Variations in the Economic Resiliency of US Cities during the COVID-19 Pandemic: An Analysis of Small Business Revenues and Job Vacancies During the 2020 COVID-19 Recession

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April 2021

Abstract

This paper studies how metro areas in the United States experienced different economic outcomes during the COVID-19 recession which were persistent up to 270 days after the first COVID-19 case. My empirical strategy uses regressions of small business revenues, low-preparation job vacancies, and high-preparation job vacancies on pre-pandemic and metro-area mobility. The results show that metros with residents who sheltered in place more rigorously experienced significantly lower small business revenues and low-preparation job vacancies. Metros with higher pre-pandemic per-capita accommodation spending had lower small business revenues and low-preparation vacancies and this effect grows stronger in later periods. Metro areas with higher percentages of voters for Donald Trump in 2016 had significantly higher small business revenues and low-preparation vacancies during the first 270 days of the pandemic. However, residents of those cities sheltered in place less even after controlling for local COVID-19 case rates and experienced significantly higher COVID-19 case rates.

1 Introduction

The United States was devastated by the COVID-19 pandemic, which infected over twenty-eight million Americans as of February 2021. The virus is spread through close contact with infected people, and cities, normally the nation's source of production and wealth, have been mostly locked down. Cities dealt with the virus in different ways, from stay-at-home orders to reduced capacity at restaurants and workspaces. The lives of Americans appear to be somewhat bifurcated: such as Boise or Omaha, life by the end of 2020 may have felt "back to normal"; meanwhile, New Yorkers and Detroiters remained in strict lockdown. This is completely in contrast to the Great Recession when economic conditions and sentiment were poor across the United States. This paper seeks to explain differences in small business revenue and job

[1] I am grateful for Professor Linda Tesar and Professor Christopher House for their suggestions and encouragement on my thesis. Also, I owe thanks to Professor Kathryn Dominguez for her support and guidance.

vacancies between cities using pre-pandemic and pandemic variables to determine what factors influenced how deep and persistent a COVID-19 recession was experienced by different large US cities.

There exists wide variation between cities in terms of economic indicators, social distancing measures, and COVID-19 cases, and this variation allows one to compare the effects of the COVID-19 recession between individual cities. Just as in past recessions, individual variations can determine the severity on the local level. For example, Arias et al. (2016) found that, during the Great Recession, cities with more educated labor forces and elastic housing supplies experienced a less severe downturn. Differences between cities should be even more pronounced during this COVID-19 recession, as some have restricted mobility more than others. However, Aum et al. (2020) found that, in South Korea, job losses occurred without lockdowns; they extrapolate these results to the US and UK to estimate that no more than half of the early job loss can be attributed to lockdowns.

The motivation for this paper is to examine what variables explain which cities were affected the most by COVID-19 in terms of the depth of their recession, their resiliency during COVID-19, and their recovery from the maximum decrease in job vacancies and small business revenues. Cities will be examined from the time of their first registered COVID-19 case as well as the trough of their recession in terms of small business revenues and job vacancies. In addition to factors such as the rate of novel coronavirus in the population and the mobility of residents (which is thought to be correlated with spreading the virus), static economic factors such as population, education, household income, density, and the share of high digital skill jobs will be analyzed for their explanatory power regarding the depth of the recession in each city and the ensuing recovery.

For this paper, the data sources that have been selected are small business revenue and job vacancies. Small business revenue is useful to examine because, as of 2019, it represents 44% of US GDP and 47.3% of the labor force (59.9 million employees). As of 2019, small businesses represent more than half of all workers in the accommodation, construction, professional services, wholesale trade, real estate, and entertainment & recreation, industries. Therefore, this data gives insight into real-time economic conditions in individual cities.

Job vacancies are useful because they indicate the present conditions and the future expectations of firms. Generally, workers are hired (especially in jobs that require training) with the expectation that they will be employed for months, if not years. Low rates of job vacancies could show that businesses in a respective city expect economic conditions to be poor for the foreseeable future and do not demand labor in the present. Forsythe et al. (2020) found that almost all industries saw contractions in vacancies in March and April 2020 regardless of work-from-home capability, except for essential retail. However, as the pandemic progresses, and the future is increasingly uncertain, high-preparation job vacancies may remain depressed due to firms' uncertainty regarding future earnings.

