set out to focus on community college districts—they are referenced only indirectly in my conceptual framework—yet these boundaries influence the accessibility of a region’s community colleges: Students who are in-district benefit from close proximity and lower tuition. These boundaries reflect social processes in that they carry with them the historical policies that explain their existence and placement (Baker et al., 2021); they also influence social processes, since living on the border of a district can influence whether a student enrolls in college and whether they enroll at a two- or four-year college (Denning, 2017; McFarlin et al., 2017). In the case of Chicago, these boundaries could influence the community college in which a student enrolls.

Future theorizing on the geography of postsecondary education can more holistically explore the role that community college districts play in constraining or expanding geographic access for populations historically excluded from or underserved by higher education. Baker et al. (2021) begin this work by employing the student exchange framework in their evaluation of potential gerrymandering in Texas districts. In this framework, the emphasis is not on individual-
level endogenous decisions wherein students opt into certain school districts but exogenous
decisions in which “schools choose students through irregular boundaries that include certain
students at the expense of others” (Richards, 2014, p. 1124). The framework is a natural
bedfellow of Soja’s (2010) spatial justice framework since it centers an exogenous spatial
process (the drawing of district boundaries) to examine a spatial injustice (segregated districts).
That said, the student exchange framework remains focused on the present-day consequences of
the boundaries, thereby foregoing exploration of the historical processes that led to their creation.
A more explicit coupling of Soja’s (2010) framework and the student exchange framework could
uncover the original motivations for these boundaries, then link these motivations with the
consequences for populations with historically limited access to higher education.

Future Research Directions

The findings of this study and the preceding discussion reveal several valuable new
research directions, which I chronicle here. First, in retrospect, my capacity to link my research
findings to specific facets of the conceptual framework is limited by the study’s singular use of
quantitative methodologies. The existing research design, coupled with a historical evaluation of
each study area’s postsecondary landscape, would better enable scholars to reflect on the specific
spatial processes that contributed to the empirical patterns that I observe.

Second, by constructing a mode-adjusted measure of accessibility, I incorporate transit
reliance into my calculation of accessibility but necessarily obfuscate the unique patterns of
accessibility for transit-reliant households. The story of accessibility may look different if the
starting question was not “how does overall accessibility vary,” but instead “does transit reliance
constrain community-level access to less selective public colleges?” For example, as I find when
I consider transit travel times for transit-reliant households in both Lansing and Chicago, even in
high accessibility tracts, transit reliant households must travel over two hours to the median BAC in both study areas, but only 23 minutes by car in Lansing (Table 8.4) and 46 minutes by car in Chicago (Table 8.10). A complementary study could singularly investigate accessibility for transit reliant individuals and, in doing so, center the time costs incurred by place-bound students with no other means of arriving to and departing from campus.

Third, future studies could link the non-pecuniary and non-time-based consequences of transit reliance to students’ academic outcomes. Existing studies provide compelling evidence that transit reliant students experience social exclusion on campus resulting from the inflexibility of transit schedules (Kenyon, 2011) and that bus commuting is not only time consuming but requires commuters to ride dirty buses and encounter criminalizing messaging (Dache, 2022). A study of the psychological costs of transit reliance finds that stress is reduced after improvements to public transit are implemented (Wener et al., 2003), and more predictable commutes are correlated with lower stress in commuting workers (Gottholmseder et al., 2009). Put differently, riders may experience higher levels of stress when public transit service quality is poor. In each case, there is the potential for the experience of transit reliance to negatively affect other aspects of a rider’s life, yet the literature review I conducted did not surface studies that directly link academic outcomes with qualitative measures of the transit experience. Future studies could evaluate how transit reliance may negatively affect students’ day-to-day lives and, indirectly, their capacity to remain enrolled in college and earn a credential.

Lastly, rather than consider accessibility to all BACs in a region, future work could conduct a system-level evaluation of accessibility to in-district community college campuses for census tracts the community college’s district. This approach would be especially informative in Chicago, where every tract is in a community college district but not all community colleges
have multiple campuses. A system-level approach has the benefit of focusing narrowly on the region from which community colleges likely enroll most of their students and therefore the region for which variable accessibility matters most. There is also policy relevance to this line of inquiry, as it provides a direct service to community college districts interested in the contours of accessibility for their catchment area. Related work could estimate border tracts’ accessibility to both the home district and the neighboring district. These values could then be compared to determine the access implications of changes in district boundaries.

**Implications for Policy and Practice**

Dismantling spatial injustice requires identifying and reversing its causes, especially the systemic factors that create and sustain a built environment that disproportionately isolates certain populations from opportunities and resources (Soja, 2010). In this section, I consider how policy and practice can reverse the uneven geographic access to higher education that I observe in my findings. Specifically, I outline possible strategies available to institutional practitioners, city/municipality officials, and state policymakers.

**Institution**

Institutional leaders committed to understanding geographic accessibility as a non-academic barrier to student success would do well to begin with data collection with the goal of identifying the access problems that enrolled students or potential students encounter when commuting to and from campus. The toolkit provides a roadmap for gathering baseline data on accessibility without the need for detailed information on students’ transportation reliance. Practitioners can supplement these data with surveys that gather details about students’ transportation needs (whether the student relies on public transportation, whether the student’s car is reliable and reliably available, whether the student can afford commuting costs). These
survey responses, in combination with the data collected in the toolkit, can then be linked to student-level data on persistence and completion to identify any correlation with student success outcomes, overall or by race/ethnicity or income.

These data can also be used to identify the most common transportation problems that students encounter, and therefore the types of strategies that the institution ought to consider. For example, during the City Colleges of Chicago’s Reinvention initiative that began in 2010, an administrator at one college remarked that system leaders had become fixated on building a bus system that transported CCC students between campuses. The administrator called this a “stupid idea” that had been proposed without evidence (Horace, 2016, p. 122). He went on to say, “So, if somebody had called me and said, ‘What about this?’ I would have said, ‘No.’ 2% of our students attend another college, and it’s very likely to be either Harold Washington, Malcolm X, or Truman, because those are the North side schools.” (Horace, 2016, p. 122). System leaders were eager to implement a solution—cross-campus buses—even though prevailing evidence suggested that the problem it was meant to address was not in fact a problem. In contrast, a Los Angeles community college’s investment in free bus passes for students resulted in increased credit accumulation and degree completion (Clay & Valentine, 2021), suggestive of a direct linkage between the cost of the bus pass and student success at that college. In either case, data-informed decision-making requires concrete identification of the underlying problem(s).

Although not directly related to transportation, institutional investments in student success ensure that place-bound students are able to enroll at a school where they can succeed. I observed lower outcomes at the institutions nearest to low-income and high proportion POC

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63 Harper College, a broad access public college in the Chicago sample, is offering ride-share subsidies. Approximately 10,000 students were invited to participate, but only 400 individuals have signed up (Povich, 2022). Adaptations to the toolkit report could provide a way for Harper College to map the take-up rate by invited participants, to identify whether there are spatial patterns underlying the decision to participate.
tracts in Chicago than at the institutions nearest to any other sub-group of census tracts. If these institutions serve hyper-local student populations (which the preceding data collection could confirm), then investments in student success are investments in the dismantling of spatial injustices in these same communities. Whole-student interventions like CUNY ASAP are costly, but cost-efficient in terms of improvements in student outcomes (Scrivener et al., 2015).

Additional strategies include the Guided Pathways model, in which colleges use structured choices and sequenced courses to move students through their educational journey (Bailey et al., 2015), and the restructuring of remedial coursework requirements, in which fewer students are placed in remedial coursework (Park-Gaghan et al., 2020) or the required remediation is offered in an accelerated format (Mohker et al., 2021).

Lastly, institutional leaders can consider geographic accessibility during relevant conversations about institutional investments. For example, college enrollment nationwide has declined by 9.4% since the start of the pandemic; this decline is most pronounced at community colleges, where enrollment has dropped by more than 15% (Saul, 2022). Institutional leaders seeking to recover lost enrollments could evaluate whether certain regions of the college’s catchment area have lower accessibility, and whether retention rates are lower among students who live in these areas. Strategies for increasing enrollment can then accommodate the transportation needs for affected students. Decisions about where to open new campuses should consider how a proposed location affects access and for whom, as well as the academic trade-offs required of students who opt to enroll at the new location. Here, the toolkit is an invaluable resource, as institutional practitioners can adjust the destination address to estimate accessibility for hypothetical locations. If most students at the college drive, then decisions about campus design could improve car accessibility (e.g., sufficient parking spaces). Information on relative
accessibility can also serve a case-making function with city officials, if college leaders find that a desirable location lacks public transit access.

**City and Municipality**

Because of its role as the entity responsible for allocating local public transportation dollars, the city or municipality in which an institution is located can pursue policies and practices that increase the geographic accessibility of the region’s colleges. As I found in Chicago, within the CCC system boundary, the lowest accessibility tracts were lower income and higher proportion POC; these tracts also had the highest percentage of households without any access to a vehicle (40% on average, as compared to the next-highest, 18%, in high accessibility tracts inside the CCC district). For these tracts, improvements in public transit will have a measurable effect on overall accessibility. If a similar narrative unfolds in other metropolitan areas with robust public transit, then attentiveness to transit reliability and service expansions can improve postsecondary accessibility for place-bound residents. This can be accomplished in several ways.

First, the city can work with transportation agencies to protect against erosions in public transit that directly and negatively affect college access. The recent initiation of transit improvement projects in Boston led to concerns among community college leaders that the disruptions would negatively affect transit-reliant students’ academic outcomes (Weissman, 2022). Said one administrator, “This particular issue with the subway being shut down in Boston—it’s going to impact, if not enrollment, definitely retention” (quoted in Weissman, 2022). This disruption is an avoidable scheduling problem, and coordination with college officials could contextualize the potential scale of the disruption and whether there is a way to minimize its effects on the college commute for transit-reliant students.
Second, the city can deliberately invest in transportation infrastructure/public transit service for communities with low educational attainment. Doing so would first entail conducting a needs assessment that identifies communities with high potential demand for postsecondary education but low or moderate geographic accessibility. The assessment could build on institution-level analyses to identify where existing service is absent, requires a prohibitively long commute or too many transfers, or limits access at certain times of day (e.g., limited service after 5pm, which constrains transportation options for students who take night courses). With this information, the city can expand service (e.g., new lines or increased frequency at key class times) and implement interventions (e.g., offering and advertising free bus passes) that directly target communities with high potential educational demand. A recent study found that 43% of community colleges lack a bus stop nearby (Crespi et al., 2021), a surface-level indication that postsecondary education is not consistently treated as a public good that ought to be accessible by public transit. For colleges outside existing transit service areas, or in regions where most students have access to a car, the local government could invest in subsidized parking facilities near college campuses, since doing so would remove parking as an obstacle that affects the commuter student’s ability to commute efficiently.

