# Plugging the [Brain] Drain

Evidence from the LinkedIn profiles of college graduates

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# 1 Abstract

Controlling for local labor demand shocks, I measure the relationship between graduating from different types of baccalaureate institutions and return migration to home labor market and state. Local labor demand is my independent variable, measured with a Bartik shift-share instrument of County Business Patterns data. The dependent variable is a binary indicator whether an individual returned to their high school labor market or state sometime after graduating college, obtained from LinkedIn. The results imply the state's return on investment for in-state tuition subsidies varies by institutional grouping. When the labor market containing a graduate's high school experiences a positive labor demand shock, in-state graduates at Regional Public Universities are over ten percentage points (or about fifteen percent) more likely than Public Flagship alumni to remain in-state after graduation. Regional Public Universities credential graduates with the strongest attachment to their home labor market and state.

# 2 Introduction

In May 2023, urban scholar Richard Florida gave a speech to state policymakers in Michigan:

> You're using Michigan taxpayer dollars to subsidize the coastal high-tech economy. Now, if I'm a youngster coming out of University of Michigan, Wayne State, Michigan Tech, MSU. I want a good job and a good place. So [we've got them] drifting for San Francisco or New York or wherever...I think I need to think about that and what would it take to keep them. (Davidson 2023)

Public research universities, especially the University of Michigan and Michigan State University, dominate public perceptions of higher education in Michigan, reinforced by high-profile athletic events, academic prestige, and robust alumni networks. In Michigan, recent media coverage of brain drain and the state's policy initiatives focus on public research universities (Growing Michigan Together Council 2023; French 2023; LeBlanc 2023a; LeBlanc and Hall 2023). Yet the most prominent examples of public higher education generally produce graduates least likely to remain in-state after graduation. Indeed, Michigan Tech, the University of Michigan and Michigan State rank second, third and fourth respectively among Michigan's 15 public universities in share of graduates moving out-of-state (Conzelmann et al. 2022; French 2023). Graduates of Michigan's research universities receive outsize attention from state policymakers, who prioritize stemming departures of graduates from research institutions (Growing Michigan Together Council 2023; LeBlanc 2023a; 2023b). Policymakers' focus on retaining graduates from research universities raises the question: why do certain types of institutions produce graduates who leave at higher rates than alumni of others? This paper explores how institutional characteristics affect migration decisions of college graduates using data from LinkedIn (LI) profiles. Controlling for local labor demand shocks, I measure the relationship between graduating from different types of baccalaureate institutions and return migration to home labor market and state. This paper makes a novel contribution to the literature on educational sorting by analyzing migration microdata from LI. With microdata, I control for individual characteristics like in-state status and link graduates to educational institutions and geographic locations.

## 2.1 Educational Sorting

College graduates increasingly live in different metropolitan areas than non-graduates, with the disparity growing over the last four decades (Diamond and Gaubert 2022; Diamond 2016). College graduates provide benefits to the communities they inhabit, including social benefits like lowered crime and improved health outcomes (Moretti 2003). Locales with higher proportions of college-educated workers enjoy stronger productivity and wage growth for all workers, regardless of educational attainment (Diamond 2016). Yet those locales are increasingly concentrated on coasts. High-cost areas like Washington, California, New York, and the District of Columbia are net importers of college graduates, while nation's interior exports graduates (Conzelmann et al. 2022). The college wage premium allows educated workers to maintain or boost consumption in high-cost metros, but workers without college degrees must cut consumption in expensive metropolitan areas (Diamond and Moretti 2021). Spatial clustering of educated workers worsens inequality across the country and within the migration destinations of educated workers.

The clustering of college graduates accelerates regional economic divergence, entrenching regional winners and losers within the United States. Regional economic divergence defies the spatial convergence predicted by standard economic frameworks like the Rosen-Roback model (Roback 1982). Technological advancement and de-industrialization remain the dominant economic explanations for the divergence (Autor, Dorn, and Hanson 2013). Institutional changes over the last four decades, such as weakened antitrust enforcement and increased competition between local governments for economic development, potentially exacerbate regional economic divergence (Manduca 2019; Pacewicz 2016). Economic divergence gnaws at national cohesion, complicating the work of national policymakers constrained by a single budget and interest rate (Manduca 2019). As college graduates cluster, regional inequality across the United States worsens, contributing to political polarization (Autor et al. 2020) and wide variation in social mobility (Chetty et al. 2014). From the perspective of taxpayers, the clustering of college graduates generates spatial variation in the return on investment for public higher education (Conzelmann et al. 2022). Across the United States, high-wage urban areas retained more college graduates per dollar invested in higher education. Locales that import college graduates enjoy more of the social benefits wrought by holders of bachelor's degrees (Conzelmann et al. 2022).

In short, institutional characteristics matter as policymakers attempt to smooth the spatial concentration of college graduates. Given the outsize role migration plays in regional economic divergence, college graduate settlement patterns yield important ramifications for the macroeconomic cohesion of the United States. The macro-level pattern of clustered college graduates reflects millions of individual migration decisions. At the micro-level, individual preferences about amenities, employment opportunities, and proximity to friends and family mold migration decisions. Relative to other populations, college graduates place particular weight on employment opportunities (Hershbein and Stuart 2022; Wozniak 2010). Thus, local labor markets mediate college graduates' decision to remain or relocate. Spatial variation in local labor demand makes certain locations more or less desirable as migration destinations.

## 2.2 Labor Demand Shocks and Migration

While amenities likely figure into most people's migration decisions (Florida 2002), college graduates place heavy weight on labor market conditions (Conzelmann et al. 2022; Wozniak 2010; Bound and Holzer 2000; Notowidigdo 2020). Even though college graduates are particularly sensitive to labor market conditions (Hershbein and Stuart 2022; Wozniak 2010), 41 percent of the college graduates in the sample of LI users described in 5.1 returned to their high school labor market. Most people esteem local ties, deriving high utility from their network of coworkers, friends, and family (Zabek 2019). The attachment to place persists during economic downturns, driving down real wages and lowering labor force participation rates. Hershbein and Stuart 2022 find out-migration rates fell in labor markets with the most severe employment declines during recessions. Instead, lower rates of in-migration drive population losses in communities with steep employment declines. In many cases, the appeal of local social networks blunts the effects of adverse labor market conditions.

College graduates are more mobile than the rest of the population, driven by strong attachment to the labor market (Notowidigdo 2020). Yet migration behavior varies substantially depending on where an individual obtained a bachelor's degree (Conzelmann et al. 2022). Social ties and local labor demand are not the only considerations in college graduates' migration decisions: where someone went to college matters too.

## 2.3 Institutional Effects

The United States contains thousands of institutions granting bachelor's degrees, serving more than 15 million students (National Center for Education Statistics 2022). Unsurprisingly, undergraduate experiences and post-graduation outcomes vary by institution. Post-graduation earnings trajectories, occupational profiles, spatial distributions, and socioeconomic compositions differ greatly by institution type (Chetty et al. 2020; Conzelmann et al. 2022). Socioeconomic inequality drives some of the variation in outcomes. American higher education segregates by socioeconomic status, with students from top fifth of the income distribution seven times more likely to enroll at Private

Non-Profit or Public Flagship[1] institutions than the bottom fifth (Chetty et al. 2014). Despite intra-institution segregation by socioeconomic status, post-secondary institutions facilitate movement across social classes (Chetty et al. 2020). Parental income also shapes migration patterns. Sprung-Keyser, Hendren, and Porter 2022 finds a clear relationship between parental income and probability of relocation: as parental income increases, children are more likely to relocate to distant labor markets as adults. Perhaps unsurprisingly, idiosyncratic structures like alumni networks and university career centers potentially contribute to the spatial concentration of college graduates, at least among alumni of elite universities (Manduca 2022). Despite the outsize role institutional characteristics play in migration of college graduates, literature exploring the interaction between institution type and migration remains sparse.

## 2.4 Limitations of Current Literature

Data limitations contribute to the paucity of literature. Limited data linking workers to hometowns constrains analysis of the relationship between hometown and migration preferences (Dahl and Sorenson 2010; Carr and Kefalas 2010; Sprung-Keyser, Hendren, and Porter 2022). The sample tracked by Sprung-Keyser, Hendren, and Porter 2022 only includes educational attainment for individuals who responded to the American Community Survey (ACS). Earlier analyses suffered even greater limitations. Most rely on five percent samples of the Decennial Censuses or the ACS, depending on the time frame (Diamond and Gaubert 2022; Wozniak 2010; Bound and Holzer 2000). The ACS nor the Decennial Census samples only include state of birth, precluding exploration at a more detailed spatial level.

Large national surveys may collect data on baccalaureate institution and migration, though LI sample sizes are scales of magnitude larger, allowing for greater geographic coverage. The Panel Study of Income Dynamics asks respondents about where they attended college, but geolocation and secondary school data are restricted-access only. Likewise, the National Longitudinal Survey includes a migration distance variable, though data isn't as reliable as state and county of residence

1. Section 5.3 defines the Public Flagship and Private Non-Profit institutional groupings, plus additional categories for other baccalaureate institutions.

variables. The Census Bureau's new Post-Secondary Employment Outcomes (PSEO) dataset offers promise, though coverage varies greatly by state and sample sizes remain miniscule (Conzelmann et al. 2022). For example, the only institution in Michigan included in PSEO is the University of Michigan–Ann Arbor. By contrast, LI enables analysis of sub-state migration matters *and* characteristics of post-secondary institutions.

Using LI data, Conzelmann et al. 2022 find graduates of more selective institutions travel further and exhibit greater spatial dispersion. However Conzelmann et al. 2022 relies on summary data by institution, rather than individual-level microdata linking high schools, colleges, and post-graduation outcomes. Due to data constraints, limited research contextualizes post-college migration decisions with hometowns. Given the importance of local ties in shaping migration decisions, analyses of migration that exclude origin data likely suffer from omitted variables bias (Zabek 2019; Hershbein and Stuart 2022). The structure of LI summary data prevents Conzelmann et al. 2022 from analyzing heterogeneity in migration decisions with respect to in-state status. With micro-data, I can evaluate the association between in-state status and migration. State higher education appropriations, which subsidize tuition for in-state students at public universities, face increasingly stiff political headwinds (Bound et al. 2019). Thus, the value of subsidies for in-state students remains a relevant venue for policy research.

## 2.5 Summary of Findings

Adapting the empirical strategy in Notowidigdo 2020 and Bound and Holzer 2000, I use a Bartik (or shift-share) instrument to estimate local labor demand shocks. The instrument projects local employment growth based on national employment growth and local industrial mix, constituting the independent variable (Bartik 1991). The instrument decomposes employment growth stemming from supply factors and global shifts in demand, creating a "plausibly exogenous" measure of local labor demand (Notowidigdo 2020; Wozniak 2010; Bound and Holzer 2000). The dependent variable is binary, indicating whether an individual returned to the state containing their high school at any point after graduating college.

Much of the analysis focuses on public universities, delineating between large research-intensive flagship institutions (PFs) and regional public universities (RPUs) with greater emphases on undergraduate education. Graduates of flagship institutions leave their high school labor market at significantly higher rates than RPU alumni. Unsurprisingly, in-state graduates return at higher rates than out-of-state students. When their high school labor market experiences a positive labor demand shock, in-state RPU graduates are ten percentage points more likely than in-state PF alumni to remain in the same state as their college and high school. The difference between graduates of PFs and RPUs is statistically significant at the 0.1 percent level. PF graduates are less sensitive to demand shocks in their high school labor market than graduates of RPUs.

Relative to RPU alumni, in-state graduates of PFs exhibit weak attachment to the state that subsidizes their education, suggesting the state's return on investment for in-state tuition subsidies varies by institutional grouping. Furthermore, RPUs, especially less selective ones, face intense demographic and fiscal headwinds as small post-Recession cohorts approach matriculation (Grawe 2018). Thus, the institutions most vulnerable to the economic and demographic vicissitudes of the next few decades produce graduates with the strongest attachment to their home labor market and state.