Small business revenues are also important to understand the effect of the COVID-19 pandemic on US cities. According to work from Sahin et al. (2011), small businesses experienced larger relative declines during the Great Recession due in part to economic uncertainty and constrained credit. These same issues are likely to be problematic for small businesses during the COVID-19 recession along with the health and safety issues that threaten the business models of many small businesses altogether.

These insights can be compared to previous work on metro business cycles and the Great Recession (Arias et al. 2016) to see if cities that recovered faster from the Great Recession are also faring better in this 2020 COVID-19 recession. For example, Arias et al. (2016) discovered that cities with higher levels of education and more elastic housing supplies were less affected by the Great Recession. However, given the completely different nature of this COVID-19 recession, there is still much work to be done to determine if these same factors or completely different variables can explain which cities experienced the worst effects of COVID-19 on their local economies.

Finally, daily and weekly data are critical for understanding how COVID-19 affects cities because not all cities experienced their first COVID-19 case at the same time. Therefore, comparing how cities are affected by COVID-19 after the first case arrives in each city (as opposed to the first case in the US) could unveil how much of this COVID-19 recession is national and how much is due to the individual situations with the virus in each city. There is a wide variation in COVID-19 case rates among cities in the sample. After COVID-19 cases spiked in early April, there was a second large increase in cases in July and August across the country. Then, an even larger in late 2020 dwarfed the previous spikes: new daily cases nationwide were four times higher in January 2021 than in July 2020. Some cities, such as Detroit, largely avoided this second or third wave; however, some cities, like Boise, saw a large spike in cases. While over 11% of Los Angeles's population has contracted COVID-19 as of February 4th, 2021, fewer than 6% of Sacramento's population has contracted the virus. The variation in city-level differences is particularly important for analysis.

It is important to note that the new case rate data can contain repeat cases; however, these infections likely represent a very small percentage of the total. Public Health England estimates that contracting COVID-19 prevents reinfection for up to five months and a study of over 6,000 participants revealed an 83% rate of protection from reinfection. Additionally, these case rates remain comparable between cities as there is currently no data showing the risk of reinfection as higher in certain locales. This may be subject to change, however, as new strains of the virus from South Africa and the United Kingdom have entered the United States in 2021.

2 Literature Review

This paper draws upon a diverse set of literature primarily focused on business cycles, labor economics, urban economics, and the COVID-19 pandemic. There is a strongly developed literature around business cycles and, in particular, the Great Recession. The work of Arias et al. (2016) on recessions in American cities is highly influential because it represents the intersection of urban economics and business cycles. Arias et al. (2020) seek to explain why some cities experienced less severe recessions with attention to the Great Recession and this paper searches for similar explanatory factors for the COVID-19 pandemic. Similarly, Chernick et al. (2011) focus on cities and business cycles to understand how city governments handle the fiscal pressure of a recession. Although this paper primarily concerns itself with private firms, the role of local governments in ensuring a strong recovery from the COVID-19 recession cannot be overlooked.

2.1 Labor Economics

COVID-19 has massively disrupted the American labor market due to business closures, working from home, social distancing requirements, and a demand shock. Karanassou et al. (2006) describe three fundamental theories of macroeconomics of the labor market including the prolonged adjustment view (also known as chain reaction theory) and the hysteresis view. Prolonged adjustment explains how unemployment does not gravitate to its natural rate due to frictional growth, and hysteresis is the idea that transitory business cycle fluctuations lead to permanent changes in the unemployment rate. The slow rebound of job vacancies during the COVID-19 pandemic could be explained by this prolonged adjustment theory, and a permanently lower vacancy rate after this pandemic could be supported by the hysteresis view. However, it is currently too early to surmise which of these theories best explains the state of the labor market of American cities.