State

Many of the above policies and practices are necessarily localized to individual institutions or the municipalities in which these institutions are embedded. That said, there are still state policy strategies that can minimize the potential consequences of variable accessibility within regions. First, states can invest dollars in supporting regional partnerships that seek to improve college access and attainment by addressing non-academic barriers to student success. Placing dollars in the hands of regional partnerships enables the state to signal its priorities for
advancing college student success without prescribing the solution. This money can then be used by regional partnerships to support the institution- or city-level solutions outlined above.

Second, in states where community colleges collect local tax dollars and/or charge in-district tuition rates, state-level agencies could modify the conditions under which a community college can propose a change in the millage rate or district boundary. With respect to boundary changes, the state could require a detailed analysis of how residents and potential students will be affected by the change, disaggregated by race/ethnicity, income, and educational attainment. These changes may be especially pronounced for individuals just outside the district, for whom a boundary change could directly affect not only their tax rate but their accessibility to broad access public colleges. Simon (2020) finds that expansions of taxing districts in Texas increase property values for new and existing residents’ homes. However, these changes also induce substitution from the four-year to the two-year sector (McFarlin et al., 2017), which lowers the probability of bachelor’s degree attainment (Reynolds & DesJardins, 2009).

Furthermore, the reliance on local tax dollars could result in a concentration of resources in high income or predominantly White districts, as occurs in K-12 school districts. Higher property values in high income districts translate to more property tax revenue, and property tax increases for educational spending are less likely to pass in racially diverse districts (Alvord & Rauscher, 2021; Nations & Martin, 2020; Silverman, 2011). Districts where income inequality is attributable to between-racial group differences in income are least likely to pass such measures (An et al., 2018). At the K-12 level, one proposed policy solution is federal grants to schools with the express purpose of equalizing funding (Sargrad et al., 2020); the higher education corollary could involve block grant-style adjustments to annual appropriations to equalize per-

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64 In some states, this decision-making is controlled by the legislature, whereas in other states the higher education coordinating board oversees the process (Baker et al., 2021).
FTE state and local funding across public institutions. A more radical solution would be the
dissolution of district boundaries—either for taxing or tuition purposes—and a shift to state-level
funding for all community colleges. Doing so would erase arbitrary tuition boundaries that
constrain affordability, and thus access, for students on the border of a district.

Concluding Statement

The findings in this study tell a story of place: Where within a region someone lives
matters more to their accessibility than whether they live in a region with many or few
opportunities. Portions of both Lansing and Chicago experience lower accessibility, borne of
long drives, out-of-district status, or limited transit coverage. Although broad access public
colleges in both study areas are in higher poverty and racially diverse neighborhoods—indicative
of high accessibility for populations historically excluded from or underserved by higher
education—this fact ignores the many residents who fit these demographics but do not live
adjacent to a broad access college. Regardless of whether a college is in their neighborhood,
these same populations tend to live nearest to a less selective college with lower outcomes than
those observed at institutions closer to higher income, predominantly White neighborhoods.
Low-accessibility tracts in both regions are also home to high percentages of residents with high
potential demand for postsecondary education, suggestive of a spatial mismatch between
communities with low educational attainment and the colleges that could reverse this trend.

Geographic access is a necessary condition for place-bound students’ college enrollment.
This exploratory study surfaces underlying inconsistencies in geographic access and provides
practitioners with concrete strategies for assessing accessibility within their student bodies. My
findings join Dache-Gerbino’s (2018) findings on variable accessibility in Rochester and, in
doing so, complicate the assessment that accessibility to higher education can be captured by the
presence or absence of colleges in the surrounding area (Hillman, 2016). Even in a region with more than 20 broad access public colleges, measures of accessibility remain tied to poverty rates and racial demographics, borne of differences in the severity of the spatial mismatch between colleges and communities and systemic patterns of lower accessibility for residents with a long history of exclusion from higher education. There are ample new directions of research worthy of exploration—to more holistically unravel how college access intersects with spatial justice. This study begins to quantify the scale of problem that geographic accessibility poses for place-bound students in pursuit of a college degree, both nationwide and for communities within cities.
### Appendix A: Supplemental Tables and Figures

#### Table A.1: LL and AIC Values for Alternative Spatial Weights Matrices

**Panel A: Lansing Analyses**

<table>
<thead>
<tr>
<th>Spatial Weights</th>
<th>Lansing In-District LL</th>
<th>Lansing In-District AIC</th>
<th>Lansing Out-of-District LL</th>
<th>Lansing Out-of-District AIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Queen’s (pref.)</td>
<td>116.67</td>
<td>-195.33</td>
<td>77.74</td>
<td>-117.47</td>
</tr>
<tr>
<td>knn3</td>
<td>88.35</td>
<td>-138.71</td>
<td>74.72</td>
<td>-111.43</td>
</tr>
<tr>
<td>knn4</td>
<td>89.94</td>
<td>-141.88</td>
<td>77.16</td>
<td>-116.32</td>
</tr>
<tr>
<td>knn5</td>
<td>88.68</td>
<td>-139.35</td>
<td>76.16</td>
<td>-114.33</td>
</tr>
<tr>
<td>knn6</td>
<td>88.64</td>
<td>-139.28</td>
<td>78.31</td>
<td>-118.62</td>
</tr>
<tr>
<td>knn7</td>
<td>91.05</td>
<td>-144.10</td>
<td>78.18</td>
<td>-118.35</td>
</tr>
<tr>
<td>knn8</td>
<td>91.13</td>
<td>-144.26</td>
<td>77.27</td>
<td>-116.55</td>
</tr>
<tr>
<td>knn9</td>
<td>90.25</td>
<td>-142.50</td>
<td>78.81</td>
<td>-119.61</td>
</tr>
<tr>
<td>knn10</td>
<td>89.25</td>
<td>-140.50</td>
<td>78.55</td>
<td>-119.10</td>
</tr>
</tbody>
</table>

**Panel B: Chicago Analyses**

<table>
<thead>
<tr>
<th>Spatial Weights</th>
<th>Chicago In-District LL</th>
<th>Chicago In-District AIC</th>
<th>Chicago In-District LL</th>
<th>Chicago In-District AIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Queen’s (pref.)</td>
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<td>-1723.40</td>
</tr>
<tr>
<td>knn3</td>
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<td>638.29</td>
<td>-1206.60</td>
</tr>
<tr>
<td>knn4</td>
<td>43.78</td>
<td>-51.56</td>
<td>639.20</td>
<td>-1206.40</td>
</tr>
<tr>
<td>knn5</td>
<td>43.54</td>
<td>-51.08</td>
<td>641.63</td>
<td>-1209.30</td>
</tr>
<tr>
<td>knn6</td>
<td>44.51</td>
<td>-53.03</td>
<td>639.76</td>
<td>-1205.50</td>
</tr>
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<td>knn7</td>
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<td>-51.31</td>
<td>638.91</td>
<td>-1203.80</td>
</tr>
<tr>
<td>knn8</td>
<td>43.67</td>
<td>-51.35</td>
<td>636.90</td>
<td>-1199.80</td>
</tr>
<tr>
<td>knn9</td>
<td>42.94</td>
<td>-49.87</td>
<td>636.81</td>
<td>-1199.60</td>
</tr>
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<td>knn10</td>
<td>43.50</td>
<td>-51.01</td>
<td>637.14</td>
<td>-1200.30</td>
</tr>
</tbody>
</table>

*Sources:* Author’s calculations of U.S. Census ACS 5-year estimates 2015-2019; IPEDS 2019; CDAC O-D Matrix

*Notes:* Table details the log likelihood and AIC values for model specifications in each of the four sub-regions using alternative spatial weights matrices (k nearest neighbors, ranging from 1 to 10), in keeping with the comparison process outlined by LeSage and Pace (2009).
Table A.2 Changes in Statistical Significance after Manual Inflation of Standard Errors

<table>
<thead>
<tr>
<th>Panel A: Lansing In-District</th>
<th>Direct Effect</th>
<th>Indirect Effect</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pct. Poverty</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>Educational Attainment</td>
<td>5% → 10%</td>
<td>—</td>
</tr>
<tr>
<td>Pct. Black</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>Pct. Latinx</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>Pct. Asian</td>
<td>1% → 5%</td>
<td>—</td>
</tr>
<tr>
<td>Pct. AI/AN/PI/MR/Other</td>
<td>—</td>
<td>5% → 10%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B: Lansing Out-of-District</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Pct. Poverty</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>Educational Attainment</td>
<td>5% → 10%</td>
<td>—</td>
</tr>
<tr>
<td>Pct. Black</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>Pct. Latinx</td>
<td>—</td>
<td>5% → 10%</td>
</tr>
<tr>
<td>Pct. Asian</td>
<td>5% → 10%</td>
<td>—</td>
</tr>
<tr>
<td>Pct. AI/AN/PI/MR/Other</td>
<td>—</td>
<td>—</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel C: Chicago In-District</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Pct. Poverty</td>
<td>Maintains 1%</td>
<td>—</td>
</tr>
<tr>
<td>Educational Attainment</td>
<td>Maintains 1%</td>
<td>—</td>
</tr>
<tr>
<td>Pct. Black</td>
<td>Maintains 10%</td>
<td>—</td>
</tr>
<tr>
<td>Pct. Latinx</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>Pct. Asian</td>
<td>10% → Not Stat. Sig</td>
<td>—</td>
</tr>
<tr>
<td>Pct. AI/AN/PI/MR/Other</td>
<td>—</td>
<td>—</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel D: Chicago Out-of-District</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Pct. Poverty</td>
<td>0.1% → 1%</td>
<td>—</td>
</tr>
<tr>
<td>Educational Attainment</td>
<td>1% → 5%</td>
<td>1% → 5%</td>
</tr>
<tr>
<td>Pct. Black</td>
<td>5% → 10%</td>
<td>5% → 10%</td>
</tr>
<tr>
<td>Pct. Latinx</td>
<td>5% → 10%</td>
<td>1% → 5%</td>
</tr>
<tr>
<td>Pct. Asian</td>
<td>—</td>
<td>Maintains 1%</td>
</tr>
<tr>
<td>Pct. AI/AN/PI/MR/Other</td>
<td>5% → 10%</td>
<td>Maintains 0.1%</td>
</tr>
</tbody>
</table>

Sources: U.S. Census ACS 5-year estimates 2015-2019; IPEDS 2019; CDAC O-D Matrix
Notes: Changes in statistical significance estimated using the following procedure: (1) All standard errors for coefficients with p-values less than 0.10 manually inflated by 15%. (2) I then multiply each new SE by the relevant t-statistic based on the degrees of freedom for the model and the coefficient’s original significance level. (3) Next, I subtract this number from the absolute value of the coefficient. If the value is positive, meaning the new confidence interval does not cross zero, I conclude that the coefficient’s statistical significance level would not change after adjusting for heteroskedasticity. (4) If the value is negative, I repeat steps 2 and 3 at the next significance level. For instance, if the coefficient is not statistically significant at its original 5% level with the manually inflated SE, I test whether it is statistically significant at the 10% level.
Table A.3: Summary Statistics for Census Tract Sub-Groups, by Poverty Rate (Lansing; RQ2)