## 3 Theoretical Framework

To understand how individuals make migration decisions, consider how they weigh the costs and benefits of moving (Wozniak 2010; Sprung-Keyser, Hendren, and Porter 2022). Let $C$ be a set of locations, where individual $i$ inhabits one such location $j$ and considers $k$ a potential destination.[2] Individual $i$ belongs to some educational group $e$, which correlates with human capital. The econometrician cannot directly observe human capital, only its correlates like educational attainment or baccalaureate institutional characteristics (Sprung-Keyser, Hendren, and Porter 2022). Let the model include two time periods: $\{t_0, t_1\} \in T$. The choice problem is the following:

$$\arg\max_{k \in C} \; U(\omega_k) = \left\{ \sum_{t}^{T} \left[ \frac{E(w(e)_{kt})}{P_{kt}} - r(e)_{jk} \right] \right\} - o(e)_{jk} \tag{1}$$

2. For the purposes of my analysis $\{j, k\}$ are sub-state labor markets and $C$ is the United States

where $U(\omega_k)$ is the utility individual $i$ derives from inhabiting location $k$ and $e$ represents an educational group. Education group correlates with human capital. Wozniak 2010 operationalized $e$ as educational attainment. By contrast, I use institutional groupings based on selectivity, flagship status, and control as the basis for $e$.

Individuals in each educational group expect different wages so $E[w(e)_{kt}]$ is the average wage of education group $e$ in location $k$ at time $t$. Economic theory predicts a relationship between wages and labor demand shocks: positive demand shocks will boost wages and negative ones will diminish wages (Bartik 1991). $P_{kt}$ is the price level at location $k$ at time $t$, Thus, $\frac{E(w(e)_{kt})}{P_{kt}}$ measures real wages for educational group $e$ in location $k$ at time $t$.[3]

Individuals face both recurring and one-time moving costs (Wozniak 2010), represented by $r(e)$ and $o(e)$ respectively. Assume $r(e)_{jk} = o(e)_{jk} = 0$ when $j = k$, so individuals bear no moving costs for remaining in the same location. One-time moving costs consist of expenses typically associated with physical relocation, like beer and pizza for movers, truck rental, and boxes. Recurrent moving costs include the psychological cost of being far from friends and family, return travel costs, and preferences for local amenities in $j$ (Sprung-Keyser, Hendren, and Porter 2022). Thus, the costs depend entirely on subjective considerations like individual preferences towards proximity to family, and local amenities. As a result, measurement of recurrent moving costs isn't possible from existing public data. However, LinkedIn profiles listing high school and college offer a means of (imperfectly) estimating recurrent moving costs. Social ties drive attachment to place, and educational institutions facilitate the formation of social ties (Zabek 2019). If an individual is attached to a place, the location is likely the site of either secondary or post-secondary educational experiences. Secondary schooling garners particular importance because most people reside with their parents during high school, an effective proxy for familial ties. Thus, I can estimate recurrent moving costs based on the locations of an individual's high school and college. Educational experiences shape the spatial arrangement of an individual's social ties, a substantial component of the recurrent moving costs in migration decisions.

3. Yagan 2014 notes individuals move for two reasons. Some migrate for better labor market opportunities, while others migrate to weaker labor markets to enjoy a lower cost of living. By treating relocation decisions as a function of real wages, I implicitly account for spatial variation in the cost of living.

According to the model, individual $i$ seeks to live in a location that maximizes utility relative to all other locations, after accounting for moving costs. Put another way, individuals who relocate must satisfy the inequality:

$$\left\{ \left( \sum_{t}^{T} \left[ \frac{E(w(e)_{kt})}{P_{kt}} - r(e)_{jk} \right] - o(e)_{jk} \right) \geq \sum_{t}^{T} \left[ \frac{E(w(e)_{jt})}{P_{jt}} \right] \,\middle|\, j \neq k \right\} \tag{2}$$

For an individual to relocate, their destination must offer a higher wage, even after accounting for fixed and one-time moving costs. The framework helps explain why domestic out-migration is relatively uncommon (Zabek 2019; Hershbein and Stuart 2022). Preferences for one's current location $j$ embedded in $c(e)_{jk}$ raise the cost of moving. As a result, widespread out-migration requires paltry wages or strong attachment to the labor market. High rates of out-migration among low-income workers in Appalachia or the Mississippi Delta satisfy the first condition, driven away due to low equilibrium wages (Sprung-Keyser, Hendren, and Porter 2022). The second condition is the focus of the paper. In general, college graduates migrate at higher rates than their peers without college degrees, suggesting college strengthens attachment to the labor market at the expense of place (Notowidigdo 2020; Wozniak 2010). I want to know whether institutional characteristics like selectivity, flagship status, and control are salient parameters in migration decisions.

# 4 Empirical Strategy

I can operationalize my research question by treating local labor demand as exogenous and residence in the high school labor market (and state) as the dependent variable.

## 4.1 Regression Model

I measure all post-graduation migration behavior, constrained by the time horizon of County Business Patterns data from Eckert et al. 2021. Ultimately, the early extent of the time horizon matters little because half of the LI user sample graduated from college in the last 10 years.[4] Likewise,

4. Figures 1, 2, 3, and 4 characterize the age distribution of the sample in greater detail.

the first decade after college graduation heavily influences long-term settlement decisions (Wozniak 2010). Less likely to be constrained by complex familial considerations, Americans exhibit the most mobility in their twenties, when most people obtain post-secondary credentials (Wozniak 2010).

I index observations by the labor market of the high school, denoted by $j$. Importantly, only the high school needs to be in $j$; the college can be anywhere in the United States. However, people who stay in the same labor market for high school and college ($j = k$) face a different decision-making process than people who leave their high school labor market for their bachelor's degree ($j \neq k$). People who attend college elsewhere compare the conditions of their home labor market $j$ relative to their college labor market $k$. Those who stay cannot make such a comparison. Their decision to remain depends on the conditions of the labor market where they attended both college and high school. Equation 3 describes the return rate as a function of local economic conditions in the labor market of the high school $j$ and college $k$ if $j \neq k$:

$$stay_{ij} = \beta_1 hsLD_{jt} + \beta_2 colLD_{kt} + \beta_3 colType + \beta_4(colType \times s_i) + \beta X'_{jkt} + \phi_M + \alpha_t + \mu_{ijt} \quad (3)$$

where $stay_{ij}$ is a binary indicator for individual $i$ ever residing in their high school labor market $j$ (or state $M$) at any time $t \in T$ after college graduation such that

$stay_{ij} =$

$$\begin{cases} 1 & \text{Individual } i \text{ attended high school in labor market } j \text{ and resided in labor market } j \text{ at a time } t \in T \\ 0 & \text{Individual } i \text{ attended high school in labor market } j \text{ and never resided in } j \text{ at a time } t \in T \end{cases}$$

$hsLD_{jt}$ is the labor demand shock at time $t$ in the labor market $j$ containing the high school,

$colLD_{kt}$ is the labor demand shock at time $t$ in labor market $k$ containing the college,

$colType$ is the institutional grouping of the college, described more in Section 5.3

$s_i =$

$$\begin{cases} 1 & \text{Individual } i \text{ received bachelor's degree from institution in same state as high school} \\ 0 & \text{Individual } i \text{ did not receive bachelor's degree from institution in same state as high school} \end{cases}$$

$X_i'$ is a vector of individual controls: transfer status, age at bachelor's attainment, and major,

$\phi_M$ measures fixed effects in state $M$ containing high school labor market $j$ such that $j \subseteq M$,

$\alpha_t$ reports proportional shocks across all labor markets in a given time period, and

$\mu_{ijt}$ captures unobservable error.

I also include an alternative specification, switching out the in-state interaction term with an term interacting institution type and the labor demand shock

$$stay_{ij} = \beta_1 hsLD_{jt} + \beta_2 colLD_{kt} + \beta_3 colType + \beta_4 (colType \times hsLD_{jt}) + \beta X_{jkt}' + \phi_M + \alpha_t + \mu_{ijt} \quad (4)$$

The alternative specification allows me to explore how graduates of different types of institutions respond to identical labor demand shocks.

## 4.2 Bartik Local Labor Demand Instrument

I use the Bartik shift-share instrument to estimate local labor demand variables $hsLD_{jt}$ and $colLD_{kt}$ (Bartik 1991). The Bartik instrument enables direct comparison of labor demand shifts of equal magnitude but opposite sign (Notowidigdo 2020). Both Wozniak 2010 and Bound and Holzer 2000 employ the Bartik instrument to gauge the relationship between local labor market conditions and migration.

### 4.2.1 Assumptions

Importantly, Bartik instruments assume no correlation between national employment growth by industry and local labor supply shocks (Bartik 1991). Thus, the instrument detects "plausibly exogenous" (demand-induced) variation at the labor market level (Notowidigdo 2020). Further, the model in Equation 3 assumes that the instrument does not correlate with unobserved shocks in the local labor supply (represented by $\epsilon$).

#### 4.2.2 Formal Definition

The Bartik instrument interacts cross-sectional differences in industrial structure with national changes in employment growth by industry (Goldsmith-Pinkham, Sorkin, and Swift 2020). The formal definition begins by calculating predicted employment change $\pi_{i,t,}$ below:

$$\pi_{i,t} = \sum_{k=1}^{K} \gamma_{i,k,t-\tau} \left( \frac{v_{k,t} - v_{k,t-\tau}}{v_{k,t-\tau}} \right) \tag{5}$$

where $i$ indexes labor markets, $t$ indexes time periods, $k$ indexes industries $\in K$. Let $\tau$ represent the time period for measuring change such that $t-\tau$ represents the start of the period and $t$ marks the end of the period. Thus, $\gamma_{i,k,t-\tau}$ records the share of local employment in industry $k$ at time $t-\tau$. The Bartik instrument measures national industry employment growth rates $v_{k,t} - v_{k,t-\tau}$. Since national shifts do not require summation at the labor market level, $v_{k,t}$ does not use the labor market index $i$. The instrument then calculates predicted employment change between time $t-\tau$ and $t$:

$$\hat{E}_{i,t} = (1 + \pi_{i,t}) E_{i,t-\tau} \tag{6}$$

where $E_{i,t-\tau}$ consists of total local employment at time $t-\tau$ and $(1+\pi_{i,t})$ converts predicted employment change to a ratio. The proxy for labor demand appears below:

$$\Delta\hat{\theta}_{i,t} = \frac{(\hat{E}_{i,t} - E_{i,t-\tau})}{E_{i,t-\tau}} \tag{7}$$

where $E_{i,t-\tau}$ remains local employment at time $t-\tau$ and $\hat{E}_{i,t}$ records the total employment predicted by the instrument for time $t$. Thus, $\Delta\hat{\theta}_{i,t}$ is the difference between predicted and actual employment, divided by the actual employment at time $t-\tau$.

Thus, the results in subsequent sections of the paper estimate demand using $\Delta\hat{\theta}$ for two local labor markets: $j$ containing high school and $k$ containing baccalaureate institution.

$$\Delta\hat{\theta}_{j,t} = hsLD_{jt} \tag{8}$$

$$\Delta\hat{\theta}_{k,t} = colLD_{kt} \tag{9}$$

# 5 Data

Equation 3 combines four types of data: geographic and demographic data from LinkedIn profiles, secondary and post-secondary institutional characteristics from the National Center for Education Statistics, Barron's selectivity ratings, and labor demand shocks estimated with County Business Patterns data.

## 5.1 LinkedIn

I created a database of individual-level educational attainment and migration behavior using LinkedIn profile data. Revelio Labs pulled the data, then the Brookings Institution's Workforce of the Future Research Initiative provided access to the data.[5] Each profile includes information on:

- Which high school an individual attended
- Which college an individual attended
- Where an individual lived after graduating from college

### 5.1.1 Resumes as Migration Microdata

A LinkedIn profile that includes a high school, college, and some post-graduation work experience tells a story missed by standard survey data like the American Community Survey or even administrative data from the IRS. LI links degrees to educational institutions and employment to spatially-defined labor markets. In other words, LI provides a record of the educational institution an individual attended and residential choices post-graduation.

The two most common methods for exploring migration, ACS microdata and Decennial Census samples, suffer from limitations. The ACS asks respondents about the field and degree obtained,

5. I am incredibly grateful to Gregory Wright and Ian Seyal at Brookings for granting me access to the data during my internship in summer 2022. I am also indebted to Ana Reynoso of the University of Michigan, who generously provided space on her server for the massive dataset.

but not the institution. The five percent Decennial Census samples remove any possibility of sub-state analysis, since states are the most granular geography describing birthplace and residence in the microdata. Like the ACS, the samples from Decennial Census also lack data on the characteristics of baccalaureate institutions. By contrast, LI enables analysis of sub-state migration *and* characteristics of post-secondary institutions.