Lazear and Spletzer (2012) use a theoretical understanding of the labor market to empirically analyze the effect of the Great Recession. In particular, their concept of churn is particularly useful to analyze the job market vacancy data used in this paper. Also, the research of Faberman and Kudlyak (2016) on online job searching and its implications for the labor market colors the interpretation of the Burning Glass job vacancy data used in this paper. Faberman and Kudlyak (2016) find that online job searching is generally faster and more effective than traditional searching and, over the last two decades, had 'become the norm'. This conclusion validates the use of online job search data in this paper and also provides information on the makeup and tendencies of online searchers.

Four papers focus specifically on the labor market during the COVID-19 pandemic. Forsythe et al. (2020) analyzed job vacancies during the onset of the COVID-19 pandemic with a focus on industries and occupations while Campello et al. (2020) are concerned with local labor markets and the hiring decisions of firms. Aum et al. (2020) study the South Korean labor market during COVID-19 and contrast it with the United States and the United Kingdom. This paper uses differences-in-differences to estimate the causal effect of a COVID-19 outbreak to show that lockdowns are not the sole reason for job losses in the US or South Korea. This result is extrapolated in this paper as uncertainty in the labor market, particularly for high-preparation jobs, appears to be a significant factor during this pandemic.

The fourth paper, also by Forsythe et al. (2020), is an extension of the interim report on the COVID-19 labor market. This paper finds that, after rebounding to 80% of pre-pandemic levels by June, job vacancies stagnated between July and November. This trend is likely due to individuals on temporary layoff not searching for new employment and virus-related concerns suppressing job search activity. Labor market tightness, which increases when more firms are looking for workers to fill jobs, fell by 75% between January and April 2020. This means that many individuals are competing for the same job, and this is especially true in the market for high-preparation jobs that require college degrees.

2.2 Business Cycles and Small Business Revenues

At the intersection of business cycles and small businesses, which are a primary focus for this work, Sahin et al. (2011) found that small firms experienced the largest relative declines in business and were affected more by economic uncertainty. Additionally, the paper describes how small firms are constrained by credit and have difficulty raising new funds for investment. Although the COVID-19 recession is fundamentally different from the Great Recession, these issues for small businesses could still be present; this makes small business revenues a particularly important indicator for analysis in this paper.

Examining business cycles from a macroeconomic lens, Bivens (2016) sought to explain why the recovery from the Great Recession was much slower than previous recessions. Bivens finds that conventional monetary policy had a more limited effect than previous recessions, the length of the recession was in part related to the severity of its trough, and that federal fiscal austerity likely was instrumental as well. Although it is far too early to examine the COVID-19 recession from a historical perspective, special attention will be paid to the maximum depth (or 'trough') of business revenues and job vacancies in this paper. Additionally, this paper does build upon the work of Chetty et al. (2020) to analyze the fiscal stimulus of the Paycheck Protection Program.

2.3 COVID-19 Pandemic Literature

Due to the recency of the COVID-19 pandemic, the literature around it is still developing. However, there are several important working papers focused on the pandemic from which this paper draws upon. Chetty et al. (2020) based their research around their Opportunity Insights Economic Tracker, whose near real-time economic data is also utilized in this paper. Chetty et al. focused on the pandemic amplifying inequality in the United States and conducted a detailed analysis of the Paycheck Protection Program.

Regarding COVID-19 as a demand shock, Alekseev et al. (2020) use survey data to understand how small businesses are coping with the effects of the pandemic. This work is particularly useful to understand how firms view the COVID-19 pandemic and make their decisions to hire and furlough workers. Bloom et al. (2020) also use survey data from 2,500 small businesses which shows that revenues were down 29% on average. Over 40% of firms reported a non-negative effect on revenues while 25% of firms reported losses of over 50%. As expected, larger firms with an online presence (such as a restaurant that supports online ordering) fared better than those without an online presence.