<table>
<thead>
<tr>
<th></th>
<th>High-Poverty Tracts (n=34)</th>
<th>Low-Poverty Tracts (n=35)</th>
<th>All Other Tracts (n=70)</th>
<th>K-W H Statistic (P-Value)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>SD</td>
<td>Mean</td>
<td>SD</td>
</tr>
<tr>
<td>Land area (mi$^2$)</td>
<td>1.05</td>
<td>0.89</td>
<td>29.68</td>
<td>25.83</td>
</tr>
<tr>
<td>Tract population</td>
<td>3,395</td>
<td>1,222</td>
<td>4,236</td>
<td>1,361</td>
</tr>
<tr>
<td>Population density</td>
<td>4634.95</td>
<td>2952.19</td>
<td>602.09</td>
<td>758.59</td>
</tr>
<tr>
<td>Pct. HH with zero vehicles</td>
<td>0.14</td>
<td>0.08</td>
<td>0.02</td>
<td>0.02</td>
</tr>
<tr>
<td>Median household income</td>
<td>$36,179</td>
<td>$9,579</td>
<td>$80,613</td>
<td>$18,400</td>
</tr>
<tr>
<td>Pct. poverty (all residents)</td>
<td>0.36</td>
<td>0.15</td>
<td>0.05</td>
<td>0.02</td>
</tr>
<tr>
<td>Pct. poverty (residents of color)</td>
<td>0.40</td>
<td>0.16</td>
<td>0.10</td>
<td>0.10</td>
</tr>
<tr>
<td>Pct. poverty (White residents)</td>
<td>0.32</td>
<td>0.18</td>
<td>0.04</td>
<td>0.02</td>
</tr>
<tr>
<td>Pct. residents aged 25+ w less than AA</td>
<td>0.58</td>
<td>0.23</td>
<td>0.54</td>
<td>0.16</td>
</tr>
<tr>
<td>Pct. White</td>
<td>0.56</td>
<td>0.17</td>
<td>0.89</td>
<td>0.09</td>
</tr>
<tr>
<td>Pct. Black</td>
<td>0.19</td>
<td>0.13</td>
<td>0.02</td>
<td>0.04</td>
</tr>
<tr>
<td>Pct. Latinx</td>
<td>0.11</td>
<td>0.07</td>
<td>0.04</td>
<td>0.03</td>
</tr>
<tr>
<td>Pct. Asian</td>
<td>0.09</td>
<td>0.12</td>
<td>0.03</td>
<td>0.06</td>
</tr>
<tr>
<td>Pct. AI/AN/PI/MR/Other</td>
<td>0.06</td>
<td>0.05</td>
<td>0.02</td>
<td>0.02</td>
</tr>
<tr>
<td>Pct. veterans</td>
<td>0.04</td>
<td>0.02</td>
<td>0.08</td>
<td>0.02</td>
</tr>
</tbody>
</table>

Sources: U.S. Census ACS 5-year estimates 2015-2019
Table A.4: Summary Statistics for Census Tract Sub-Groups, by Race/Ethnicity Composition (Lansing; RQ2)

<table>
<thead>
<tr>
<th></th>
<th>High POC Tracts (n=34)</th>
<th>High White Tracts (n=34)</th>
<th>All Other Tracts (n=71)</th>
<th>K-W H Statistic (P-Value)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>SD</td>
<td>Mean</td>
<td>SD</td>
</tr>
<tr>
<td>Land area (mi^2)</td>
<td>1.54</td>
<td>2.52</td>
<td>35.18</td>
<td>29.51</td>
</tr>
<tr>
<td>Tract population</td>
<td>3,408</td>
<td>1,179</td>
<td>4,008</td>
<td>1,044</td>
</tr>
<tr>
<td>Population density</td>
<td>4,106.77</td>
<td>2,247.43</td>
<td>654.35</td>
<td>1,047.90</td>
</tr>
<tr>
<td>Pop. HH with zero vehicles</td>
<td>0.13</td>
<td>0.08</td>
<td>0.04</td>
<td>0.04</td>
</tr>
<tr>
<td>Median household income</td>
<td>$42,295</td>
<td>$15,593</td>
<td>$65,394</td>
<td>$14,088</td>
</tr>
<tr>
<td>Pop. poverty (all residents)</td>
<td>0.28</td>
<td>0.15</td>
<td>0.09</td>
<td>0.04</td>
</tr>
<tr>
<td>Pop. poverty (residents of color)</td>
<td>0.32</td>
<td>0.17</td>
<td>0.18</td>
<td>0.15</td>
</tr>
<tr>
<td>Pop. poverty (White residents)</td>
<td>0.23</td>
<td>0.16</td>
<td>0.08</td>
<td>0.04</td>
</tr>
<tr>
<td>Pop. residents aged 25+ w less than AA</td>
<td>0.61</td>
<td>0.18</td>
<td>0.67</td>
<td>0.11</td>
</tr>
<tr>
<td>Pop. White</td>
<td>0.50</td>
<td>0.11</td>
<td>0.95</td>
<td>0.01</td>
</tr>
<tr>
<td>Pop. Black</td>
<td>0.21</td>
<td>0.11</td>
<td>0.01</td>
<td>0.01</td>
</tr>
<tr>
<td>Pop. Latinx</td>
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<td>0.06</td>
<td>0.03</td>
<td>0.01</td>
</tr>
<tr>
<td>Pop. Asian</td>
<td>0.09</td>
<td>0.12</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Pop. AI/AN/PI/MR/Other</td>
<td>0.07</td>
<td>0.05</td>
<td>0.02</td>
<td>0.01</td>
</tr>
<tr>
<td>Pop. veterans</td>
<td>0.05</td>
<td>0.03</td>
<td>0.08</td>
<td>0.02</td>
</tr>
</tbody>
</table>

Sources: U.S. Census ACS 5-year estimates 2015-2019
Table A.5: Summary Statistics for Census Tract Sub-Groups, by Poverty Rate (Chicago; RQ2)

<table>
<thead>
<tr>
<th></th>
<th>High-Poverty Tracts (n=487)</th>
<th>Low-Poverty Tracts (n=517)</th>
<th>All Other Tracts (n=1,025)</th>
<th>K-W H Statistic (P-Value)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>SD</td>
<td>Mean</td>
<td>SD</td>
</tr>
<tr>
<td>Land area (mi^2)</td>
<td>0.52</td>
<td>1.01</td>
<td>2.45</td>
<td>4.64</td>
</tr>
<tr>
<td>Tract population</td>
<td>3,365</td>
<td>1,745</td>
<td>4,817</td>
<td>2156</td>
</tr>
<tr>
<td>Population density</td>
<td>14,085.66</td>
<td>10,976.81</td>
<td>5,423.95</td>
<td>7,041.85</td>
</tr>
<tr>
<td>Pct. HH with zero vehicles</td>
<td>0.30</td>
<td>0.16</td>
<td>0.04</td>
<td>0.06</td>
</tr>
<tr>
<td>Median household income</td>
<td>$37,892</td>
<td>$14,302</td>
<td>$116,908</td>
<td>$35,167</td>
</tr>
<tr>
<td>Pct. poverty (all residents)</td>
<td>0.31</td>
<td>0.10</td>
<td>0.03</td>
<td>0.01</td>
</tr>
<tr>
<td>Pct. poverty (residents of color)</td>
<td>0.32</td>
<td>0.10</td>
<td>0.04</td>
<td>0.04</td>
</tr>
<tr>
<td>Pct. poverty (White residents)</td>
<td>0.27</td>
<td>0.28</td>
<td>0.03</td>
<td>0.02</td>
</tr>
<tr>
<td>Pct. residents aged 25+ w less than AA</td>
<td>0.73</td>
<td>0.17</td>
<td>0.38</td>
<td>0.16</td>
</tr>
<tr>
<td>Pct. White</td>
<td>0.13</td>
<td>0.16</td>
<td>0.74</td>
<td>0.16</td>
</tr>
<tr>
<td>Pct. Black</td>
<td>0.54</td>
<td>0.38</td>
<td>0.05</td>
<td>0.11</td>
</tr>
<tr>
<td>Pct. Latinx</td>
<td>0.27</td>
<td>0.30</td>
<td>0.10</td>
<td>0.10</td>
</tr>
<tr>
<td>Pct. Asian</td>
<td>0.04</td>
<td>0.11</td>
<td>0.09</td>
<td>0.09</td>
</tr>
<tr>
<td>Pct. AI/AN/PI/MR/Other</td>
<td>0.02</td>
<td>0.02</td>
<td>0.02</td>
<td>0.02</td>
</tr>
<tr>
<td>Pct. veterans</td>
<td>0.04</td>
<td>0.02</td>
<td>0.05</td>
<td>0.02</td>
</tr>
</tbody>
</table>

Sources: U.S. Census ACS 5-year estimates 2015-2019
Table A.6 Summary Statistics for Census Tract Sub-Groups, by Race/Ethnicity Composition (Chicago; RQ2)

<table>
<thead>
<tr>
<th></th>
<th>High POC Tracts (n=487)</th>
<th>High White Tracts (n=530)</th>
<th>All Other Tracts (n=1,012)</th>
<th>K-W H Statistic (P-Value)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Land area (mi²)</td>
<td>Mean = 0.46, SD = 0.63</td>
<td>Mean = 2.14, SD = 4.20</td>
<td>Mean = 1.33, SD = 2.68</td>
<td>297.66 (0.00)</td>
</tr>
<tr>
<td>Tract population</td>
<td>3,371</td>
<td>4,493</td>
<td>4,600</td>
<td>143.20 (0.00)</td>
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<tr>
<td>Population density</td>
<td>12,296.85</td>
<td>8,254.46</td>
<td>11,584.46</td>
<td>216.69 (0.00)</td>
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<tr>
<td>Pct. HH with zero vehicles</td>
<td>0.27</td>
<td>0.08</td>
<td>0.12</td>
<td>509.26 (0.00)</td>
</tr>
<tr>
<td>Median household income</td>
<td>$38965</td>
<td>$112143</td>
<td>$76,807</td>
<td>1100.33 (0.00)</td>
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<tr>
<td>Pct. poverty (all residents)</td>
<td>0.27</td>
<td>0.05</td>
<td>0.11</td>
<td>985.39 (0.00)</td>
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<tr>
<td>Pct. poverty (residents of color)</td>
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<td>0.08</td>
<td>0.14</td>
<td>670.37 (0.00)</td>
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<tr>
<td>Pct. poverty (White residents)</td>
<td>0.26</td>
<td>0.05</td>
<td>0.08</td>
<td>242.17 (0.00)</td>
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<tr>
<td>Pct. residents aged 25+ w less than AA</td>
<td>0.77</td>
<td>0.37</td>
<td>0.52</td>
<td>892.59 (0.00)</td>
</tr>
<tr>
<td>Pct. White</td>
<td>0.04</td>
<td>0.84</td>
<td>0.49</td>
<td>1714.45 (0.00)</td>
</tr>
<tr>
<td>Pct. Black</td>
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<td>0.11</td>
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<tr>
<td>Pct. AI/AN/PI/MR/Other</td>
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<td>0.02</td>
<td>0.03</td>
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</tr>
<tr>
<td>Pct. veterans</td>
<td>0.04</td>
<td>0.05</td>
<td>0.04</td>
<td>70.96 (0.00)</td>
</tr>
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Sources: U.S. Census ACS 5-year estimates 2015-2019
Table A.7 Raw Coefficients for Lansing In-District and Out-of-District Spatial Durbin Model Regressions (RQ4)