### 5.1.2 Demographic Representation in LinkedIn Profiles

Of course, LI suffers from limitations (Kreisman, Smith, and Arifin 2021). Crucially, self-reporting of educational experiences leads to systematic under-reporting of certain experiences, namely non-completion of degrees. Despite accounting for nearly half of all college attendees and roughly one-third of workers, non-completers often hide their post-secondary education. Individuals who attended for less than two years or attended non-selective institutions omit educational experiences at the highest rates (Kreisman, Smith, and Arifin 2021). LI users skew young and college-educated (Conzelmann et al. 2022). Nonetheless, the sheer size of the user population offers research opportunities.

### 5.1.3 Cleaning and Discarding Observations

Not all LI profiles contain the same quantity of data. Culling the dataset of profiles with limited information improves the quality of the remaining observations. Most importantly, users must include a high school and a college in the United States. Less than ten percent of college graduates include a high school, and future research should explore whether those who omit high schools may skew towards selective schools and globalized industries. For the current analysis, I impose the following restrictions:

- Graduated from college 1982-2021[6]
- Bachelor's degree listed in profile
- High school name listed in profile

6. The choice of 1982 reflects data limitations. Eckert et al. 2021 provide harmonized data starting in 1975, meaning 1982 is the first year where a seven-year average could be calculated.

- At least one job after college graduation with a location listed

Table 1 documents the effect of each restriction on sample size. Since I wanted to focus on domestic migration patterns, I omitted individuals who attended college or high school outside the United States. Users need to list at least one position after their college graduation in the United States with a start date before the end date. While it might seem trivial, some users list jobs with start dates *after* end dates.

Table 1 indicates that the first restriction imposed (requiring college graduates to include a high school) proves most costly to sample sizes.

Table 1: Effect of data cleaning on sample size.

| Reason | Sample |
|---|---|
| All BA Completers in US | 32,128,789 |
| Include HS | 2,152,022 |
| Work history has geodata | 2,088,215 |
| Work history has end date after start | 2,070,820 |
| Work history has start or end date | 2,070,716 |
| Work history between 1975 and 2023 | 1,847,609 |
| College appears in IPEDS | 1,786,291 |
| Graduated college [1982,2021] and born [1930,2002] | 1,557,165 |
| Educational institutions in 50 states or DC | 1,557,078 |
| Final analytic sample | 1,557,062 |

Most LI users omit their high school, eliminating more than 90 percent of college graduates on the site. Imposing the requirement of at least one position with a location, start date, and end date removes users with minimal information on their profiles. Availability of County Business Patterns data from Eckert et al. 2021 and the US Census Bureau resulted in the restrictions on college graduation. County-level estimates of labor demand shocks are only available until 2021. Most of the observations removed from the sample were people who graduated after 2021. The limits on estimated year of birth remove obvious outliers that likely stem from data entry errors, like two users allegedly born in 1882 but graduating from college in 1997.

**Age** LinkedIn users are younger than the working population, so analytical sample over-represents workers born between 1986 and 2000. Figure 1 reports the age distribution of both the sample and college graduates in the labor force according to the 2022 American Community Survey. Most of the sample falls into the youngest quartile of the labor force (those born after 1987). Accordingly,

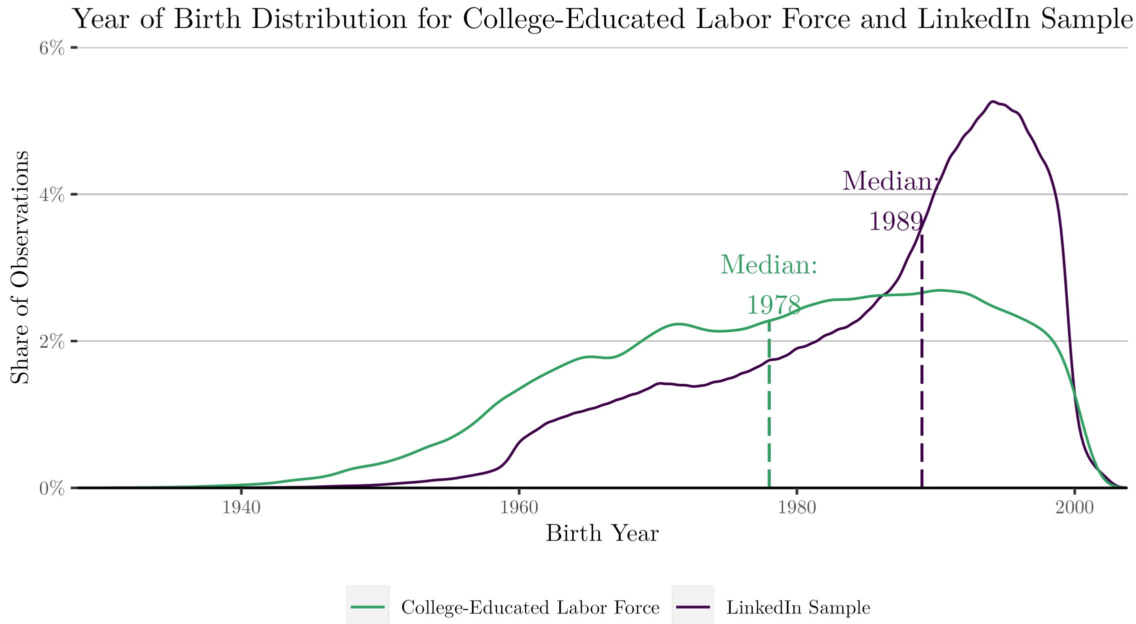



Figure 1: Age distribution of analytical sample compared to college-educated workforce according to 2022 American Community Survey microdata. The sample over-represents users born between 1986 and 2000. Likewise, the median observation in the analytical sample is 11 years younger than the median college-educated worker (1978 vs. 1989), falling in the youngest quartile of college-educated labor force. The older half of the college-educated workforce represents less than a quarter of the sample.

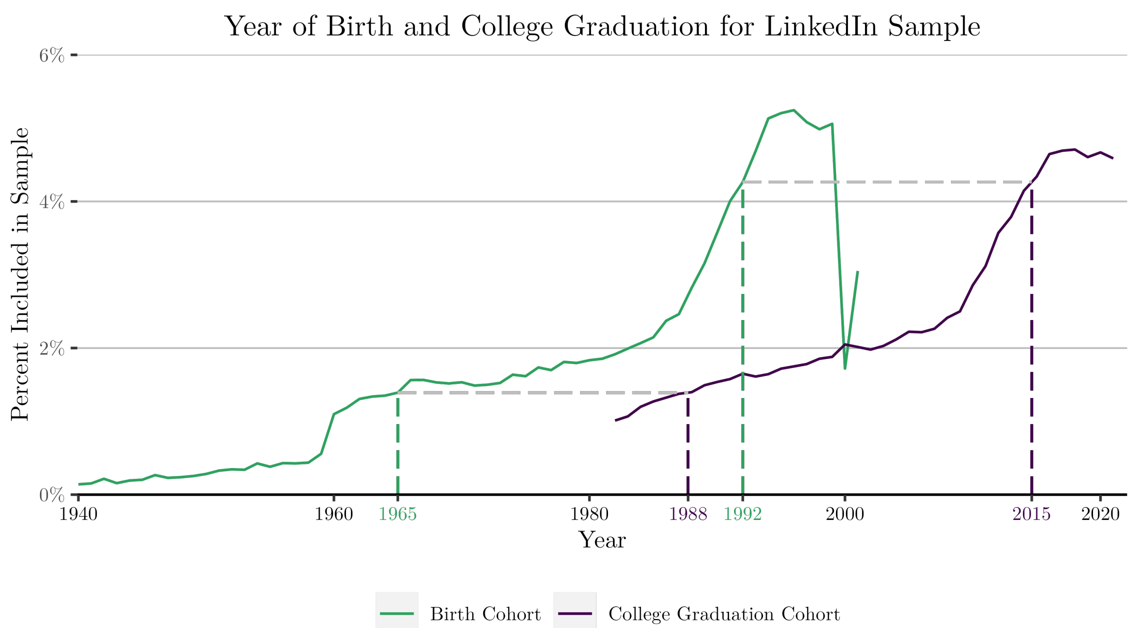



Figure 2: The y-axis measures the LI user sample as a share of all college graduates, by birth and college graduation year. Estimates of birth years come from 2022 American Community Survey microdata and college graduation dates from the 2022 Digest of Education Statistics. Clearly, the analytical sample primarily includes younger workers. Cohorts born in the 1990s and graduating college in the 2010s appear at far higher rates than older workers. Coverage improves dramatically for cohorts born in the 1980s and graduating college in the 2010s. The figure also constitutes a robustness check on the process for estimating birth cohorts outlined in Section 5.1.5. Regardless of year of birth, users in the sample graduate an average of 23 years later, reflecting the fact that bachelor's completion takes more than four years for many.

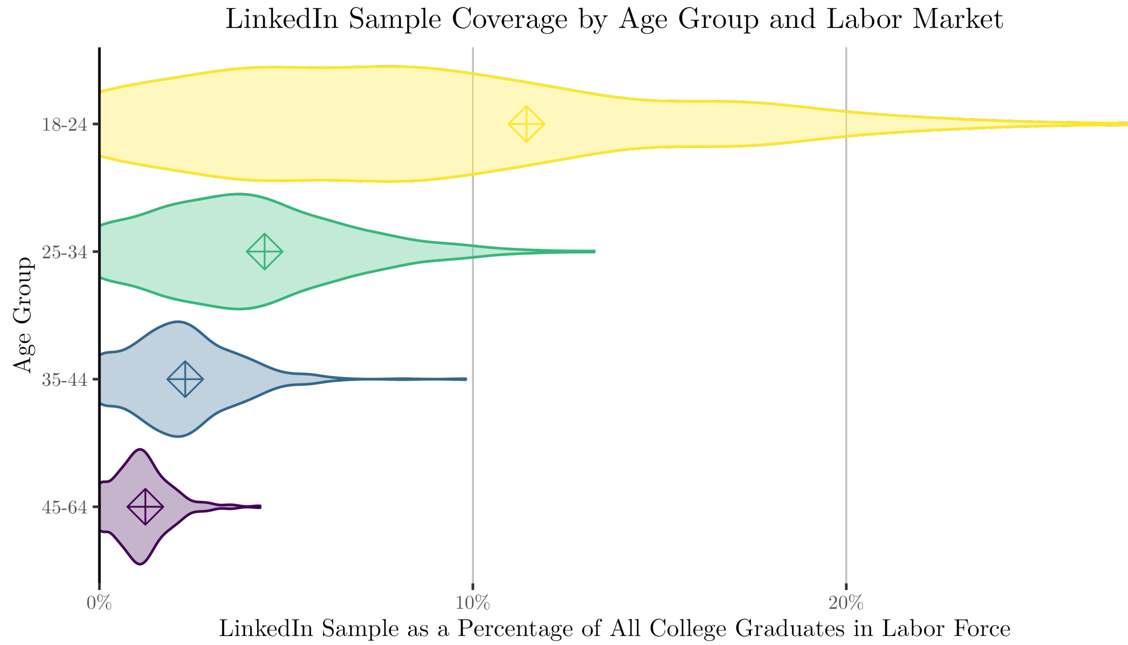



Figure 3: The share of college graduates included in the sample varies across age groups and labor markets. The rhombuses denote population-weighted medians for each age group. As users age, the tail shortens and the median approaches zero, reflecting the relative youth of LI's user base shown in Figure 1. In the median labor market, the analytical sample includes 11.4 percent of 18-24 college graduates in the labor force, 4.4 percent of those 25-34, 2.3 percent of those 35-44, and 1.2 percent of those 45-64. The widths are population-weighted frequencies. Wider bars at a particular level of coverage indicate more workers live in labor markets at that level of coverage.