Finally, Kim et al. (2020) found that small business revenues declined roughly 40% in March 2020 after the declaration of the national emergency; however, these declines are due to national factors instead of variations in local infection rates or policies. In particular, the authors find that "an increase in new infections by two standard deviations [lead] to a 1.5% decline in business revenues". Also, the sum of the effects of local 'shelter-in-place' orders and variations in COVID-19 case rates account for only 10% of the average decline in small business revenues. However, there do appear to be large effects in a few counties with significantly higher infection rates than the national rate.

3 Data

The primary source of data is Raj Chetty's Opportunity Insights Economic Tracker (Chetty et al., 2020). This tracker is updated weekly and draws on public and private datasets that cover various economic indicators. The data has been cut by cities and states and includes 52 large metropolitan areas (49 have populations above 500,000) across 33 states in the continental US. The Opportunity Insights job vacancy data is sourced from Burning Glass Technologies, which scrapes over 40,000 job boards in the United States weekly (Chetty et al., 2020). The volume of job postings is measured weekly and indexed to the average number of job postings in the same city during January 4-31, 2020. This data is not seasonally adjusted.

The job vacancy data is classified by O*NET, which places jobs into one of five categories based on how much preparation is needed to be hired for the role. Descriptions of these five categories can be found in the table below. Chetty et al. have combined these five zones into two categories for easier comparison: low-preparation job vacancies (O*NET Zones 1-2) and high-preparation job vacancies (O*NET Zones 3-5). Thus, the data shows how the relative volume of low-preparation and high-preparation job vacancies for a given city is changing relative to January 2020.

O*NET Zones Descriptive Table

*O*NET Job Zone*	*Educational Requirement*	*Examples of Jobs in the O*NET Zone*
Zone 1 (Low-Preparation)	GED Certificate	Dishwashers, Landscaping and Groundskeeping, Baristas
Zone 2 (Low-Preparation)	High School Diploma	Rental Clerks, Customer Service Representatives, Tellers
Zone 3 (High-Preparation)	Vocational School or Associate Degree	Electricians, Barbers, Medical Assistants
Zone 4 (High-Preparation)	Bachelor’s Degree	Real Estate Broker, Sales Manager, Database Administrator
Zone 5 (High-Preparation)	Master’s Degree or Doctoral Degree	Pharmacists, Lawyers, Veterinarians

The small business revenue is sourced from Womply, a company that aggregates credit card processing data (Chetty et al., 2020). The small business revenues are measured as a percentage change, with zero representing no change in small business revenues in an individual city (a value of -0.5, for example, would represent a 50% decrease in revenue). First, the daily data is converted to a seven-day moving average (the average for the day and the six previous days). The seven-day moving average is indexed to January 4-31, 2020 in the same city and seasonally adjusted based on data from the same seven-day moving average in 2019 indexed to January 4-

31, 2019. Differences in the dates of federal holidays are accounted for by shifting the 2019 reference data to align the holidays before performing the year-over-year division.

The mobility data is provided by Google Mobility, which tracks cell phone usage to create a mobility index for each city (Chetty et al., 2020). The data is indexed to the average mobility in a city from January 3rd to February 6th, 2020.

The *New York Times* COVID-19 case data is reported as the number of COVID-19 cases per 100,000 residents; however, for ease of understanding, it has been rebased as cases per one hundred residents which represents roughly the percentage of the total population that has contracted COVID-19 (without factoring in the relatively small number of repeat cases).

The New York Times is also the source of the 2016 Presidential Election results, which are reported at the county level. IPUMS USA, which collects U.S. census microdata, is responsible for the mapping of counties to metro statistical areas.

This paper focuses on COVID-19 cases and not COVID-19 deaths as these case rates represent a larger proportion of the population and are not subjective in terms of underlying health complications or elderly populations in different areas of the country. The COVID-19 death rates range from 0.03% to 0.32% for all metros in the sample, while the COVID-19 case rates range between 2% and 11% of the metro population as of February 2021. The case rate and death rate have a correlation coefficient of 0.41, which suggests there are other contributing health factors outside of the scope of this paper. This analysis has not been repeated using the COVID-19 death rates, so it is uncertain if these findings are robust to the death rate.