<table>
<thead>
<tr>
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<th>Lansing Out-of-District</th>
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<td>Coeff.</td>
<td>S.E</td>
<td>P-Value</td>
<td>Coeff.</td>
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<td>rho</td>
<td>0.417</td>
<td>0.105</td>
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</tr>
<tr>
<td>Intercept</td>
<td>2.906</td>
<td>0.598</td>
<td>0.000</td>
<td>3.031</td>
</tr>
<tr>
<td>Pct. Poverty</td>
<td>0.000</td>
<td>0.001</td>
<td>0.813</td>
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<td>Educ. Attain.</td>
<td>-0.002</td>
<td>0.001</td>
<td>0.025</td>
<td>-0.003</td>
</tr>
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<td>Pct. Asian</td>
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</tr>
<tr>
<td>Pct. AI/AN/PI/MR/Other</td>
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<td>0.002</td>
<td>-0.002</td>
</tr>
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<td>log(popdensity)</td>
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</tr>
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<td>0.019</td>
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<td>Lagged Pct. Asian</td>
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<td>Lagged Pct. Other</td>
<td>0.011</td>
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<td>0.063</td>
<td>0.006</td>
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</table>

Sources: Author’s calculations of U.S. Census ACS 5-year estimates 2015-2019; IPEDS 2019; CDAC O-D Matrix
Table A.8 Raw Coefficients for Chicago In-District and Out-of-District Spatial Durbin Model Regressions (RQ4)

<table>
<thead>
<tr>
<th></th>
<th>Chicago In-District</th>
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<th></th>
<th>Chicago Out-of-District</th>
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<td>Coeff.</td>
<td>S.E.</td>
<td>P-Value</td>
<td></td>
<td>Coeff.</td>
<td>S.E.</td>
<td>P-Value</td>
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<td>rho</td>
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<td>0.020</td>
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<td>0.025</td>
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<tr>
<td>Intercept</td>
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<td>5.137</td>
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<tr>
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<td>0.000</td>
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<td>0.000</td>
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<td>0.004</td>
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Sources: Author’s calculations of U.S. Census ACS 5-year estimates 2015-2019; IPEDS 2019; CDAC O-D Matrix
Figure A.1: Q-Q Plots for Spatial Durbin Model Regression Analyses

Panel A: Lansing In-District

Panel B: Lansing Out-of-District

Panel C: Chicago In-District

Panel D: Chicago Out-of-District

Sources: Author’s calculations of U.S. Census ACS 5-year estimates 2015-2019; IPEDS 2019; CDAC O-D Matrix
Notes: Created in R. Plots are the quantile-quantile plots from each of the four sub-region analyses following the estimation of a Spatial Durbin Model (SDM) using a queen’s contiguity matrix.
Figure A.2: Residual Plots for Spatial Durbin Model Regression Analyses

Panel A: Lansing In-District

Panel B: Lansing Out-of-District

Panel C: Chicago In-District

Panel D: Chicago Out-of-District

Sources: Author’s calculations of U.S. Census ACS 5-year estimates 2015-2019; IPEDS 2019; CDAC O-D Matrix
Notes: Created in R. Plots are the residual plots from each of the four sub-region analyses following the estimation of a Spatial Durbin Model (SDM) using a queen’s contiguity matrix.
Figure A.3: CV Maps for Census Tract Covariates (Lansing)

Panel A: Tract Population

Panel B: Pct. HH Zero Vehicles

Panel C: Pct. 25+ with Less Than an AA

Panel D: Median Household Income

Panel E: Pct. Poverty (All Residents)

Panel F: Pct. Poverty (Residents of Color)
Panel M: Pct. Veterans

Sources: U.S. Census 2010 census tract shape files; U.S. Census ACS 5-year estimates 2015-2019
Notes: Created in R. Maps are color-coded to represent the level of reliance that can be attributed to the census estimates for each tract; calculated using the protocol outlined in US Census, 2020 and categorized based on ESRI (2011) guidance on what constitutes high, medium, and low reliability CVs.
Figure A.4: CV Maps for Census Tract Covariates (Chicago)

Panel A: Tract Population

Panel B: Pct. HH Zero Vehicles

Panel C: Pct. 25+ with Less Than an AA

Panel D: Median Household Income

Panel E: Pct. Poverty (All Residents)

Panel F: Pct. Poverty (Residents of Color)
Panel M: Pct. Veterans

Sources: U.S. Census 2010 census tract shape files; U.S. Census ACS 5-year estimates 2015-2019
Notes: Created in R. Maps are color-coded to represent the level of reliability that can be attributed to the census estimates for each tract; calculated using the protocol outlined in US Census, 2020 and categorized based on ESRI (2011) guidance on what constitutes high, medium, and low reliability CVs.
Figure A.5: Alternative Distance Decay Factor Covariate Plots for Lansing In-District SDM Regression Analysis (Direct Effects)

Panel A: Pct. Poverty

Panel B: Pct. 25+ with less than an AA

Panel C: Pct. Black

Panel D: Pct. Latinx

Panel E: Pct. Asian

Panel F: Pct. AI/AN/PI/MR/Other

Sources: Author’s calculations of U.S. Census ACS 5-year estimates 2015-2019; IPEDS 2019; CDAC O-D Matrix

Notes: Created in Stata. Plots correspond to the coefficient point estimate and 95% confidence interval for each of the direct effects estimated in the Spatial Durbin Model for the Lansing in-district analyses.
Figure A.6: Alternative Distance Decay Factor Covariate Plots for Lansing In-District SDM Regression Analysis (Indirect Effects)

Panel A: Pct. Poverty

Panel B: Pct. 25+ with less than an AA

Panel C: Pct. Black

Panel D: Pct. Latinx

Panel E: Pct. Asian

Panel F: Pct. AI/AN/PI/MR/Other

Sources: Author’s calculations of U.S. Census ACS 5-year estimates 2015-2019; IPEDS 2019; CDAC O-D Matrix
Notes: Created in Stata. Plots correspond to the coefficient point estimate and 95% confidence interval for each of the indirect effects estimated in the Spatial Durbin Model for the Lansing in-district analyses.
Figure A.7: Alternative Distance Decay Factor Covariate Plots for Lansing Out-of-District SDM Regression Analysis (Direct Effects)

Panel A: Pct. Poverty

Panel B: Pct. 25+ with less than an AA

Panel C: Pct. Black

Panel D: Pct. Latinx

Panel E: Pct. Asian

Panel F: Pct. AI/AN/PI/MR/Other

Sources: Author’s calculations of U.S. Census ACS 5-year estimates 2015-2019; IPEDS 2019; CDAC O-D Matrix

Notes: Created in Stata. Plots correspond to the coefficient point estimate and 95% confidence interval for each of the direct effects estimated in the Spatial Durbin Model for the Lansing out-of-district analyses.
Figure A.8: Alternative Distance Decay Factor Covariate Plots for Lansing Out-of-District SDM Regression Analysis (Indirect Effects)

Panel A: Pct. Poverty

Panel B: Pct. 25+ with less than an AA

Panel C: Pct. Black

Panel D: Pct. Latinx

Panel E: Pct. Asian

Panel F: Pct. AI/AN/PI/MR/Other

Sources: Author’s calculations of U.S. Census ACS 5-year estimates 2015-2019; IPEDS 2019; CDAC O-D Matrix
Notes: Created in Stata. Plots correspond to the coefficient point estimate and 95% confidence interval for each of the indirect effects estimated in the Spatial Durbin Model for the Lansing out-of-district analyses.
Figure A.9: Alternative Distance Decay Factor Covariate Plots for Chicago In-District SDM Regression Analysis (Direct Effects)

Panel A: Pct. Poverty

Panel B: Pct. 25+ with less than an AA

Panel C: Pct. Black

Panel D: Pct. Latinx

Panel E: Pct. Asian

Panel F: Pct. AI/AN/PI/MR/Other

Sources: Author’s calculations of U.S. Census ACS 5-year estimates 2015-2019; IPEDS 2019; CDAC O-D Matrix
Notes: Created in Stata. Plots correspond to the coefficient point estimate and 95% confidence interval for each of the direct effects estimated in the Spatial Durbin Model for the Chicago in-district analyses.
Figure A.10: Alternative Distance Decay Factor Covariate Plots for Chicago In-District SDM Regression Analysis (Indirect Effects)

Panel A: Pct. Poverty

Panel B: Pct. 25+ with less than an AA

Panel C: Pct. Black

Panel D: Pct. Latinx

Panel E: Pct. Asian

Panel F: Pct. AI/AN/PI/MR/Other

Sources: Author’s calculations of U.S. Census ACS 5-year estimates 2015-2019; IPEDS 2019; CDAC O-D Matrix
Notes: Created in Stata. Plots correspond to the coefficient point estimate and 95% confidence interval for each of the indirect effects estimated in the Spatial Durbin Model for the Chicago in-district analyses.
Figure A.11: Alternative Distance Decay Factor Covariate Plots for Chicago Out-of-District SDM Regression Analysis (Direct Effects)

Panel A: Pct. Poverty

Panel B: Pct. 25+ with less than an AA

Panel C: Pct. Black

Panel D: Pct. Latinx

Panel E: Pct. Asian

Panel F: Pct. AI/AN/PI/MR/Other

Sources: Author’s calculations of U.S. Census ACS 5-year estimates 2015-2019; IPEDS 2019; CDAC O-D Matrix
Notes: Created in Stata. Plots correspond to the coefficient point estimate and 95% confidence interval for each of the direct effects estimated in the Spatial Durbin Model for the Chicago out-of-district analyses.
Figure A.12: Alternative Distance Decay Factor Covariate Plots for Chicago Out-of-District SDM Regression Analysis (Indirect Effects)

Panel A: Pct. Poverty

Panel B: Pct. 25+ with less than an AA

Panel C: Pct. Black

Panel D: Pct. Latinx

Panel E: Pct. Asian

Panel F: Pct. AI/AN/PI/MR/Other

Sources: Author’s calculations of U.S. Census ACS 5-year estimates 2015-2019; IPEDS 2019; CDAC O-D Matrix
Notes: Created in Stata. Plots correspond to the coefficient point estimate and 95% confidence interval for each of the indirect effects estimated in the Spatial Durbin Model for the Chicago out-of-district analyses.
Appendix B: Instructional Guide for Practitioner Toolkit
Overview of the Postsecondary Accessibility Toolkit
This toolkit enables institutional practitioners to evaluate the geographic accessibility of their student population, linking estimated commute times (via either driving or public transit) to demographic information (race/ethnicity, Pell receipt, enrollment intensity) and student outcomes (retention, graduation). Development of the toolkit report requires that the User (1) adapt several components of the included files to the institution’s needs and (2) construct a student-level dataset (described in “Requirements for Institutional Dataset Format” below).