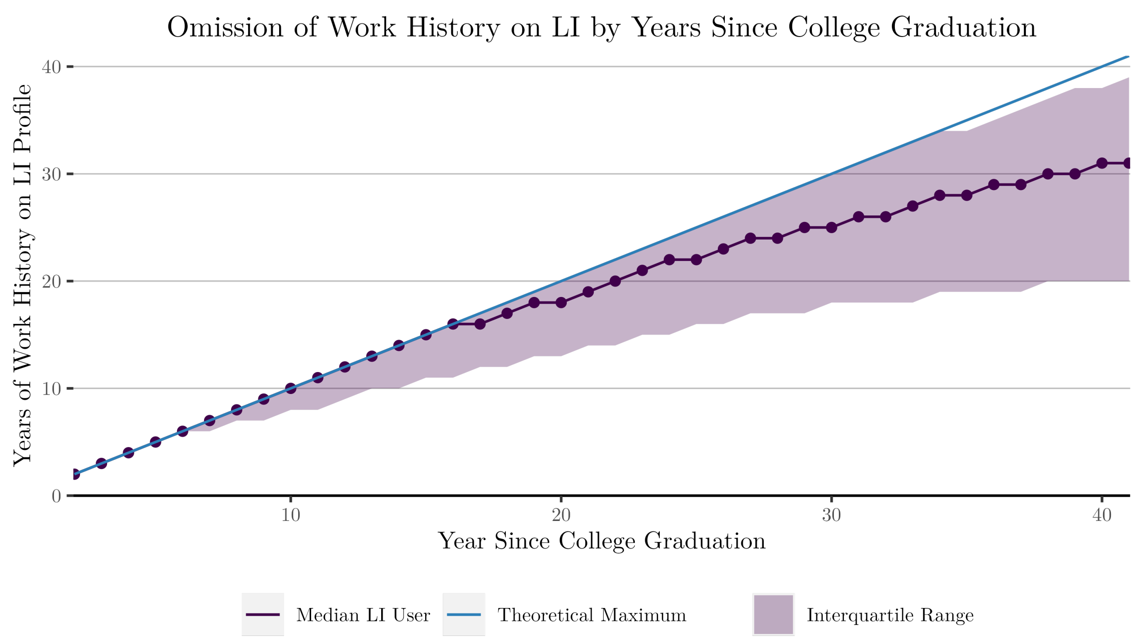



Figure 4: If every LI user continuously worked and recorded their entire employment history on their LI profile, everyone would follow the blue line. However, many users strategically omit information, particularly older users (Kreisman, Smith, and Arifin 2021). Likewise, labor force participation fluctuates by age, particularly for childbearing women (Pilkauskas, Waldfogel, and Brooks-Gunn 2016). Sixteen years after graduating college, the median LI user's profile no longer covers every year after graduation. The purple shading shows the middle 50 percent of LI users, indicating most LI users keep no more than 20 years of employment history on their profile.

Figure 2 shows the sample includes more than 3 percent of all college-educated workers born in the late 1980s and 1990s, but fewer than 2 percent for cohorts born before 1983.

LinkedIn users rarely include their entire work history. As workers age, they often omit early work experiences. According to Figure 4, the median LI user begins omitting post-college employment history 15 years after graduation. Omission could occur because a user dropped out of the labor market or strategic omission (Kreisman, Smith, and Arifin 2021). Regardless of the reason for omission, LI profiles generally include no more than two decades of work history, even if a worker graduated from college more than 20 years ago.

The share of working college graduates appearing in the sample varies by labor market and age group, with the tail shrinking and the median approaching zero among older age groups. Figure 3 disaggregates the prime-age population from Figure 6 to show the distribution of coverage by age group in different labor markets. Clearly, coverage varies substantially by age and geography, with younger workers represented more heavily in the LI user sample.

**Geography** The sample's coverage of college-educated prime-age workers in the labor force varies by labor market. Figure 6 depicts the proportion of prime-age college graduates covered by the sample by labor market. Generally, northern labor markets report higher rates of coverage, with some pockets of high coverage in the lower Mississippi Valley. By contrast, major Sun Belt labor markets in California, Texas, Florida, Georgia, and North Carolina show relatively low rates of coverage.

Next, I test how certain characteristics of labor markets affect coverage rates. LI users make strategic decisions when they include information on their profile (Kreisman, Smith, and Arifin 2021). Requiring a high school imposes the greatest tax on sample size according to Table 1. Thus, the coverage rates probably reflect more users including a high school on their profile. The inclusion of high school might offer more benefits in smaller labor markets where employers and coworkers live in close proximity. Similarly, college graduates might include high school in regions with lower rates on in-migration, since incumbent workers dominate the labor market.

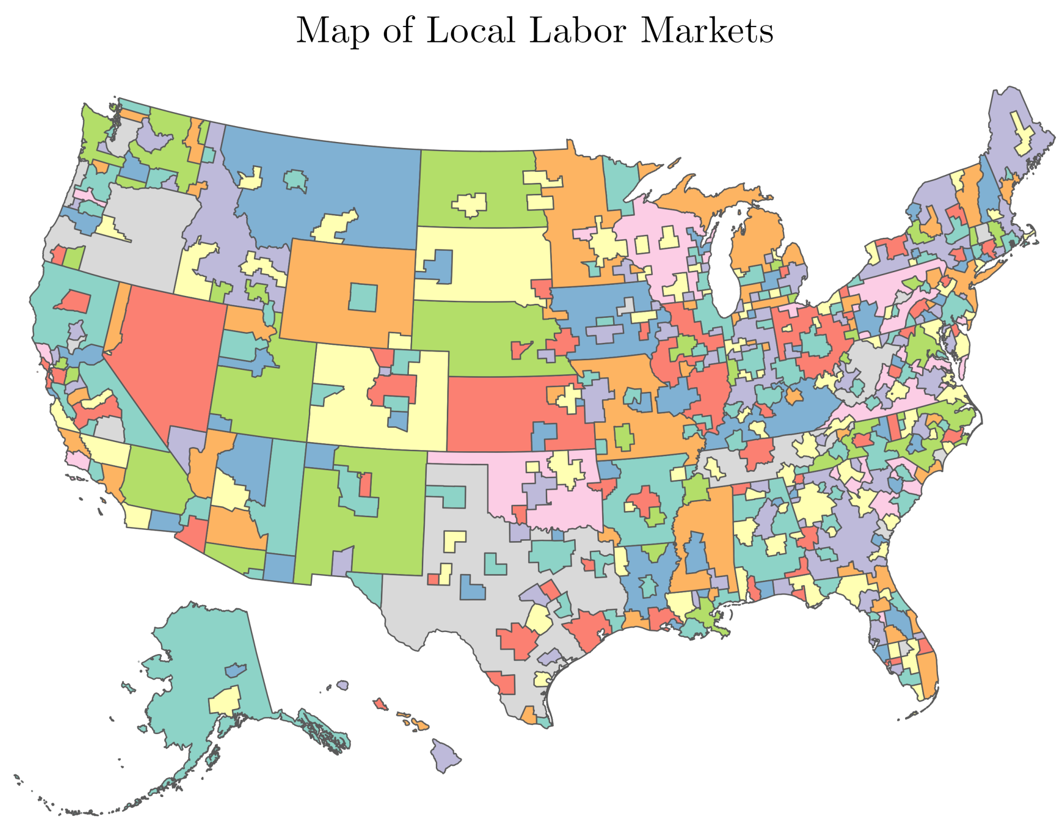
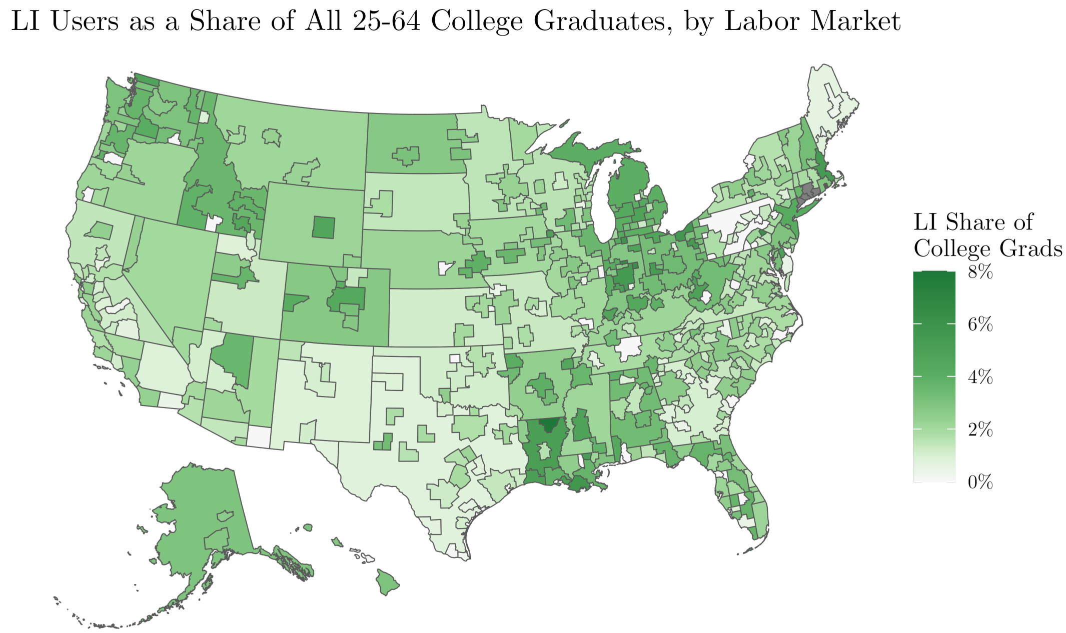
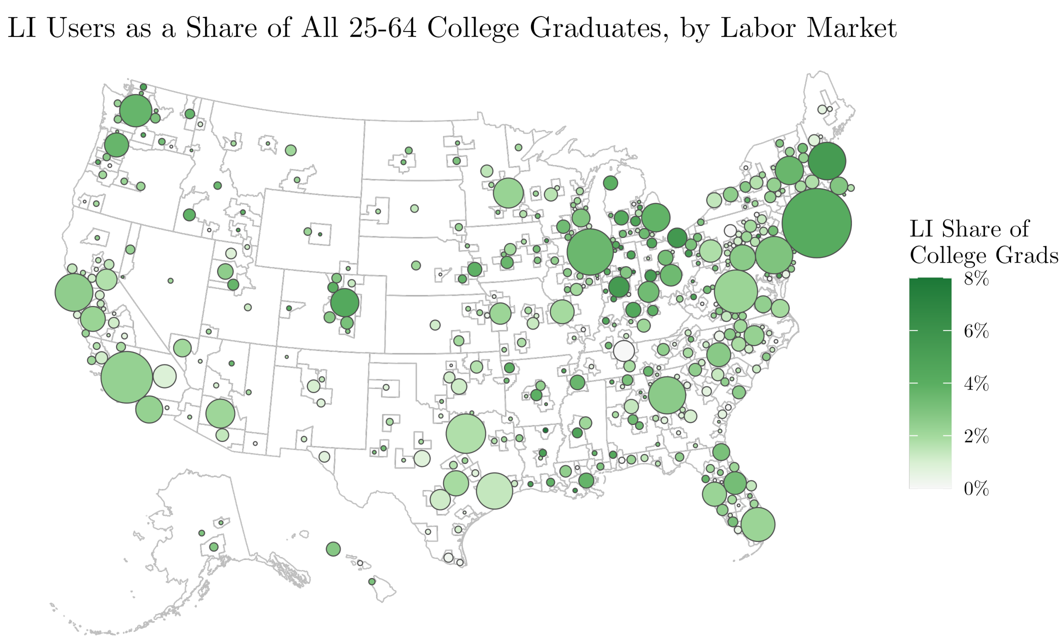



Figure 5: Local labor market definition used for analysis. LinkedIn aggregates user data to geographies that imperfectly approximate metropolitan statistical areas (Conzelmann et al. 2022). To maximize geographic granularity, I incorporate any metropolitan or micropolitan statistical areas included in LI. LinkedIn groups all non-metropolitan areas within a state together. Notice that non-metropolitan areas may not be contiguous, even though metropolitan labor markets are contiguous.