Additionally, the US Census Bureau is used as a source for several economic variables, including median household income, the percentage of residents with high school and college diplomas, and population-weighted urban density. Housing elasticity data primarily comes from Malpezzi (2017), and the four geographic regions are determined by the US Census Bureau. Finally, CNN Politics 'Where did $380B in PPP money go?' is the source of state-level Paycheck Protection

Program data. There is additional information on these variables in Appendix Tables A.1, A.2, A.3, and A.4. Definitions of variables are provided in the Appendix.

There is data available from Opportunity Insights at the time of writing from January 2020 to February 2021. Therefore, variables have been extended as far out in time as possible to understand how cities are recovering from the maximum depth of their recession. As more data is made available these estimates will be updated, and there will be a greater understanding of cities and their resilience in the face of COVID-19.

To date, there is data available for almost one year after the first COVID-19 case in every city in the sample, and there is data available up to 270 days after the first COVID-19 case in each city for the dependent variables: small business revenues, low-preparation vacancies, and high-preparation vacancies.

4 Methodology

My paper uses similar methodologies to Arias et al. (2016) and Forsythe et al. (2020) regarding recession data. This data, in particular job vacancies, can also be split into multiple categories for a more thorough understanding of the situation in individual cities. My paper will be divided into three parts: testing for (1) the effects of COVID-19 cases on small business revenues and job vacancies after a city receives its first case, (2) the effects of static economic variables in explaining which cities experienced the largest maximum decline in small business revenues and vacancies, and (3) examining which cities experienced the fastest recovery after their maximum decline.

4.1 Comparing the effects of COVID-19 case rates across cities

In addition to comparing cities across a fixed period (after COVID-19 has entered the US), it is also important to control for the day that the virus arrived in each city and compare how each city is faring economically between periods of roughly one, three, five and seven months after the first registered COVID-19 case. There is decent variability in the time of arrival. The first city in the sample to record the presence of novel coronavirus was Chicago on January 24th, and the last city to confirm a COVID-19 case was Kansas City on March 20th, 2020. This is recorded by the variable *Days to First Case*, which has a mean of 61 and a standard deviation around 14.5.

The farthest period that will be compared between cities is 151 to 210 days after the first case was recorded. This period was chosen because the data is available for all cities and is intended to see, given several months, which cities can best respond and return to work in the face of COVID-19. Importantly, this also allows one to examine the effect of the number of COVID-19 cases that occurred before the period and observe how COVID-19 cases are increasing during the first seven months of the pandemic.

For Tables 1, 5, and 9 I use cross-sectional OLS regressions to analyze the data unless otherwise specified. The basic regression takes the linear form

$$y_i = \mathrm{X}_i\boldsymbol{\beta} + e_i \; for \; i = 1 \ldots 52$$

where *i* indexes each of the 52 cities. Here, $\boldsymbol{\beta}$ is a 1x2 vector and X_i is a 2x1 matrix where each respective column represents the percentage of the population that tested positive for COVID-19 in the first 270 days after the first case was recorded in the city and the average Google mobility index between 151-210 days after the first positive COVID-19 case in a city. The dependent variable y_i is a 52x1 vector with the average change in the index of small business revenues, low-preparation job vacancies, and high-preparation job vacancies, respectively, for each of Tables 1, 3, and 5.

4.1 Differences in Mobility Between Cities

For Tables 2, 6, and 10 I use cross-sectional OLS regressions to analyze the data unless otherwise specified. The basic regression takes the linear form

$$y_i = \mathrm{X}_i\boldsymbol{\beta} + e_i \; for \; i = 1 \ldots 52$$

where *i* indexes each of the 52 cities in the sample. This regression is run a total of fifteen times as there are three dependent variables, small business revenues, low-preparation job vacancies, and high-preparation job vacancies, measured over five distinct time periods (0 to 30 days, 31 to 90 days, 91 to 150 days, 151 to 210, and 211 to 270 days after each city's respective first case). This means each dependent variable y_i is a 52x1 vector that contains the average change in the index of the dependent variable over the respective time period. Here, $\boldsymbol{\beta}$ is a 1x3 vector and X_i is a 3x1 matrix where each respective column represents average mobility during the time period indexed to January 2020, per-resident accommodation spending, and the share of voters in the metro area who voted for Donald Trump in the 2016 Presidential election. The dependent variable y_i is a 52x1 vector with the average change in the index of small business revenues, low-preparation job vacancies, and high-preparation job vacancies, respectively, for each of Tables 2, 6, and 10.