The toolkit was developed as part of KC Deane’s doctoral dissertation on the geographic accessibility of broad access public colleges, completed in 2022. For more information, email deanek@umich.edu with the subject line “PSA Toolkit Query.”

System and Software Requirements
- Stata 16 or later, including user-installed commands (see do-files)
- File paths all assume a Windows operating system

Use of Block Groups as Students’ Place of Residence
The toolkit in its base form calculates driving and public transit commute times between census block groups’ weighted centroids and a single location (e.g., the institution’s main campus). This approach was chosen to maximize usability and minimize risks to student privacy (since student identifying information is therefore not required when using the third-party platforms that enable public transit routing).

Two relevant consequences of this decision:

- **The User must have the GEOID for each student’s census block group.** Identifying a block group for a street address is most easily done with the U.S. Census’ Geocoder batch service (here), though User must confirm that its use does not violate institutional privacy policies.

- **The resultant commute time estimates are less granular than would occur with the use of addresses.** Although block groups are the smallest unit for which U.S. Census American Community Survey estimates are available, block groups still range in land area. In cases where the block group is quite small—easily walkable in a short time—the use of a block group weighted centroid will sufficiently proxy for the commute times of students living in that block group. In larger block groups, the proxy will be less precise. Relatedly, calculating time from a block group weighted centroid means assigning the same travel times to all students in that block group.

Reliance on Third-Party Platforms for Public Transit Routing
Calculating travel time for public transit requires the use of a third-party mapping service via an API and comes at the cost to the User. The toolkit in its base form relies on the HERE API, as there exists Stata commands that integrate with the HERE platform. To get a HERE API key, User must sign up for a new account and incur any per-transaction costs that exceed the monthly limit of free transactions (see details in the section below). It is at the User’s discretion to confirm that the creation of a HERE account and use of the information is in accordance with the User institution’s policies.

HERE’s public transit routing does not return a result when the origin and destination requires more than 2,000m of walking at 1 meter per second. These constraints cannot be adjusted in the current version of the georoute Stata program, which results in increased right-censorship in public transit commute times.
Open Source (Free) Alternative: Though not detailed here, the Spatial Access for PySAL provides documentation and code to calculate travel time using Python and OpenTripPlanner. (Link)

Summary of Download Folder
The psa_toolkit.zip folder includes the necessary files and documentation to produce the Transportation Accessibility Report for a single campus. Extract the entire folder and its contents to the desired location on your computer’s hard drive. Since the do-files require the incorporation of student-level information on demographics and academic outcomes, User is advised to save the psa_toolkit folder and its accompanying materials in a secure location that adheres to User institution’s privacy protocols.

In the main folder, there are five sub-folders and four files, none of which should be deleted, moved, or re-named. There are three additional files in the folder named “00_starthere_dofiles.” Any changes to the underlying folder structure or filenames could prevent report production.

Sub-Folders

<table>
<thead>
<tr>
<th>00_starthere_dofiles</th>
<th>Includes 3 do-files necessary to produce the report. For more details on each do-file, see the “Included Files” sub-section below.</th>
</tr>
</thead>
<tbody>
<tr>
<td>data</td>
<td>Begins empty. Data produced via the do-files will automatically save here.*</td>
</tr>
<tr>
<td>logs</td>
<td>Begins empty. Logs created via the do-files will automatically save here.</td>
</tr>
<tr>
<td>output</td>
<td>Begins empty. Images created via the do-files will automatically save here.</td>
</tr>
<tr>
<td>source</td>
<td>Begins empty. User will save two relevant Census downloads to this folder (see “Census Data Download Requirements” below).</td>
</tr>
</tbody>
</table>

Included files

<table>
<thead>
<tr>
<th>File Name</th>
<th>In Folder</th>
<th>Purpose</th>
</tr>
</thead>
<tbody>
<tr>
<td>00_instructions.docx</td>
<td>psa_toolkit</td>
<td>Instructing. Welcome!</td>
</tr>
<tr>
<td>header.txt</td>
<td>psa_toolkit</td>
<td>Includes formatting code for the report document; called upon in toolkit_report_markdown.txt</td>
</tr>
<tr>
<td>stmarkdown.css</td>
<td>psa_toolkit</td>
<td>Stata-created style sheet used to format text elements in the toolkit_report_markdown.txt</td>
</tr>
<tr>
<td>toolkit_report_markdown.txt</td>
<td>psa_toolkit</td>
<td>Source markdown file for Stata report creation. Called in the Stata command “dyndoc” in 03_toolkit_report.do</td>
</tr>
<tr>
<td>01_toolkit_prep_censusdata.do</td>
<td>00_starthere_dofiles</td>
<td>Inputs, cleans, and formats U.S. Census data required to compile the report. Requires (1) a U.S. Census API key and (2) user-downloaded block group weighted centroid data and shape files.</td>
</tr>
<tr>
<td>02_toolkit_travelcalculations.do</td>
<td>00_starthere_dofiles</td>
<td>Formats the institutional dataset to ready for use with the HERE API. Also saves a CSV that can be used to access the Google Distance</td>
</tr>
</tbody>
</table>
Matrix API.

| 03_toolkit_report.do | 00_startthere_dofiles | Creates necessary variables and graphs, and then creates a .html file of the report itself. |

Census Data Download Requirements

Production of the toolkit report requires several components of U.S. Census data, all of which are publicly available and easily accessed. Instructions below detail how to download and where to save.

**State-Level Block Group Shape Files** ([Download here](#))

The toolkit relies on 2020 Block Groups and corresponding shape files. The above link opens to a list of .zip files, one for each state. Download the .zip file that corresponds to the institution’s state, where state is represented by a 2-digit FIPS code. A look-up table for FIPS codes is available [here](#).

*Example:*

- For an institution in Michigan, User downloads “tl_2020_26_bg.zip”

*Where to save:*

- Unzip the folder to the “source” sub-folder in the psa_toolkit folder.
- Copy x2 files to the psa_toolkit main folder:
  - tl_2020_`fips'_bg.dbf
  - tl_2020_`fips'_bg.shp

**State-Level Block Group Weighted Centroids** ([Download Here](#))

From the drop-down menu under “Centers of Population by Block Group” in the link above, select User institution’s state. This will open a new browser window with a .txt file.

*Where to save:*

- Download this .txt file to the “source” sub-folder.
- Do not re-name the file. It should have the following format: “CenPop2020_Mean_BG`fips'.txt”

**Sign up for a Census API Key** ([Here](#))

Because the toolkit incorporates tract-level information on the percentage of households without access to a vehicle, User will need to procure an API Key from the U.S. Census. The above link opens to a sign-up page. The API Key is emailed shortly after sign-up. This key will be copied by User into the 01_toolkit_prep_censusdata.do file.

*Note: API stands for Application Programming Interface, and it serves as a means of accessing the Census data through programming software such as Stata/Python/R, rather than using point-and-click methods on the Census website. The key is the credential that enables access.*
### Required Changes to Do-Files and Markdown File

#### 01_toolkit_prep_censusdata.do

<table>
<thead>
<tr>
<th>Line</th>
<th>Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>36</td>
<td>Add User’s U.S. Census API Key</td>
</tr>
<tr>
<td>37</td>
<td>Change state FIPS code to correspond to User institution’s state</td>
</tr>
<tr>
<td>39</td>
<td>Change working directory filepath</td>
</tr>
</tbody>
</table>

#### 02_toolkit_travelcalculations.do

<table>
<thead>
<tr>
<th>Line</th>
<th>Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>39</td>
<td>Add HERE API Key</td>
</tr>
<tr>
<td>41</td>
<td>Change working directory filepath</td>
</tr>
<tr>
<td></td>
<td>Throughout</td>
</tr>
<tr>
<td></td>
<td>Change day-month-year according to user preferences</td>
</tr>
</tbody>
</table>

#### 03_toolkit_report.do

<table>
<thead>
<tr>
<th>Line</th>
<th>Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>34</td>
<td>‘dyn’ directory filepath. Note that the filepath requires the use of the “/” separator for the subsequent “dyndoc” command to function properly.</td>
</tr>
<tr>
<td>36</td>
<td>Change working directory filepath</td>
</tr>
</tbody>
</table>

#### toolkit_report_markdown.txt

<table>
<thead>
<tr>
<th>Line</th>
<th>Change</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Change “YOUR COLLEGE NAME” to User institution’s name (x2 instances)</td>
</tr>
<tr>
<td></td>
<td>Change “DATE HERE” to correspond to the date on which User accessed the HERE API.</td>
</tr>
<tr>
<td></td>
<td>Change filepath to location of the institution_long_traveltimes.dta file on User computer (path should end with: \pse_toolkit\data\institution_long_traveltimes.dta)</td>
</tr>
<tr>
<td></td>
<td>Change YOUR REGION’S NAME to User’s preferred name for User Institution’s region</td>
</tr>
<tr>
<td></td>
<td>Change DOLLAR AMOUNT to reflect the cost of a transit pass in your region. Change source URL to align with the transit agency that services your region. If there is no price per semester, the corresponding line of the markdown file can be deleted.</td>
</tr>
<tr>
<td></td>
<td>NOTE: Do not delete the “$” that precedes the dollar amount. This text tells markdown to place a $ before the dollar amount.</td>
</tr>
</tbody>
</table>

### Requirements for Institutional Dataset Format

**Note: All student-level information is excluded from the dataset prior to accessing the HERE API.**

This report requires an institutional dataset that is unique at the student level and includes a specific set of variables named and defined as outlined below. The format assumes that the User is evaluating accessibility for a cohort of students for whom 150% graduation rates are available.