**Chloropleth Map**




**Population-Weighted Cartogram**

Figure 6: While both maps rely on identical data, the cartogram visually weights population rather than land (Dorling 1996). Population weighting distinguishes the Snow Belt from the Sun Belt. From Seattle to Boston, roughly five percent of prime-age college-educated workers appear in most large northern labor markets. By contrast, the major employment centers in the south report lower coverage. Recall from Table 1 that restricting to LI users with a high school shrunk the analytical sample by more than 90 percent. The LI user sample covers smaller shares of prime-age college-educated workers in Sun Belt labor markets, which generally enjoyed robust in-migration over the last 50 years (Frey 2022; Sprung-Keyser, Hendren, and Porter 2022). The figure suggests at a relationship between out-migration and inclusion of high school on LI profiles. Table 2 explores the relationship in greater detail.

Table 2 shows the result of a population-weighted regression:

$$inclusion_j = \beta_0 + \beta_1 \log(totalusers_j) + \beta_2 birthstate_j + \beta_3 stayed_j + \beta_4 instate_j + \beta_5 nearby_j + \mu_j \quad (10)$$

where $j$ indexes the local labor markets described in Figure 5 on page 19, $coverage_j$ is the proportion of college graduates aged 25-64 in the labor force included in the sample, $\log(totalusers)$ is the total number of 25-64 college graduates in labor force in labor market $j$, $birthstate_j$ is the proportion of college graduates born in same state as labor market $j$ according to 2018-2022 American Community Survey data, $stayed_j$ is the proportion of users attending both high school and college in $j$, $instate_j$ is the proportion of users graduating college in same state as high school in $j$, and $nearby_j$ is the proportion of users graduating college less than 150 miles from their high school in $j$.

Table 2 indicates coverage increases as a labor market hosts more prime-age college-educated workers. A 1 percent increase in the prime-age college graduate population increases coverage by 0.27 percentage points, suggesting LinkedIn enjoys network effects. Table 2 also implies LI users strategically include information, corroborating Kreisman, Smith, and Arifin 2021. When more of the workers in a region attend high school and college nearby, the sample covers a significantly higher share of the prime-age college educated labor force. [7] When the proportion of users attending a college nearby increases by 1 percentage point, the coverage rate increases by 5.1 percentage points. Table 2 suggests the payoff for including high school might be higher in regions where most workers attend college nearby and return post-graduation.

#### 5.1.4 Linking Educational Experiences to NCES Data

LinkedIn users provide a high school name but not a location, meaning I must guess the location of the high school. In most cases, the name denotes a single school, with one location. Unfortunately, roughly one-third of high schools in the United States have a duplicate name, so the name leaves some ambiguity regarding the home labor market. In these instances, I calculated the distance between the centroid of the user's college ZIP code and the centroids of potential high school ZIP

7. Figure 8 in the Appendix presents the spatial distribution of workers graduating from a college in the same labor market and state as their high school.

Table 2: Regressing population size and labor market characteristics on sample coverage of prime-age college graduates

| | Size Only | Size and LM Characteristics |
|---|---|---|
| *log*(Prime-Age College Grads Population) | 0.00264*** | 0.00267*** |
| | (0.00036) | (0.00033) |
| College Graduates Born in Same State | | −0.00130 |
| | | (0.00286) |
| College and HS in Same LM | | −0.00686 |
| | | (0.00747) |
| College and HS in Same State | | −0.00455 |
| | | (0.00531) |
| Attending Nearby College | | 0.05096*** |
| | | (0.00527) |
| $R^2$ | 0.11274 | 0.51427 |
| Adj. $R^2$ | 0.11066 | 0.50850 |
| Num. obs. | 427 | 427 |

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

The left column shows a parsimonious model, regressing logged population on coverage. Coverage rates increase as the prime-age college graduate population grows. A 1 percent increase in the prime-age college graduate population increases coverage by 0.264 percentage points. The right column shows results of the model described in Equation 10. The relationship between logged population and coverage persists with the addition of labor market characteristics. When the proportion of users attending a college nearby increases by 1 percentage point, the coverage rate increases by 5.1 percentage points. The significance of the result suggests the payoff to including a high school on LinkedIn varies by region. When more of the employers and employees in a region attend high school and college nearby, the sample covers a significantly higher share of the prime-age college educated labor force. The additional variables boost the explanatory power of the model. Log college-educated worker population and labor market characteristics explain 51 percent of the spatial variation in coverage, compared to 11 percent for log population alone.

codes. I keep the high school with the minimum distance. Colleges proved more straightforward for matching. In some cases multiple colleges exist, though matching on college name and state ameliorated any issues.

### 5.1.5 Estimating Age with Graduation Dates

If someone included a graduation date from high school or college, I subtracted 18 to estimate birth the year. Compared to other graduation dates, high school graduations are the best predictor of age because most graduates are 17 or 18. By contrast, more than 27 percent of first-time full-time students who entered college in 2014 graduated in more than four years, accounting for roughly one-third of all graduates from the cohort. Clearly, college graduation dates vary more than high school graduations for a given age cohort. I circumvent the problem by taking the start year of a bachelor's degree included on LinkedIn. For first-time full-time students, start dates should not exhibit such wide variation. If a user includes a bachelor's degree with a start year, I subtract 18.

If individuals attended multiple institutions in the United States for bachelor's degrees (i.e. transfer students), I estimate age using the start date of the earliest institution and measure post-graduation behavior based on the end date at the latest institution.

## 5.2 Educational Institution Characteristics

The National Center for Educational Statistics at the US Department of Education centralizes data on secondary and post-secondary institutions in the United States.

### 5.2.1 Secondary Institutions

I obtained data on private and public secondary schools through the 2020-21 Education Demographic Geographic Estimates program, which provides school-level enrollment and geodata. The public school file included enrollment by grade. I excluded any institutions with 0 enrollment in grade 12, namely elementary and middle schools.

### 5.2.2 Post-Secondary Institutions

I used the Integrated Post-Secondary Education Data System (IPEDS) for post-secondary data. The 2021 Institutional Characteristics Complete Data File includes geodata, enrollment, Carnegie classifications, public status, and myriad other useful variables at the branch (not system) level. I excluded schools that did not offer a bachelor's degree according to the 2021 data.

## 5.3 Institutional Groups

### 5.3.1 Barron's Selectivity Index

Emulating earlier scholarship, I partition post-secondary institutions using Barron's selectivity index, among other measures (Chetty et al. 2020; Deming et al. 2015; Conzelmann et al. 2022). Barron's data is not perfect: the cutoffs between institutional groups are arbitrary and perhaps overly reliant on admissions data. Nonetheless, the ratings capture a notion of academic prestige that profoundly affects American higher education. When possible, I used the replication data from Chetty et al. 2020, available on the Opportunity Insights website. However, their data uses system-level OPEIDs to classify institutions, obscuring any distinction between institutions in states with integrated public university systems like Arizona, South Dakota, and Pennsylvania. When necessary (i.e. states with university systems containing multiple campuses) I used selectivity ratings from Barron's Education Series 2000. Barron's selectivity index rates institutions based on a combination of student admissions statistics (Berg et al. 2023):

**Most Competitive** Institutions admitting less than a quarter of all applicants, with most students in the top decile of their high school graduating class. Example: University of Chicago

**Highly Competitive** Institutions admitting 25-50 percent of all applicants, with most students in the top third of their high school graduating class. Examples: Kalamazoo College and University of Michigan-Ann Arbor

**Very Competitive** Institutions admitting 50-75 percent of all applicants, with most students in the top 65 percent of their high school graduating class. Example: Michigan State University

**Competitive** Institutions admitting 75-85 percent of all applicants, with most graduating in the top 50-65 percent of their high school graduating class. Example: Western Michigan University

**Less Competitive** Institutions admitting 85-98 percent of all applicants, with high school grade point average below a C. Examples: Lake Superior State University or Siena Heights University

**Non-Competitive** Institutions either admitting more than 98 percent of all applicants or accepting all in-state applicants (with restrictions for out-of-state students). Example: Jackson College

**Special Focus** Specialized institutions often geared towards professional degrees in fine art, music, or design. Example: College for Creative Studies

### 5.3.2 Control

While public and private educational institutions must evolve as the Enrollment Cliff approaches, public institutions face additional pressure to stimulate local economies with state appropriations (Grawe 2018). As combating brain drain gains salience as a political issue, policymakers focus most of their energies on public institutions (Growing Michigan Together Council 2023; French 2023; LeBlanc and Hall 2023). For better or worse, the governance structures of public universities allow state policymakers to effect change through appropriations and personnel decisions. Private non-profit universities face similar pressures, though state government wields fewer policy levers for enacting reform. The incentives of private for-profit universities differ from both public and private non-profit institution types. For-profit institutions' reliance on virtual educational services complicates measurement of brain drain, since degree seekers can live anywhere in the US.

Since public institutions award most of the degrees in the United States and face the greatest scrutiny from policymakers, the institutional groupings described in Section 5.3.4 focus on categorizing public colleges and universities.

#### 5.3.3 Flagship Status

The Department of Education does not officially classify institutions as "flagship". Nonetheless, I wanted to distinguish the large research universities that often play an outsize role in policy debates about higher education (Bound et al. 2019). Modifying the methodology in Bound et al. 2019, I define public institutions as flagship if they satisfy at least one of the following criteria:

- Federally-recognized land-grant college or university
- Member of the American Association of Universities

Bound et al. 2019 defines flagship using AAU members alone. I found the definition overly restrictive since the AAU only counts eight members across the South and six in the west outside of California. I wanted at least one "flagship" institution in every state. By taking the union of Land Grant and AAU members, I incorporate the geographic spread of the Land Grant institutions, which appear in all 50 states and DC, without overlooking prominent public institutions established prior to the Morrill Act, such as the University of Virginia and University of Michigan. Table 9 in the Appendix lists all institutions classified as Flagship.

#### 5.3.4 Resulting Institutional Groupings

I want to distinguish between regional public universities (RPUs) and flagship universities. Flagship public universities and RPUs respond to tightening state appropriations in distinct ways: flagships often make up for shortfalls by recruiting out-of-state and international students while RPUs struggle to increase enrollment (Bound et al. 2019; Bound, Hershbein, and Long 2009). I use the following system for characterizing baccalaureate institutions.

**Flagship** Public institutions that are federally-recognized Land Grant Colleges or Universities, members of the American Association of Universities, or both.

**RPU, More Selective** Public institutions not satisfying the requirements for Flagship, but rated by Barron's as Most Competitive, Highly Competitive, or Very Competitive.

**RPU, Less Selective** All remaining public institutions in IPEDS.

**Private, Non-Profit** Institutions classified as private and not-for-profit in IPEDS.

**Private, For-Profit** Institutions classified as private and for-profit in IPEDS.

## 5.4 Labor Demand

Since LinkedIn data only includes metropolitan statistical areas (MSA), a subset of the full universe of core-based statistical areas, I use a blend of state and MSA-level data for estimates. Counties outside of metropolitan areas were grouped together by state, forming pseudo-MSAs which aren't necessarily contiguous. However, all Census-defined MSAs exhibit contiguity. For the rest of the paper, I use the labor market to denote the county-delimited sub-state geography.

I used 3-digit NAICS codes for the industries, measuring dozens of industries across labor markets. By using 3-digit codes at a geography as small as the labor market, I avoid the risks proposed in Goldsmith-Pinkham, Sorkin, and Swift 2020, which affect shift-shares using few industry classifications and geographies. I average the shock in the seven years preceding an individual's graduation year since perceptions of the local economy form over years. Thus, shocks vary by cohort and high school labor market ($j$ in the notation of Equation 3 on page 10).

Since the US Census Bureau suppresses County Business Pattern data at small sample sizes, the public data omits many industries with relatively few employees in a particular geography. In a small labor market such suppression can skew the employment shifts using the Bartik instrument. I circumvented the suppressions by using Unsuppressed County Business Patterns estimated by Eckert et al. 2021. The Unsuppressed County Business Patterns cover 1975-2017. Starting in 2018, the Census Bureau infused noise into industry-county cells, meaning no values are suppressed (Eckert et al. 2021). As a result, I use 2018-21 County Business Patterns from the Census Bureau website. In aggregate, the infusion of noise adds approximately 2.2 percent to employment totals at the county level relative to the national totals.