4.3 Comparing the effects of pre-pandemic variables on city-level economic outcomes

For all remaining tables I use cross-sectional OLS regressions to analyze the data unless otherwise specified. The basic regression takes the linear form

$$y_i = \mathrm{X}_i\boldsymbol{\beta} + e_i \; for \; i = 1 \ldots 52$$

where *i* indexes each of the 52 cities in the sample. This means each dependent variable y_i is a 52x1 vector that contains the average change in the index of the dependent variable over the respective time period listed on the table. For Tables 3, 4, 7, 8, 11, and 12 $\boldsymbol{\beta}$ is a 1x5 vector and X_i is a 5x1 matrix where each respective column represents per-resident accommodation spending, the share of voters in the metro area who voted for Donald Trump in the 2016 Presidential election, median household income, the share of high digital skill jobs in the metro area, and the population-weighted density of the metro area.

For Table 13 $\boldsymbol{\beta}$ is a 1x2 vector and X_i is a 2x1 matrix where each respective column represents the percentage of the population that tested positive for COVID-19 in the first 270 days after the first case was recorded in the city and the share of voters in the metro area who voted for Donald Trump in the 2016 Presidential election.

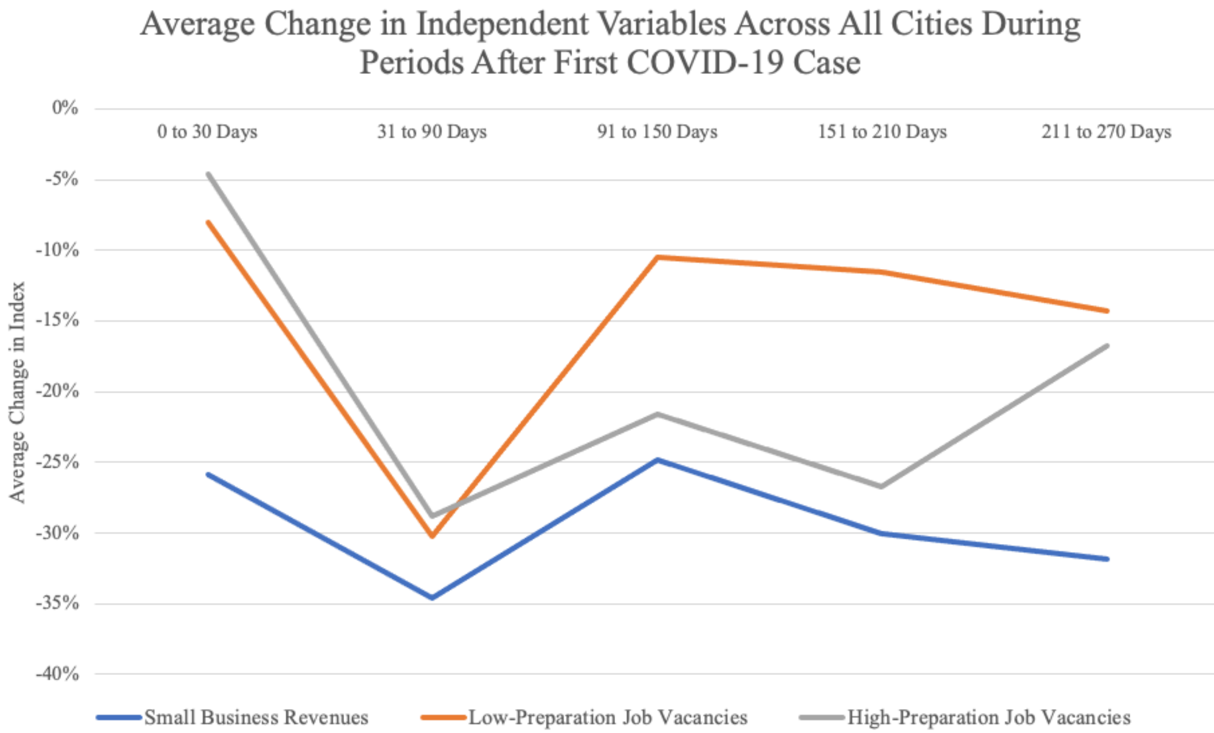
5 Analysis

In the following section, the results of the regressions are separated by the dependent variable. Tables 1-4 analyze how small business revenues are affected by COVID-19, Tables 5-8 contain the low-preparation job vacancy regressions, and Tables 8-12 show