Stata is case-sensitive, so all variable names should be lower-case. Note that the variables will be automatically labeled based on the below values in the 03_toolkit_report.do do-file.
<table>
<thead>
<tr>
<th>Variable Name</th>
<th>Description</th>
<th>Format</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>studentid</td>
<td>Unique ID. It is advised that User create a random ID for each student and store the formal ID-random ID crosswalk separately from the rest of the toolkit files, in a manner that aligns with the User’s institution’s privacy policies.</td>
<td>numeric</td>
<td></td>
</tr>
<tr>
<td>fips_statecountytract</td>
<td>11-digit string variable that corresponds to the student’s census tract, using the following format: state fips + county fips + tract fips (2 + 3 + 6 digits = 11 digits)</td>
<td>string</td>
<td></td>
</tr>
<tr>
<td>geoid</td>
<td>12-digit string variable that corresponds to the student’s block group, using the following format: state fips + county fips + tract fips + block group fips (2 + 3 + 6 + 1 = 12 digits)</td>
<td>string</td>
<td></td>
</tr>
</tbody>
</table>
| race              | Categorical variable identifying a student’s race/ethnicity. Categories correspond to those used in IPEDS reporting. | numeric | 1 White  
2 Black  
3 Hispanic/Latinx  
4 Asian  
5 American Indian or Alaska Native  
6 Native Hawaiian / Pacific Islander  
7 Multiracial  
8 Race/Ethnicity Unknown  
9 Non-Resident Alien |
| enrollment_intensity | Indicates whether the student was enrolled full- or part-time in the first semester of enrollment, where definitions of full- versus part-time are at the User’s discretion. | numeric | 0 Part-Time  
1 Full-Time |
| retention_ft      | Indicates whether the full-time student persisted in the educational program a year after initially enrolling (as measured in the fall semester; e.g., fall-to-fall first-year persistence). | numeric | 0 Not Retained  
1 Retained  
. Not full-time |
| retention_pt      | Indicates whether the part-time student persisted in the educational program a year after initially enrolling (as measured in the fall semester; e.g., fall-to-fall first-year persistence). | Numeric | 0 Not Retained  
1 Retained  
. Not part-time |
| pell_receipt      | Indicates whether a student received the Pell Grant in their first semester of enrollment. | Numeric | 0 No Pell  
1 Received Pell |
| grad150pct        | Indicates whether a student graduated within 150% time of program length. | numeric | 0 No Grad  
1 Grad 150% |
| institution_long  | Campus longitude in decimal points                                           | numeric |                                                                        |
| institution_lat   | Campus latitude in decimal points                                             | numeric |                                                                        |
Using the HERE API

Note: All student-level information is excluded from the dataset prior to accessing the HERE API.

HERE is a mapping platform; this toolkit relies on its routing API, integrated with Stata via the user-written `georoute` program, to calculate driving and public transit travel times. Pricing for the HERE API is available at this link. The Limited Plan account option provides the user with 1,000 free daily HERE Location Services transactions. The Base Plan requires a credit card for billing but expands the available number of free transactions to 5,000 per month for transit and 30,000 per month for cars. After these limits, the price expands to $2.50 per 1,000 transactions for public transit routing and $0.75 per 1,000 transactions for car routing.

Pricing information accurate as of April 2022.

Steps to access a HERE API Key:
- Sign up for an account and choose a plan
- Create a new app and activate the API key (instructions here)
- Copy the API Key into 03_toolkit_report.do

How to calculate how many transactions will be required to run the report:
- Multiply the number of unique block groups represented in the institution dataset by the number of travel modes (x2; car, public transit) and times of day (x3; morning, afternoon, evening)
  - This is most easily done by using the distinct command in Stata with the final form of the institution.dta dataset open:
    distinct geoid

Creating the Report

Once all the files are downloaded to the appropriate location and all of the user-necessary changes are made to the files listed in the above section (including the inclusion of the Census and HERE API Keys), User is ready to create the report! Execute the three do-files in numerical order:
- 01_toolkit_prep_censusdata.do
- 02_toolkit_travelcalculations.do
- 03_toolkit_report.do

Once all three do-files have successfully run, an HTML version of the report will save to the psa_toolkit root folder (psa_toolkit_report.html). To facilitate easier sharing, the document is formatted for printing to pdf. It is recommended that the page is scaled to 65% when printing to PDF.

Disclaimer

User is responsible for complying with all API policies and adhering to institutional, state, and federal privacy requirements for student data. User is responsible for any costs incurred by accessing third-party APIs.
Appendix C: Stata Do-Files for Practitioner Toolkit

01_toolkit_prep_censusdata.do

* POSTSECONDARY ACCESSIBILITY INSTITUTIONAL TOOLKIT PROTOTYPE
* This do file inputs key data elements from the U.S. Census.
* *
* USING DATASETS: tl_2020_statefips_bg20.shp | tl_2020_statefips_bg20.dbf
* CenPop2020_Mean_BG`statefips'.txt
* *
* MERGED DATASETS: None
* *
* SAVED DATASETS: tl_2020_statefips_bg20.dta
* tl_2020_statefips_bg_shp.dta
* census_bg_weightedcentroids.dta
* census_tract_veh0.dta
* *
* CREATED BY: KC Deane, April 2022
*
* Update Notes
* *
* 2020/12/31 by KCD: Created file to begin process. Relies on Census API to pull needed variables
*
*
**********************************************
***** STANDARD HEADERS & MACROS *****
**********************************************
clear all
version 16.0
set more off, perm
display c(current_date)

local censuskey YOURKEYHERE
local statefips 26

cd "YOURFILEPATH\090_toolkit\"
capture log close
log using "logs\01_toolkit_prep_censusdata.log", replace

**************************************************************************
***** STANDARD HEADERS & MACROS                                      *****
**************************************************************************
ssc install shp2dta, replace
***** (1) Prepare the Census Shape File *****
Note: See Part X of the instruction sheet on downloading *****
spshape2dta "tl_2020_'statefips'_bg.shp", replace

***** (2) Prepare the Census Block Groups Weighted Centroids File *****
Note: See Part X of the instruction sheet on downloading *****
clear all
insheet using "source\CenPop2020_Mean_BG`statefips'.txt", comma

** Format Key Variables (See below URL) **
** https://www.census.gov/programs-surveys/geography/guidance/geo-identifiers.html **

** Create String Variables for each GEOID component **
gen state_string = string(STATEFP, "%02.0f") // State FIPS (2-digit)
gen county_string = string(countyfp, "%03.0f") // County FIPS (3-digit)
gen tract_string = string(tractce, "%06.0f") // Tract FIPS (6-digit)
gen bg_string = string(blkgrpce, "%01.0f") // Block Group FIPS (1-digit)

** Create a state-county-tract-bg string **
gen geoid = state_string + county_string + tract_string + bg_string

* Drop Unneeded Variables
drop STATEFP countyfp tractce blkgrpce state_string county_string tract_string bg_string

* Order
order geoid

** Rename and Label Variables **

rename population bg_population
rename latitude bg_weighted_lat
rename longitude bg_weighted_long

label var geoid "String FIPS (State+County+Tract+BG; 2+3+6+1)"
label var bg_population "2010 Census population for BG"
label var bg_weighted_lat "2010 Latitude of BG's Weighted Population Center"
label var bg_weighted_long "2010 Longitude of BG's Weighted Population Center"

***** Save File *****
notes drop _dta
compress
save "data\census_bg_weightedcentroids.dta", replace
(3) Download Census Tract-Level Information on Car Ownership

Note: See pg. 3 of the instruction sheet on downloading

```
censusapi,

c/** Create + clean necessary variables **
cgen state_string = string(state, "%02.0f")
cgen county_string = string(county, "%03.0f")
cgen tract_string = string(tract, "%06.0f")
cgen fips_statecountytract = state_string + county_string + tract_string

drop state county tract name state_string county_string tract_string
c
label var b08201_001e "All Households"
clabel var b08201_002e "No Vehicle Available"
clabel var b08201_003e "1 Vehicle"
clabel var b08201_004e "2 Vehicles"
clabel var b08201_005e "3 vehicles"
clabel var b08201_006e "4 or more vehicles"

cgen tract_pct0veh = b08201_002e/b08201_001e

ckeep fips_statecountytract tract_pct0veh

c/** Save the file! **
ccompress
csave "data\census_tract_veh0.dta", replace
```
02_toolkit_travelcalculations.do

* POSTSECONDARY ACCESSIBILITY INSTITUTIONAL TOOLKIT PROTOTYPE
* TRAVEL TIME CALCULATION DO-FILE
* This do file calculates travel times between students' places of residence
* (measured at weighted centroid of block group) and a single institution.
*
* USING DATASETS: institution.dta
* institution_long.dta
*
* MERGED DATASETS: census_bg_weightedcentroids.dta
* toolkit_HEREapi.dta
*
* SAVED DATASETS: institution_long.dta
* institution_forHERE.dta
* toolkit_HEREapi.dta
* institution_long_traveltimes.dta
*
* CREATED BY: KC Deane, April 2022
* 
* Update Notes
* 
* 

****** STANDARD HEADERS & MACROS ******
clear all
version 16.0
set more off, perm
display c(current_date)

global apikey YOURKEYHERE
cd "YOURFILEPATH\090_toolkit\"
capture log close
log using "logs\02_toolkit_travelcalculations.log", replace

** Install User-Written Commands **
ssc install distinct, replace
ssc install georoute, replace

****** (1) Open institution dataset and format for HERE + Google APIs ******
use "data\institution.dta"
*
** Merge on the student's BG's weighted centroid **
*
merge m:1 geoid using "data\census_bg_weightedcentroids.dta"
drop if _merge==2
drop _merge
*
** Merge on tract-level information on **
** household-level car access **
*
merge m:1 fips_statecountytract using "data\census_tract_veh0.dta"
keep if _merge==3
drop _merge
*
** Expand dataset to include: **
** x2 modes (driving, public transit) **
** x3 travel times (researchers' choice) **
*
expand 2, gen(mode)
tostring mode, replace
replace mode = "car" if mode=="1"
replace mode = "publicTransit" if mode=="0"
expand 3, gen(time_string)
tostring time, replace
bysort studentid mode: replace time_string="25Apr2022 08:00:00" if _n==1
bysort studentid mode: replace time_string="25Apr2022 11:00:00" if _n==2
bysort studentid mode: replace time_string="25Apr2022 20:00:00" if _n==3
*
* Format time in Stata format to comply with the HERE API
gen double time = clock(time_string, "DMYhms")
format time %tc
*
** Save this long version of the institution dataset **
*
save "data\institution_long.dta", replace
*
** IF YOU ARE NOT USING A STUDENT'S BLOCK GROUP, LEAVE FILE AS-IS **
** IF YOU ARE USING A STUDENT'S BLOCK GROUP, DROP DUPLICATE OBS **
** AT THE BLOCK GROUP LEVEL TO MINIMIZE THE TOTAL # OF API HITS **
*
bysort geoid mode time: gen count=_n
keep if count==1
distinct geoid
*
* Drop the student-level variables that confuse the merge
drop studentid-grad150pct tract_pct0veh hascar
* Save .dta file for use with Stata's georoute program *
** Save .dta file for use with Stata's georoute program **
******************************
compress
save "data\institution_forHERE.dta", replace
******************************
** (2) Calculate Travel Time using georoute/here API **
******************************
clear all
use "data\institution_forHERE.dta"
* Note: If you have more than 1,000 observations per mode per time of day,
* I recommend batching the observations to lower the speed
* at which you hit the HERE API