# 6 Results

I ran OLS on the reduced form functions described on page 10. Table 10 on page E reports Equations 3 and 4 as written, with $stay_{ij}$ indicating whether an individual $i$ returned to their high school labor market $j$ at some time $t \in T$. Table 5 on page 31 slightly varies the dependent variable to $stay_{iM}$, instead reporting whether an individual $i$ returned to their high school *state* $M$ at some time $t \in T$.

Tables 5 and 10 include two columns, corresponding to two regression specifications. The left column reports Equation 3 while the right column reports Equation 4, which includes a different a interaction term. The results in the tables use normalized 7-year average labor demand shocks as the independent variable. In general, most coefficient estimates were robust across the different averaging schemes.

## 6.1 Summary Statistics

### 6.1.1 Return Rates by Institution Group

According to Table 3, in-state graduates of PFs exhibit weaker attachment to home state than any other institutional grouping. Only 78.3 percent of in-state PF graduates stay in the state containing their high school and college, while the same measure exceeds 82 percent for all other institutional groupings. By contrast, out-of-state PF graduates are ten percentage points more likely to return to their home state than RPU alumni. The low rates of return migration among RPU graduates suggests the institutions offer a narrower "radius of opportunity" (Sprung-Keyser, Hendren, and Porter 2022). RPUs might deposit alumni nearby because they train students for jobs with more localized labor markets. Additionally, the wide gap between in-state and out-of-state students at RPUs suggests the in-state tuition subsidy plays a larger role in migration decisions than among graduates of PFs.

Table 3: Rate of return to state containing high school, by institutional grouping.

| Institutional Grouping | Pct Returning, In-State | Pct Returning, Out-of-State | Difference |
|---|---|---|---|
| Public Flagship | 78.3 | 25.2 | 53.1 |
| RPU, More Selective | 84.2 | 15.5 | 68.7 |
| RPU, Less Selective | 86.6 | 14.4 | 72.2 |
| Private, Non-Profit | 82.2 | 29.0 | 53.2 |
| Private, For-Profit | 82.7 | 35.2 | 47.5 |

For in-state students, return rates vary with selectivity, as reported by Conzelmann et al. 2022. In-state graduates of PFs exhibit weaker attachment to home state than any other institutional grouping. Only 78.3 percent of PF graduates return to home state, while the same measure exceeds 82 percent for all other institutional groupings. Graduates of More Selective RPUs return to their home state at lower rates than alumni of Less Selective RPUs, corroborating the selectivity gradient observed by Conzelmann et al. 2022 Out-of-state PF graduates return to their home state at rates comparable to Private, Non-Profit alumni. In fact, PFs and Private Non-Profit institutions see a similar gap in return rates between in-state and out-of-state students (53.1 percent and 53.2 percent respectively). Out-of-state graduates of RPUs return to their home state as almost half the rate of PF graduates.

#### 6.1.2 Labor Demand Shocks

Since labor demand shocks were normalized into deciles, the coefficients estimated in Tables 5 and 10 measure the average effect of increasing one decile higher. While convenient for measurement, decile-normalized labor demand shocks are a bit abstract. Table 4 presents the average labor demand shock per decile, prior to normalization

Graduates of More Selective RPUs stay in the state where they attended high school and college at a rate 11.5 percentage points higher than Public Flagship alumni. The gap grows to 14.6 percentage points for graduates of Less Selective RPUs.

### 6.2 Main Specification

Public Flagships dominate policy debate and popular imagination surrounding public higher education (Bound et al. 2019). Yet Regional Public Universities produce graduates more attached to the states where they graduated from high school. Attachment to state grows more pronounced for less selective institutions.

Table 4: Average employment shock by decile in 2021

| Decile | 1-Year Shock | 3-Year Average | 5-Year Average | 7-Year Average |
|---|---|---|---|---|
| 1 | −0.050 | −0.041 | −0.044 | −0.035 |
| 2 | −0.024 | −0.034 | −0.013 | −0.013 |
| 3 | −0.018 | −0.028 | −0.010 | −0.009 |
| 4 | −0.012 | −0.020 | −0.007 | −0.006 |
| 5 | −0.005 | −0.011 | −0.004 | −0.002 |
| 6 | 0.006 | −0.006 | 0.0002 | −0.0002 |
| 7 | 0.014 | 0.004 | 0.003 | 0.004 |
| 8 | 0.020 | 0.014 | 0.008 | 0.008 |
| 9 | 0.028 | 0.037 | 0.012 | 0.012 |
| 10 | 0.048 | 0.094 | 0.021 | 0.019 |

The shocks are proportions of the total labor force in 2021. Thus, the upper-leftmostmost value indicates the average labor market in the bottom decile of the distribution had a -5.0 percent shock in labor demand relative to 2020. Labor demand shocks are not uniformly or symmetrically distributed, instead clustering asymmetrically around 0. Unsurprisingly, as the number of years included in the average grows, the upper and lower tails on the distribution shrink.

The third through tenth rows in Tables 5 and 10 show the interaction between in-state status and institutional grouping on migration.[8] Rows 3-6 measure migration behavior of out-of-state students relative to out-of-state PF alumni, while Rows 7-10 measure migration behavior of in-state students relative to in-state PF graduates. Given the dominance of state-based higher education systems, I focus on migration vis-á-vis state (Table 5) though the coefficient directions and significance largely hold at the local labor market level, too (Table 10).

In-state PF graduates lag their peers at RPUs, with the difference statistically significant at the 1 percent level. Graduates of More Selective RPUs stay in the state where they attended high school and college at a rate 11.5 percentage points higher than Public Flagship alumni. The gap grows to 14.6 percentage points for graduates of Less Selective RPUs. Concurrent with Conzelmann et al. 2022, graduates of more selective institutions are more likely to migrate. In-state students receive a state-funded tuition subsidy at all three types of public institutions. Yet PF graduates are, on average, less likely to stay in the state containing their high school when faced with the

8. $\beta_3$ from Equation 3 would technically be $\sum_{c=1}^{5} \beta_c$ since I created five institutional groupings. The third through sixth rows report $\beta_c$ for $c = \{2, 3, 4, 5\}$

Table 5: Probability of returning to state containing high school, based on Equations 3 and 4

| | 7-Year Average | 7-Year Average |
|---|---|---|
| HS LD Shock | $0.005^{***}$ | $0.004^{***}$ |
| | (0.000) | (0.000) |
| College LD Shock | $-0.002^{***}$ | $-0.003^{***}$ |
| | (0.000) | (0.000) |
| Private, For-Profit | $0.111^{***}$ | $0.091^{***}$ |
| | (0.003) | (0.004) |
| Private, Non-Profit | $0.033^{***}$ | $0.011^{***}$ |
| | (0.001) | (0.002) |
| RPU, Less Selective | $-0.086^{***}$ | $-0.003$ |
| | (0.002) | (0.003) |
| RPU, More Selective | $-0.081^{***}$ | $-0.021^{***}$ |
| | (0.002) | (0.002) |
| Private, For-Profit × In-State | $-0.108^{***}$ | |
| | (0.005) | |
| Private, Non-Profit × In-State | $-0.049^{***}$ | |
| | (0.002) | |
| RPU, Less Selective × In-State | $0.146^{***}$ | |
| | (0.003) | |
| RPU, More Selective × In-State | $0.115^{***}$ | |
| | (0.002) | |
| Private, For-Profit × HS LD Shock | | $0.002^{**}$ |
| | | (0.001) |
| Private, Non-Profit × HS LD Shock | | $0.002^{***}$ |
| | | (0.000) |
| RPU, Less Selective × HS LD Shock | | $0.001^{*}$ |
| | | (0.000) |
| RPU, More Selective × HS LD Shock | | $0.001^{***}$ |
| | | (0.000) |
| College In State | $0.540^{***}$ | $0.564^{***}$ |
| | (0.002) | (0.001) |
| BA by Age 24 | $0.027^{***}$ | $0.030^{***}$ |
| | (0.001) | (0.001) |
| Transfer Student | $-0.030^{***}$ | $-0.032^{***}$ |
| | (0.001) | (0.001) |
| $R^2$ | 0.371 | 0.365 |
| Adj. $R^2$ | 0.371 | 0.365 |
| Num. obs. | 1557062 | 1557062 |

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

The outcome variable is $stay_{iM}$, measuring whether individual $i$ return to the state $M$ containing their high school, not the labor market $j$. The left column corresponds to Equation 3. Rows 3-6 measure migration behavior of out-of-state students relative to out-of-state PF alumni, while Rows 7-10 measure migration behavior of in-state students relative to in-state PF graduates. The right column reports results from Equation 4, which highlights heterogeneity in the response to identical shocks by interacting institutional grouping with high school labor demand shock. The interaction term coefficients, found in rows 11-14, measure the change in the rate of return to high school state relative to the baseline in the first row (Chouldechova 2017).

same economic conditions.

Intuitively, the behavior of graduates of private colleges should vary from public ones. Private colleges generally do not offer subsidies based on residency, so the in-state status does not affect the cost of attendance. Indeed, in-state graduates of Private Non-Profit institutions stay in the same state as their high school at a rate 4.9 percentage points lower than Public Flagship alumni.

Table 6: Parental income distribution for the class of 2013, by institutional grouping

| Grouping | Bottom | Lower Middle | Middle | Upper Middle | Top |
|---|---|---|---|---|---|
| Private, For-Profit | 29.4 | 25.4 | 20.9 | 15.6 | 8.7 |
| Private, Non-Profit | 6.5 | 10.7 | 16.1 | 22.8 | 43.9 |
| Public Flagship | 6.2 | 10.4 | 15.7 | 23.9 | 43.8 |
| RPU, Less Selective | 12.8 | 16.9 | 21.1 | 25.3 | 23.8 |
| RPU, More Selective | 5.3 | 8.3 | 12.2 | 22.3 | 51.9 |

The table relies on data from Chetty et al. 2017, which split the parental income distribution into five evenly-sized bins. The columns report the percent of students from each bin at a particular institution. Thus, the rows sum to 100 percent, but the columns do not. Private, Non-Profit and Public Flagship alumni pull from identical segments of the income distribution. More than 40 percent of alumni originate in households in the top 20 percent of earners, while 2 in 3 come from the top 40 percent. RPUs bifurcate by selectivity, with Less Selective RPUs drawing fewer students from the top 20 percent of the income distribution.

The comparison between PF and Private Non-Profit students proves particularly salient because their student bodies exhibit similar levels of financial need. Table 6 aggregates institution-level statistics on parental income from Chetty et al. 2017 to the institutional groupings used in this analysis. Chetty et al. 2017 measures the income distribution for students graduating college in 2013, though class composition of post-secondary institutions changes quite slowly, if at all. Notably, the parental income distribution of students at Private Non-Profit institutions approximates the distribution at PFs, heavily drawing from the top 40 percent of households by income. In other words, the median alumnus of a PF will be positioned similarly to the median Private Non-Profit alumnus on the income-migration gradient described in Sprung-Keyser, Hendren, and Porter 2022. Despite similar socioeconomic compositions across the institutions, in-state Private Non-Profit graduates are significantly less likely to stay in their home state compared to PF alumni.

The divergence suggests idiosyncratic institution-level factors drive migration decisions (Manduca 2022), in-state tuition subsidies might affect migration behavior, or some combination of the two.

Rows 3-6 focus on out-of-state students, who generally shoulder higher costs of attendance at public universities. Inverting the relationship for in-state students, out-of-state graduates of PFs are more likely to return to the state containing their high school than RPU alumni. Out-of-state graduates of More Selective RPUs return to the state where they attended high school at a rate 8.1 percentage points lower than out-of-state PF alumni. For Less Selective RPUs, the gap widens to 8.6 percentage points below out-of-state PF graduates. Thus, out-of-state PF graduates are *more* attached to their home state than out-of-state alumni of RPUs. In the analytical sample, distance between college and high school does not confound the results. The median PF alumnus traveled 511 miles from high school to college, while RPU graduates travel 550 miles. Thus, out-of-state PF graduates do not return to the state containing their high school because their college was closer to their high school.[9] I am unsure of other potential explanations.

## 6.3 Alternative Specification

The right column presents the alternative specification described in Equation 4, which employs a different interaction term. Interacting institutional grouping with high school labor demand shock highlights heterogeneity in the response to identical shocks. The interaction term coefficients, found in rows 11-14, measures the change in the rate of return to high school state relative to the baseline in the first row (Chouldechova 2017).