the results of the high-preparation job vacancy regressions. The analysis generally finds that local small business revenues and low-preparation job vacancies are correlated, as many small businesses such as landscapers and restaurants depend on low-skill labor. High-preparation job vacancies are more difficult to analyze as these regressions explain relatively little of the variation in vacancies between cities.

The analysis ends at 270 days (roughly nine months) after the first COVID-19 case as this is the farthest date for which there is data for all cities in the sample at the time of writing (as cities experienced their first COVID-19 case on different dates).

Accompanying the high levels of unemployment during the COVID-19 pandemic has been a decreased rate of job vacancies, particularly in high-preparation jobs as shown in Figure 1. While low-preparation job vacancies remain roughly 10% lower than before the pandemic up to 270 days after the first COVID-19 case, high-preparation job vacancies are 23% below pre-pandemic levels during the same period. According to Lazear and Spletzer (2012), an economic shock decreases the demand for labor as well as churn because few new jobs are created. Generally, churn is higher for low-skill positions as these jobs require less preparation and firms invest less in the human capital of the employees.

Figure 1



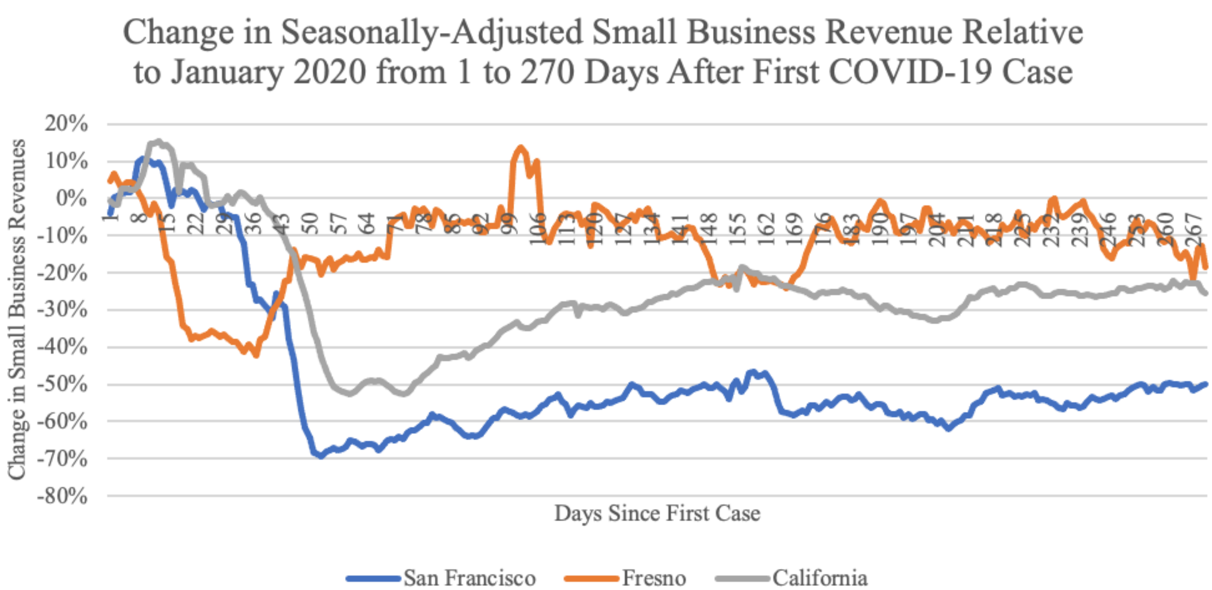
Source: Opportunity Insights. Low-Preparation Job Vacancies are comprised of vacancies in O*NET Zones 1 and 2. High-Preparation Job Vacancies are comprised of vacancies in O*NET Zones 3, 4, and 5.