** Car ** ---> ** 25Apr2022 08:00:00 **

georoute if mode=="car" & time_string=="25Apr2022 08:00:00", ///
    herekey($apikey)  ///
    startxy(bg_weighted_lat bg_weighted_long)  ///
    endxy(institution_lat institution_long)  ///
    di(georoute_dist_car_am)  ///
    time(georoute_time_car_am)  ///
    diagnostic(georoute_diagnostic_car_am)  ///
    tmode(mode) dtime(time) timer

** Car ** ---> ** 25Apr2022 15:00:00 **

georoute if mode=="car" & time_string=="25Apr2022 15:00:00", ///
    herekey($apikey)  ///
    startxy(bg_weighted_lat bg_weighted_long)  ///
    endxy(institution_lat institution_long)  ///
    di(georoute_dist_car_pm)  ///
    time(georoute_time_car_pm)  ///
    diagnostic(georoute_diagnostic_car_pm)  ///
    tmode(mode) dtime(time) timer

** Car ** ---> ** 25Apr2022 20:00:00 **
** Reverse Start/End **

georoute if mode=="car" & time_string=="25Apr2022 20:00:00", ///
    herekey($apikey)  ///
    startxy(bg_weighted_lat bg_weighted_long)  ///
    endxy(institution_lat institution_long)  ///
    di(georoute_dist_car_eve)  ///
    time(georoute_time_car_eve)  ///
    diagnostic(georoute_diagnostic_car_eve)  ///
    tmode(mode) dtime(time) timer

306
sleep 30000
georoute if mode=="car" & time_string=="25Apr2022 20:00:00", ///
    herekey($apikey) ///
    endxy(bg_weighted_lat bg_weighted_long) ///
    startxy(institution_lat institution_long) ///
    di(georoute_dist_car_eve) ///
    time(georoute_time_car_eve) ///
    diagnostic(georoute_diagnostic_car_eve) ///
    tmode(mode) dtime(time) timer

**************************  **************************
** Public Transport ** ---> ** 25Apr2022 08:00:00 **
**************************  **************************
// gen batch_pt_am = ceil(n/1000) if mode=="publicTransport" & 
    time_string=="25Apr2022 08:00:00"

sleep 30000
georoute if mode=="publicTransport" ///
    & time_string=="25Apr2022 08:00:00", ///
    herekey($apikey) ///
    startxy(bg_weighted_lat bg_weighted_long) ///
    endxy(institution_lat institution_long) ///
    di(georoute_dist_pt_am) ///
    time(georoute_time_pt_am) ///
    diagnostic(georoute_diagnostic_pt_am) ///
    tmode(mode) dtime(time) timer

**************************  **************************
** Public Transport ** ---> ** 25Apr2022 15:00:00 **
**************************  **************************
// gen batch_pt_pm = ceil(n/1000) if mode=="publicTransport" & 
    time_string=="25Apr2022 15:00:00"

sleep 30000
georoute if mode=="publicTransport" & 
    time_string=="25Apr2022 11:00:00", ///
    herekey($apikey) ///
    startxy(bg_weighted_lat bg_weighted_long) ///
    endxy(institution_lat institution_long) ///
    di(georoute_dist_pt_pm) ///
    time(georoute_time_pt_pm) ///
    diagnostic(georoute_diagnostic_pt_pm) ///
    tmode(mode) dtime(time) timer
// gen batch pt eve = ceil(_n/1000) if mode=="publicTransit" &
time_string=="25Apr2022 20:00:00"

sleep 30000
georoute if mode=="publicTransport" &
    time_string=="25Apr2022 20:00:00",
    hereKey($apikey)
endxy(bg_weighted_lat bg_weighted_long)
startxy(Institution_lat institution_long)
di(georoute_dist_pt_eve)
time(georoute_time_pt_eve)
diagnostic(georoute_diagnostic_pt_eve)
tmode(mode) dtime(time) timer

// gen batch pt_eve = ceil(_n/1000) if mode=="publicTransit" &
time_string=="25Apr2022 20:00:00"

sleep 30000
georoute if mode=="publicTransport" &
    time_string=="25Apr2022 20:00:00",
    hereKey($apikey)
endxy(bg_weighted_lat bg_weighted_long)
startxy(Institution_lat institution_long)
di(georoute_dist_pt_eve)
time(georoute_time_pt_eve)
diagnostic(georoute_diagnostic_pt_eve)
tmode(mode) dtime(time) timer

// gen batch pt_eve = ceil(_n/1000) if mode=="publicTransit" &
time_string=="25Apr2022 20:00:00"

sleep 30000
georoute if mode=="publicTransport" &
    time_string=="25Apr2022 20:00:00",
    hereKey($apikey)
endxy(bg_weighted_lat bg_weighted_long)
startxy(Institution_lat institution_long)
di(georoute_dist_pt_eve)
time(georoute_time_pt_eve)
diagnostic(georoute_diagnostic_pt_eve)
tmode(mode) dtime(time) timer

****** (3) IF USING BLOCK GROUPS, THIS STEP IS NECESSARY ******
****** Merge toolkit_HEREapi.dta with institution_long.dta ******
use "data\institution_long.dta"

****** (3) IF USING BLOCK GROUPS, THIS STEP IS NECESSARY ******
****** Merge toolkit_HEREapi.dta with institution_long.dta ******
use "data\institution_long.dta"
merge m:1 geoid mode time using "data\toolkit_HEREapi.dta"

******************************************************************************
** Clean up variable order **
******************************************************************************
order studentid geoid fips_statecountytract ///
race enrollment_intensity retention_ft retention_pt ///
pell_receipt grad150pct hascar
drop_count _merge

******************************************************************************
** Re-shape to wide (unique @ student level) **
******************************************************************************
gen t = ""
replace t = "am" if time_string=="25Apr2022 08:00:00"
replace t = "pm" if time_string=="25Apr2022 11:00:00"
replace t = "eve" if time_string=="25Apr2022 20:00:00"
replace mode = "pt" if mode=="publicTransport"
drop time time_string
reshape wide dist_georoute time_georoute, i(studentid mode) j(t) string
reshape wide dist_georouteam dist_georoutepm dist_georouteeve
time_georouteam time_georoutepm time_georouteeve, i(studentid) j(mode) string

* Clean my code up!
foreach mode in car pt {
 foreach time in am pm eve {
 rename dist_georoute`time'`mode' dist_`mode'_`time'
 rename time_georoute`time'`mode' time_`mode'_`time'
}
}

* Order the variables
order studentid geoid race enrollment_intensity retention_ft ///
retention_pt pell_receipt grad150pct hascar time* dist*

******************************************************************************
** Save dataset for use with report creation **
******************************************************************************
compress
save "data\institution_long_traveltimes.dta", replace

/**************************************************************************/
/**** Final Step: Note data file, compress, and save  ***/
/**************************************************************************/
timer off 1
timer list 1
log close
exit, clear
03_toolkit_report.do

* POSTSECONDARY ACCESSIBILITY INSTITUTIONAL TOOLKIT PROTOTYPE
* This do file generates the graphics necessary to output the markdown report
* USING DATASETS: institution_long_traveltimes.dta
* MERGED DATASETS: na
* SAVED DATASETS: na
* CREATED BY: KC Deane, April 2022
*

**************************************************************************
***** STANDARD HEADERS & MACROS                                      ****
**************************************************************************
clear all
version 16.0
set more off, perm
display c(current_date)
local dyn "YOURFILEPATH/090_toolkit/"
cd "YOURFILEPATH\090_toolkit\"
capture log close
log using "logs\03_toolkit_report.log", replace

**************************************************************************
***** (1) Open starting dataset          *****
**************************************************************************
use "data\institution_long_traveltimes.dta"

**************************************************************************
***** Label Variables **
**************************************************************************
label define race_lab 1 "White"     ///
                      2 "Black"      ///
                      3 "Hispanic/Latinx" ///
                      4 "Asian"      ///
                      5 "Amer. Indian/Alaska Native" ///
                      6 "Native Hawaiian/Pacific Islander" ///
                      7 "Multiracial" ///
                      8 "Unknown Race/Ethnicity" ///
                      9 "Non-Resident Alien", replace

label values race race_lab
label define enrollment_intensity_lab 0 "PT" 1 "FT", replace
label values enrollment_intensity enrollment_intensity_lab

label define retention 0 "Not Retained" 1 "Retained", replace
label values retention_ft retention
label values retention_pt retention

label define pell_receipt_lab 0 "No Pell" 1 "Received Pell", replace
label values pell_receipt pell_receipt_lab

label define grad150pct_lab 0 "No Grad" 1 "Grad 150%", replace
label values grad150pct grad150pct_lab

**************************************************************************
***** (1) Start building your descriptives (student-focused) *****
**************************************************************************

********************
** OVERALL AVERAGES **
** - BOTH MODES **
** - ALL TIMES **
******************

* AM GRAPH
graph set window fontface "Georgia"
graph bar (mean) time_car_am time_pt_am, ///
   graphregion(color(White)) plotRegion(color(White)) ///
   ytitle("Minutes", size(large) color(black)) ///
   margin(zero) height(7)) ///
   ylabel(0(10)50, nogrid labs(vlarge) angle(h)) ///
   bar(1, color("241 163 64")) bar(2, color("153 142 195")) ///
   legend(label(1 "Car") label(2 "Public Transit")) ///
   legend(size(medlarge) color(black) region(lstyle(none))) ///
   blabel(bar, position(outside) format(%9.1f) color(black) size(vlarge)) ///
   legend(rows(1)) legend(span)
graph export "output\avgtime_9am.png", replace width(500) height(400)

* PM GRAPH
graph bar (mean) time_car_pm time_pt_pm, ///
   graphregion(color(White)) plotRegion(color(White)) ///
   ytitle("Minutes", size(large) color(black)) ///
   margin(zero) height(7)) ///
   ylabel(0(10)50, nogrid labs(vlarge) angle(h)) ///
   bar(1, color("241 163 64")) bar(2, color("153 142 195")) ///
   legend(label(1 "Car") label(2 "Public Transit")) ///
   legend(size(medlarge) color(black) region(lstyle(none))) ///
   blabel(bar, position(outside) format(%9.1f) color(black) size(vlarge)) ///
   legend(rows(1)) legend(span)
graph export "output\avgtime_11am.png", replace width(500) height(400)
* EVE GRAPH

```
graph bar (mean) time_car_eve time_pt_eve, ///
  graphregion(color(White)) plotregion(color(White)) ///
  ytitle("Minutes", size(large) color(black)) ///
  margin(zero) height(7)) ///
  ylabel(0(10)50, nogrid labs(vlarge) angle(h)) ///
  bar(1, color("241 163 64")) bar(2, color("153 142 195")) ///
  legend(label(1 "Car") label(2 "Public Transit")) ///
  legend(size(medlarge) color(black) region(lstyle(none))) ///
  blabel(bar, position(outside) format(%9.1f) color(black) ///
  size(vlarge)) ///
legend(rows(1)) legend(span)
```

```
graph export "output\avgtime_8pm.png", replace width(500) height(400)
```