PF graduates are less sensitive to demand shocks in the high school labor market than graduates of any other type of institution, public or private. An increase of one decile in the seven-year average labor demand shock results in 0.4 percentage point increase in the rate of return to high school state for PF graduates. By contrast, the same decile increase leads to a 0.5 percentage point increase at RPUs, with the difference between RPUs and PFs significant at the five percent level. Between Private institutions and PFs, the gap grows even wider to 0.6 percentage points. PF alumni are not as responsive to improving economic conditions as graduates of other types

9. Tables 7 and 8 in the Appendix explore distance between high school and college in greater detail.

of institutions. The muted response to labor demand shocks among PF alumni implies amenities or other non-economic factors might weigh on their migration decisions more than graduates of other institutions. Congruent with Conzelmann et al. 2022, Wozniak 2010 and Bound and Holzer 2000, college graduates respond to local economic conditions, though the degree of responsiveness varies by institutional grouping: RPU graduates exhibit greater responsiveness to high school labor market conditions than PF alumni.

# 7 Conclusion

In general, college graduates exhibit greater spatial mobility than people without bachelors degrees (Conzelmann et al. 2022; Wozniak 2010; Bound and Holzer 2000). However, selectivity, research intensity, and control of baccalaureate institutions shape migration decisions. In-state RPU graduates reside in the state containing their high school and college at higher rates than graduates of PFs and Private institutions. When labor demand improves in their high school labor market, in-state RPU graduates are ten percentage points more likely than in-state PF alumni to stay in the same state as their college and high school, with the difference statistically significant at the 0.1 percent level.

In-state students receive a state-funded tuition subsidy at all three types of public institutions. Yet PF graduates are less sensitive to demand shocks in the high school labor market than graduates of other types of institutions. PF alumni also stay at lower rates, suggesting the state's return on investment for in-state tuition subsidies varies by institution type. In-state PF alumni move away from the state subsidizing their bachelor's degree at higher rates than RPU graduates. From the perspective of a state subsidizing higher education, RPU alumni generate higher returns-on-investment because they do not flee as often as PF graduates. The state can recoup the investment in post-secondary education through higher post-graduation wages and amenity improvements (Diamond 2016).

The results pertain to public policy discussions regarding the funding of post-secondary education systems. American higher education faces immense challenges in the coming decades (Kelchen

2023). In real terms, state government support for higher education continues a long decline (Bound et al. 2019). Furthermore, the pool of students dwindles as low birthrates produce ever-smaller cohorts of high school graduates. The demographic and fiscal duo will upend higher education in the United States.

## 7.1 Enrollment Cliff

Enrollment in American institutions of higher education peaked in 2010, fueled by large Millennial cohorts (National Science Board 2023). Today, post-secondary institutions face a shrinking pool of college-aged students. Since 2010, enrollment in undergraduate programs declined by 12 percent, from 18.0 million to 15.9 million (National Center for Education Statistics 2022). Yet current undergraduate students were born before the Great Recession. The year 2007 brought the single largest birth cohort in American history, narrowly outpacing 1957 (Eckholm 2009). Birth rates tumbled during the Great Recession and never fully recovered (Osterman et al. 2022). By 2030, post-Recession birth cohorts will constitute the majority of undergraduates, ushering a new era of leanness for many institutions. Importantly, not all institutions will shoulder the same burden. PFs and selective private colleges will survive the enrollment cliff thanks to endowments, reputations, and steady flows of research funding (Grawe 2018; Bound et al. 2019). Instead, the decline could ravage RPUs, particularly those in the Northeast and Midwest (Grawe 2018).

## 7.2 Declining State Appropriations

State governments fund the operations of nearly all public baccalaureate institutions in the United States (Pew Charitable Trusts 2019). Roughly 70 percent of full-time students attend public universities, meaning their fate intimately affects American higher education (Pew Charitable Trusts 2019). While the federal government provides financial aid and research funding, state governments provide 83 percent of general purpose appropriations to public universities (Pew Charitable Trusts 2019). States finance daily operations, particularly at institutions with limited endowments. General purpose appropriations pay instructional costs, fund new construction, and cover other day-to-day costs of operating a college. Yet state appropriations shrunk in most states over the last two decades (National Science Board 2023; Bound et al. 2019). State budgets face increasing competition from rising health care costs and a growing emphasis on K-12 education (Layzell 2007). In 2021, 71 percent of full-time undergraduates attended universities in states where real per capita state appropriations fell between 2000 and 2021 (National Science Board 2023). Across the entire country, real per capita appropriations from state governments declined by 11 percent during the period (National Science Board 2023).

Public institutions respond to declining state appropriations in different ways. Cuts in state appropriations have no effect on instructional costs at prestigious research universities[10] (Bound et al. 2019). As state appropriations shrink, research universities, especially elite ones, recruit high-achieving students from across the United States (Bound, Hershbein, and Long 2009) and the world (Bound et al. 2020). PFs recruit students with weaker local attachment, lowering the state's return on investment for education at the institution. Based on the model outlined in the Theoretical Framework, students attending college far from home have little incentive to stay near their college after graduation. They already face high recurring costs like missing friends and family, so they might as well enjoy increased earning power in a high-wage labor market (Diamond and Moretti 2021). Indeed, students who attend college out of state are significantly less likely to return to their home labor market.

PFs dominate popular conceptions of public higher education, reinforced by high-profile athletic teams, academic prestige, and robust alumni networks. Perceptions of the efficacy of public higher education mold taxpayers' spending priorities (Hurst, Ricks, and Simon 2021). Taxpayers, especially Republicans and older voters, were more likely to support public higher education funding if they perceived the education system as productive and effective (Hurst, Ricks, and Simon 2021). Increasingly, appropriators understand efficacy as more than educating workers (Wirtz 2003; Growing Michigan Together Council 2023; Ionescu and Polgreen 2009). Institutions should train workers who do not leave, boosting the return on investment for state education appropriations (Ionescu and Polgreen 2009). Thus, the most prominent examples of public higher education are generally least effective, if efficacy consists of graduating people who stay nearby (Conzelmann et al. 2022; French

10. Bound et al. 2019 defines "prestigious research universities" as members of the American Association of Universities, which includes many of the most prominent public and private secondary institutions in the United States.

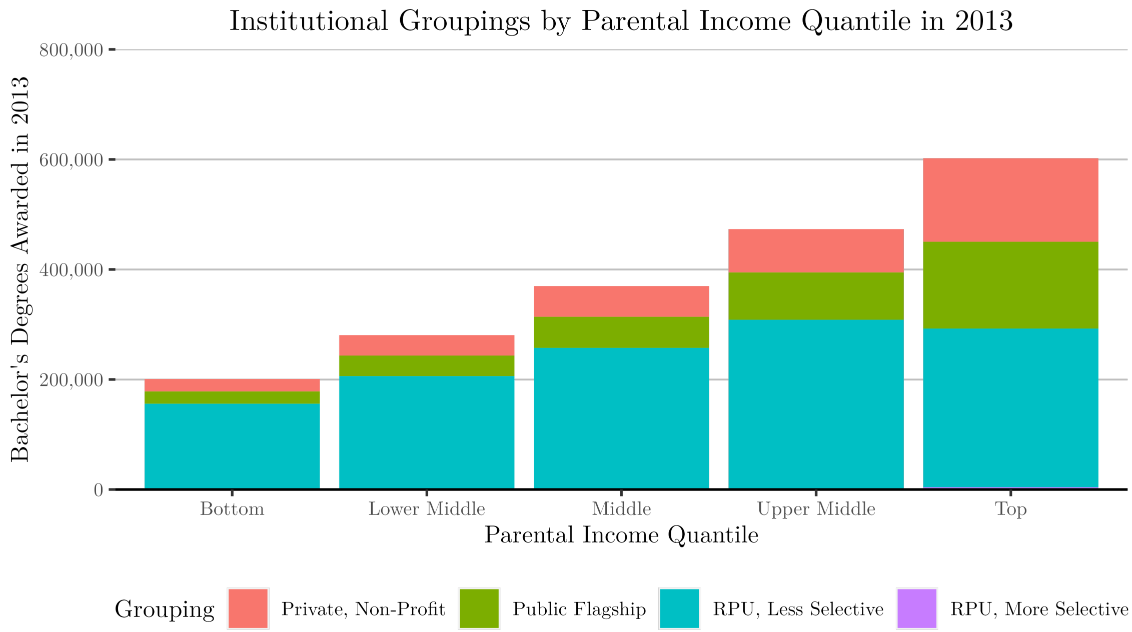



Figure 7: Institution-level data for the figure originates in Chetty et al. 2017, aggregated to institutional groupings by author. Private, For-Profit institutions excluded from figure due to their distinct operational structure and incentives. Less Selective RPUs service the bulk of the nation's educational needs. Seventy-seven percent of graduates with parents in the bottom 20 percent of the income distribution received their bachelor's degree from a Less Selective RPU. Even among the top 20 percent, Less Selective RPUs credential 48 percent of graduates. PF and Private Non-Profit institutions primarily service students from the upper 40 percent of the income distribution. Despite the ubiquity of PF and Private Non-Profit colleges, Less Selective RPUs award the majority of degrees to students from every parental income quantile except the top 20 percent.

2023). The perception of ineffectiveness depletes political will for secondary education funding.

As political will dries up, PFs draw from students from distant locales, but RPUs wither. RPUs primarily serve local educational needs, drawing more in-state students. The income distribution at RPUs differs too, drawing more students from the lower and middle portions of the parental income distribution (Chetty et al. 2017; 2020). Figure 7 measures the number of graduates per institutional grouping, by parental income quantile. Less Selective RPUs award the majority of bachelor's degrees for students from the bottom 80 percent of the income distribution. The dominance of Less Selective RPUs increases at the bottom of the income distribution: Less Selective RPUs account for 77 percent of degrees issued by public or private non-profit institutions to students from the bottom fifth of the parental income distribution. Declining state appropriations increase the gap between financial aid and tuition at RPUs, imposing financial burdens for middle- and working-class households (Bound et al. 2019). Quality or quantity of instruction declines as state appropriations fall, even though graduates of RPUs offer a greater return on investment for state governments (Bound et al. 2019; Conzelmann et al. 2022). According to Table 5, graduates of RPUs reside in their home states at higher rates than their peers graduating from PFs. Similarly, RPU graduates return at higher rates when economic conditions improve in their hometown. Yet less selective institutions, particularly public ones, face intense demographic and financial headwinds as small post-Recession cohorts approach matriculation (Grawe 2018). **Institutions most vulnerable to the economic and demographic vicissitudes of the next few decades produce graduates with the strongest attachment to their home labor market and home state.**

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# 8 Appendix

Table 7: Distance between high school and **in-state** college by institutional grouping

| Distance (Miles) | Public Flagship | Private For-Profit | Private Non-Profit | RPU Less Selective | RPU More Selective |
|---|---|---|---|---|---|
| [0,50] | 45.2 | 63.9 | 66.8 | 79.5 | 55.8 |
| (50,100] | 29.2 | 11.5 | 14.4 | 9.4 | 18.7 |
| (100,150] | 10.9 | 10.2 | 8.3 | 5.5 | 13.2 |
| (150,200] | 5.2 | 6.8 | 5.1 | 2.7 | 7.0 |
| (200,250] | 4.1 | 3.3 | 2.6 | 1.4 | 2.6 |
| (250,500] | 5.3 | 4.1 | 2.7 | 1.4 | 2.8 |
| (500,1000] | 0.1 | 0.2 | 0 | 0.1 | 0 |
| (1000,10000] | 0 | 0 | 0 | 0 | 0 |

In-state graduates of Public Flagships were less likely to attend a high school within 50 miles of their college relative to all other institutional groupings. Regional Public Universities draw from the population of nearby in-state students. The majority of RPU alumni in the sample attended colleges less than 50 miles from their high school. Less Selective RPUs demonstrate particular reliance, with almost 4 in 5 in-state students traveling 50 miles or less. As small post-Recession birth cohorts matriculate, RPUs dependent on local students might face struggles to survive (Grawe 2018). Public Flagships attract students from across the state, while RPUs heavily rely on students in the immediate vicinity.

Table 8: Distance between high school and **out-of-state** college by institutional grouping

| Distance (Miles) | Public Flagship | Private For-Profit | Private Non-Profit | RPU Less Selective | RPU More Selective |
|---|---|---|---|---|---|
| [0,50] | 1.5 | 2.0 | 5.6 | 4.7 | 3.6 |
| (50,100] | 5.2 | 1.0 | 9.0 | 4.4 | 5.3 |
| (100,150] | 8.6 | 1.2 | 8.7 | 4.3 | 5.9 |
| (150,200] | 7.0 | 1.3 | 8.9 | 3.6 | 5.3 |
| (200,250] | 6.4 | 1.8 | 6.6 | 4.1 | 4.9 |
| (250,500] | 20.5 | 12.7 | 18.7 | 20.4 | 23.4 |
| (500,1000] | 25.6 | 32.3 | 21.5 | 28.9 | 28.5 |
| (1000,10000] | 25.2 | 47.7 | 21.0 | 29.4 | 23.1 |

Unsurprisingly, out-of-state students travel further than in-state students. However, differences across institutional groupings shrink. Across all institutional groupings except Private, Non-Profit, the majority of out-of-state students traveled more than 500 miles. Out-of-state students attending Private Non-Profit colleges tend to matriculate at institutions closer to their high school. The discrepancy suggests most Private Non-Profits compete across regions of states, while Public Flagships compete across the entire country (Bound et al. 2019).

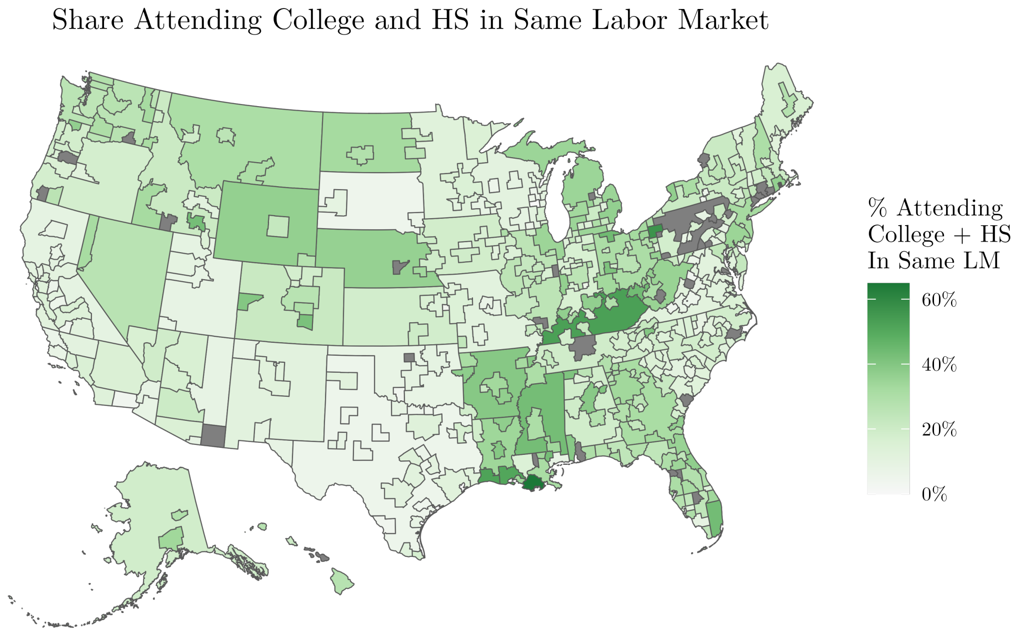
Table 9: List of public flagship institutions by state

| Institution | State |
|---|---|
| University of Alaska, Fairbanks | AK |
| Alabama A&M University | AL |
| Auburn University | AL |
| University of Arkansas | AR |
| University of Arkansas at Pine Bluff | AR |
| Arizona State University | AZ |
| University of Arizona | AZ |
| University of California, Berkeley | CA |
| University of California, Davis | CA |
| University of California, Irvine | CA |
| University of California, Los Angeles | CA |
| University of California, Merced | CA |
| University of California, Riverside | CA |
| University of California, San Diego | CA |
| University of California, San Francisco | CA |
| University of California, Santa Barbara | CA |
| University of California, Santa Cruz | CA |
| Colorado State University | CO |
| University of Colorado Boulder | CO |
| University of Connecticut | CT |
| University of the District of Columbia | DC |
| Delaware State University | DE |
| University of Delaware | DE |
| Florida A&M University | FL |
| University of Florida | FL |
| University of South Florida | FL |
| Fort Valley State University | GA |
| Georgia Institute of Technology | GA |
| Unviersity of Georgia | GA |
| University of Hawaii at Honolulu | HI |
| University of Hawaii at Manoa | HI |
| Iowa State University | IA |
| University of Iowa | IA |
| University of Idaho | ID |
| University of Illinois Urbana-Champaign | IL |
| Indiana University Bloomington | IN |
| Purdue University | IN |
| Kansas State University | KS |
| University of Kansas | KS |
| Kentucky State University | KY |
| University of Kentucky | KY |
| Louisiana State University | LA |
| Southern University and A&M College | LA |
| University of Massachusetts Amherst | MA |
| University of Maryland Eastern Shore | MD |
| University of Maryland, College Park | MD |
| University of Maine | ME |
| Michigan State University | MI |

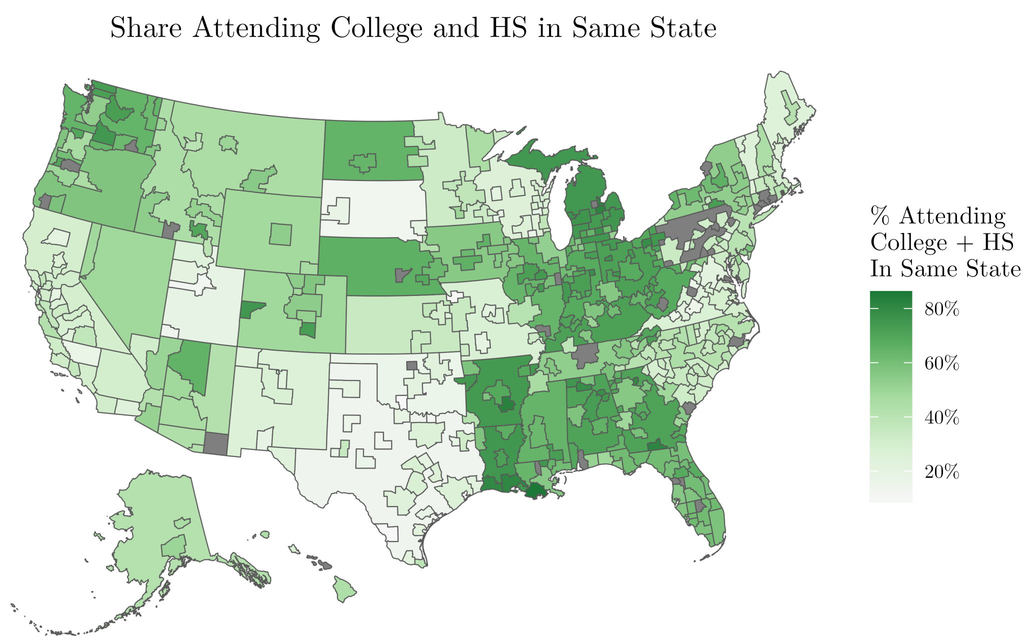
| Institution | State |
|---|---|
| University of Michigan-Ann Arbor | MI |
| University of Minnesota, Twin Cities | MN |
| Lincoln University | MO |
| University of Missouri | MO |
| Alcorn State University | MS |
| Mississippi State University | MS |
| Montana State University | MT |
| North Carolina A&T State University | NC |
| North Carolina State University | NC |
| University of North Carolina Chapel Hill | NC |
| North Dakota State University | ND |
| University of Nebraska–Lincoln | NE |
| University of New Hampshire | NH |
| Rutgers University–New Brunswick | NJ |
| New Mexico State University | NM |
| University of Nevada Reno | NV |
| Cornell University | NY |
| Stony Brook University | NY |
| SUNY Buffalo | NY |
| Central State University | OH |
| Ohio State University | OH |
| Langston University | OK |
| Oklahoma State University | OK |
| Oregon State University | OR |
| University of Oregon | OR |
| Pennsylvania State University | PA |
| University of Pittsburgh | PA |
| University of Rhode Island | RI |
| Clemson University | SC |
| South Carolina State University | SC |
| South Dakota State University | SD |
| Tennessee State University | TN |
| University of Tennessee | TN |
| Prairie View A&M University | TX |
| Texas A&M University | TX |
| University of Texas at Austin | TX |
| University of Utah | UT |
| Utah State University | UT |
| University of Virginia | VA |
| Virginia State University | VA |
| Virginia Tech | VA |
| University of Vermont | VT |
| University of Washington | WA |
| Washington State University | WA |
| University of Wisconsin–Madison | WI |
| West Virginia State University | WV |
| West Virginia University | WV |
| University of Wyoming | WY |

The public flagship classifications consists of the union of AAU members and non-tribal Land Grant colleges recognized by the US Department of Education, modifying Bound et al. 2019.

Figure 8: Share of students attending college in the same labor market or state as their high school




**Same Labor Market**




**Same State**

The share of students attending college in the same labor market varies by region. While levels are mechanically higher for the share attending in the same state, the regional patterns persist. College graduates in the triangle of states between Michigan, Louisiana, and Florida exhibit greater affinity to local baccalaureate institutions.

Table 10: Probability of returning to labor market containing high school, based on Equations 3 and 4

| | 7-Year Average | 7-Year Average |
|---|---|---|
| HS LD Shock | $0.012^{***}$ | $0.012^{***}$ |
| | (0.000) | (0.000) |
| College LD Shock | $-0.004^{***}$ | $-0.004^{***}$ |
| | (0.000) | (0.000) |
| Private, For-Profit | $0.085^{***}$ | $0.084^{***}$ |
| | (0.003) | (0.005) |
| Private, Non-Profit | $0.039^{***}$ | $0.045^{***}$ |
| | (0.001) | (0.002) |
| RPU, Less Selective | $-0.075^{***}$ | $0.044^{***}$ |
| | (0.002) | (0.003) |
| RPU, More Selective | $-0.070^{***}$ | $-0.004$ |
| | (0.002) | (0.002) |
| Private, For-Profit × In-State | 0.008 | |
| | (0.006) | |
| Private, Non-Profit × In-State | $-0.008^{***}$ | |
| | (0.002) | |
| RPU, Less Selective × In-State | $0.211^{***}$ | |
| | (0.003) | |
| RPU, More Selective × In-State | $0.113^{***}$ | |
| | (0.002) | |
| Private, For-Profit × HS LD Shock | | $0.004^{***}$ |
| | | (0.001) |
| Private, Non-Profit × HS LD Shock | | $-0.000$ |
| | | (0.000) |
| RPU, Less Selective × HS LD Shock | | $0.001^{**}$ |
| | | (0.000) |
| RPU, More Selective × HS LD Shock | | $-0.001$ |
| | | (0.000) |
| College In State | $0.345^{***}$ | $0.397^{***}$ |
| | (0.002) | (0.001) |
| BA by Age 24 | $0.031^{***}$ | $0.035^{***}$ |
| | (0.001) | (0.001) |
| Transfer Student | $-0.023^{***}$ | $-0.025^{***}$ |
| | (0.001) | (0.001) |
| $R^2$ | 0.250 | 0.245 |
| Adj. $R^2$ | 0.250 | 0.245 |
| Num. obs. | 1557062 | 1557062 |

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

The outcome variable is $stay_{ij}$, measuring whether individual $i$ return to the labor market $j$ containing their high school, not the state $M$. The left column corresponds to Equation 3. Rows 3-6 measure migration behavior of out-of-state students relative to out-of-state PF alumni, while Rows 7-10 measure migration behavior of in-state students relative to in-state PF graduates. The right column reports results from Equation 4, which highlights heterogeneity in the response to identical shocks by interacting institutional grouping with the high school labor demand shock. The interaction term coefficients, found in rows 11-14, measure the change in the rate of return to high school state relative to the baseline in the first row (Chouldechova 2017).