** AVERAGES by RACE/ETHNICITY **

** - BOTH MODES  **

** - 9am ONLY **

***********************************************************************

* Bar Graph with These Values

```
graph set window fontface "Georgia"
```

```
graph bar (mean) time_car_am time_pt_am, ///
  over(race, label(angle(30) labsize(medsmall))) ///
  graphregion(color(White)) plotregion(color(White)) ///
  ytitle("Minutes", size(large) color(black)) ///
  margin(zero) height(7)) ///
  ylabel(0(10)50, nogrid labs(medlarge) angle(h)) ///
  bar(1, color("241 163 64")) bar(2, color("153 142 195")) ///
  legend(label(1 "Car") label(2 "Public Transit")) ///
  legend(size(med) color(black) region(lstyle(none))) ///
  blabel(bar, position(outside) format(%9.1f) color(black) ///
  size(medsmall)) ///
legend(rows(1)) legend(span)
```

```
graph export "output\avgtime_race.png", replace width(1500) height(600)
```

312
line pct time_car_am if race==4 ||
line pct time_car_am if race==5 ||
line pct time_car_am if race==6 ||
line pct time_car_am if race==7 ||
line pct time_car_am if race==8 ||
line pct time_car_am if race==9,

graphregion(color(White)) plotregion(color(White))

ytitle("Population Percentile (by Race)",

size(small) color(black))

ylabel(0(10)100, nogrid labs(medsmall) angle(h))

xtitle("Driving Time (in Minutes)", size(small))

legend(size(vsmall) color(black)      
region(lstyle(none)) rows(3))

legend(label(1 "White") label(2 "Black")      
label(3 "Hispanic/Latinx") label(4 "Asian")
label(5 "Amer. Indian/Alaska Native")
label(6 "Native Hawaiian/Pacific Islander")
label(7 "Multiracial")
label(8 "Unknown Race/Ethnicity")
label(9 "Non-Resident Alien"))

graph export "output\cumultime_byrace_car.png", replace width(1500)
height(750)
drop rank count pct

* Public Transit

sort race time_pt_am
egen rank = rank(Time_pt_am), by(race)
egen count = count(time_pt_am), by(race)
gen pct = 100*(rank-0.5)/count

graph twoway

line pct time_pt_am if race==1 ||
line pct time_pt_am if race==2 ||
line pct time_pt_am if race==3 ||
line pct time_pt_am if race==4 ||
line pct time_pt_am if race==5 ||
line pct time_pt_am if race==6 ||
line pct time_pt_am if race==7 ||
line pct time_pt_am if race==8 ||
line pct time_pt_am if race==9,

graphregion(color(White)) plotregion(color(White))

ytitle("Population Percentile (by Race)",

size(small) color(black))

ylabel(0(10)100, nogrid labs(medsmall) angle(h))

xtitle("Public Transit Time (in Minutes)", size(small))

legend(size(vsmall) color(black)
region(lstyle(none)) rows(3))

legend(label(1 "White") label(2 "Black")
label(3 "Hispanic/Latinx") label(4 "Asian")
label(5 "Amer. Indian/Alaska Native")
label(6 "Native Hawaiian/Pacific Islander")
label(7 "Multiracial")
label(8 "Unknown Race/Ethnicity")
label(9 "Non-Resident Alien"))

graph export "output\cumultime_byrace_pt.png", replace width(1500)
height(750)
drop rank count pct
** Retention Rate by Travel Time Categories **

egen time_car_am_cat = cut(time_car_am), at(0,10,20,30,40,50,61)  
egen time_pt_am_cat = cut(time_pt_am), at(0,10,20,30,40,50,60,95)  

label define time_cat1  0 "0-10min"  
   10 "10-20min"  
   20 "20-30min"  
   30 "30-40min"  
   40 "40-50min"  
   50 "50-60min"  
   60 "60+ min", replace

label values time_car_am_cat time_cat1  
label values time_pt_am_cat time_cat1

replace retention_ft=retention_ft*100  
replace retention_pt=retention_pt*100

* Driving x Full-Time Retention Rate

graph bar (mean) retention_ft if enrollment_intensity==1,  
   over(time_car_am_cat, label(labsize(medsmall)))  
   graphregion(color(White)) plotregion(color(White))  
   ytitle("Retention Rate (Percent)"),  
   size(medlarge) color(black) margin(zero) height(7)  
   ylab(0(10)100, nogrid labs(medsmall) angle(h))  
   blabel(bar, position(outside) format(%9.1f) color(black)  
   size(medlarge))  
   bar(1, color("241 163 64"))

graph export "output\retention_ft_car.png", replace width(700)  
height(500)

* Driving x Part-Time Retention Rate

graph bar (mean) retention_pt if enrollment_intensity==0,  
   over(time_car_am_cat, label(labsize(medsmall)))  
   graphregion(color(White)) plotregion(color(White))  
   ytitle("Retention Rate (Percent)"),  
   size(medlarge) color(black) margin(zero) height(7)  
   ylab(0(10)100, nogrid labs(medsmall) angle(h))  
   blabel(bar, position(outside) format(%9.1f) color(black)  
   size(medlarge))  
   bar(1, color("241 163 64"))

graph export "output\retention_pt_car.png", replace width(700)  
height(500)

* Public Transit x Full-Time Retention Rate

graph bar (mean) retention_ft if enrollment_intensity==1,  
   over(time_pt_am_cat, label(labsize(medsmall)))  
   graphregion(color(White)) plotregion(color(White))  
   ytitle("Retention Rate (Percent)"),  
   size(medlarge) color(black) margin(zero) height(7)  
   ylab(0(10)100, nogrid labs(medsmall) angle(h))  
   blabel(bar, position(outside) format(%9.1f) color(black)  
   size(medlarge))  
   bar(1, color("153 142 195"))

graph export "output\retention_ft_pt.png", replace width(700)  
height(500)
* Public Transit x Part-Time Retention Rate

```stata
* graph bar (mean) retention_pt if enrollment_intensity==0, ///
  over(time_pt_am_cat, label(labsize(medsmall))) ///
  graphregion(color(White)) plotregion(color(White)) ///
  ytitle("Retention Rate (Percent)"), ///
  ylabel(0(10)100, nogrid labs(medsmall) angle(h)) ///
  bar(1, color("153 142 195")) ///
  graph export "output\retention_pt_pt.png", replace width(700) height(500)
```

* Driving/Has Car

```stata
* Driving/Has Car
replace grad150pct=grad150*100
* graph bar (mean) grad150pct, ///
  over(time_car_am_cat, label(labsize(medsmall))) ///
  graphregion(color(White)) plotregion(color(White)) ///
  ytitle("150% Graduation Rate (Percent)"), ///
  ylabel(0(10)100, nogrid labs(medsmall) angle(h)) ///
  bar(1, color("241 163 64")) ///
  graph export "output\grad150_car.png", replace width(700) height(500)
```

* Public Transit/No Car

```stata
* Public Transit/No Car
replace grad150pct=grad150*100
* graph bar (mean) grad150pct, ///
  over(time_pt_am_cat, label(labsize(medsmall))) ///
  graphregion(color(White)) plotregion(color(White)) ///
  ytitle("150% Graduation Rate (Percent)"), ///
  ylabel(0(10)100, nogrid labs(medsmall) angle(h)) ///
  bar(1, color("153 142 195")) ///
  graph export "output\grad150_pt.png", replace width(700) height(500)
```

***** (1) Create a map ******

```stata
bysort geoid: keep if _n==1
keep geoid time_car_am time_car_pm time_car_eve time_pt_am time_pt_pm
  time_pt_eve
rename geoid GEOID
merge 1:1 GEOID using "tl_2020_26_bg.dta", keep(match)
egen time_car_avg=rowmean(time_car_am time_car_pm time_car_eve) egen time_pt_avg=rowmean(time_pt_am time_pt_pm time_pt_eve)
gen transit_access=1 if time_pt_avg!=.
```

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colorpalette Greens, n(6)
grmap time_car_avg, ///
   fcolor(Greens) ndfcolor(White) clmethod(custom) ///
   clbreaks(0 10 20 30 40 50 61) legend(pos(4) ///
   ring(0) bmargin(vsmall) ///
   title(Commute (in mins), size(vsmall)))
graph export "output\map_car_avg.png", replace width(1000)

colorpalette Purples, n(7)
grmap time_pt_avg, ///
   fcolor(Purples) ndfcolor(White) clmethod(custom) ///
   clbreaks(0 10 20 30 40 50 60 95) legend(pos(4) ///
   ring(0) bmargin(vsmall) ///
   title(Commute (in mins), size(vsmall)))
graph export "output\map_pt_avg.png", replace width(1000)

**************************************************************************
***** (1) Actually create the report *****
**************************************************************************

graph close _all
dyndoc "`dyn'/toolkit_report_markdown.txt", ///
   saving("`dyn'/psa_toolkit_report.html") replace

clear all
log close
Appendix D: Example Toolkit Report (Simulated Data)
Student Commute Times at Imaginary Community College

This report summarizes driving and public transit commute times for student populations of interest at Imaginary Community College. Commute times estimated on April 22, 2022 using the georoute program in Stata 16.

Basic Information

In the Lansing/East Lansing, MI metropolitan area, 40% of students and 50% of block groups lack accessible public transit. The average student lives in a census tract where 6.6% households lack any access to a vehicle.

- Price of a Monthly Transit Pass for Students: $10 (Source: https://www.cata.org/Fare/Buy-Online/Products/Unlimited)
- Price Per Semester (if available): $25
- Nearest Bus Stop to Campus:
- Price per gallon in Region (as of date):
- Avg. Cost of Car Insurance in Region:
- Avg. Annual Cost of Car Maintenance:

Average Commute Times

By Mode and Time of Day

By Student Characteristics (9AM Home Departure Only)
Travel Time by Population Percentile
Retention Rates by Mode-Specific Commute Intervals

Driving

Full-Time

Part-Time
Public Transit

150% Graduation Rates by Mode-Specific Commute Intervals
Developed by KC Deane in 2022 as part of her dissertation on geographic accessibility of public colleges. Report produced using Markdown and the dyndoc command in Stata 16.
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