However, the lower vacancy rate of high-preparation vacancies in Figure 1 is consistent with research from Campello et al. (2020), who find that firms have cut high-skill postings more than low-skill postings and that cuts are most pronounced in local labor markets with high levels of firm concentration. Given that sampled cities do vary significantly in their high-preparation vacancy rates, further study is needed to determine which cities in the sample have more concentrated labor markets. It is also likely that quits have decreased during the pandemic, as uncertainty leads employees to stay in their current roles, and this could also depress the high-skill vacancy rate. One consequence of this reduced churn, according to Lazear and Spletzer, is that workers are not allocated to where they are most productive. This is an unmeasured result of the COVID-19 pandemic that will be difficult to ascertain until after the recession concludes.

5.1 Small Business Revenues

As seen in the figure below, it is clear that there are city-level differences in economic activity during the COVID-19 pandemic. Fresno and San Francisco are both in California and four hours apart by car; however, small business revenue in these cities was persistently different over the first 270 days of the pandemic. I find that differences in mobility have a highly positive and significant effect on small business revenues, and Fresno residents are much more active outside of their homes during this 270-day time period. Average levels of mobility are 23% lower in San Francisco during these 270 days relative to January 2020 while, in Fresno, average mobility is only 10% lower than January 2020 levels. Also, residents of Fresno were significantly more likely to vote for Donald Trump in the 2016 election. Only 22% of Los Angeles metro voters chose Donald Trump in 2016 compared to 47% of Fresno voters. Finally, I find that increasing historical levels of per-capita accommodation spending have a significant negative effect on local small business revenues, and accommodation spending is eight times higher in San Francisco than in Fresno.

Figure 2



Source: Opportunity Insights. The first COVID-19 case in California confirmed by the CDC occurred on January 26th, 2020.

This paper claims that pre-pandemic differences between cities can help explain the revenues of local small businesses during the COVID-19 pandemic. However, a challenge throughout this analysis is disentangling the connection between COVID-19 cases, mobility, and economic well-being. There is an astonishing amount of variation in the COVID-19 case rate during these 270 days. While San Jose and San Francisco both kept COVID-19 case rates below 1.4% of the metro population, Miami and El Paso had case rates of 8.9% and 10.8% respectively. On average, across the sample, the case rate over the first 270 days was 4.3% with a sample standard deviation of 1.9%.

Before considering how economic variables can explain which cities experienced the largest maximum decline and the fastest recovery, it is important to consider how much explanatory power COVID-19 cases have on small business revenue and job vacancies. In Table 1, the cumulative rate of COVID-19 cases has almost zero explanatory power for small business revenue. However, average mobility is highly significant. This is as expected as many small businesses and their employees depend heavily on foot traffic, such as coffee shops or restaurants.

The correlation coefficient between the case rate and average mobility after 270 days is 0.40, which implies that there exists some positive correlation between the cumulative case rate and the mobility of urban residents up to 270 days after the first case in the respective city. This relationship implies that higher levels of mobility in metro areas lead to higher COVID-19 case rates, and this is generally supported by most theories about pandemics and the link between movement and transmission of viruses.

As evidenced by Table 1, vacancies and small business revenues do not appear to be explained by the rate of COVID-19 cases during the first 270 days after the first COVID-19 case in a city. Controlling for the COVID-19 case rate, a 1% increase in average mobility in a metro area relative to January 2020 leads to a 1.71% increase in small business revenues relative to January 2020 over the same period. Although this nine-month window is large, this implies that an increase in cases in a city is associated with a decrease in mobility. One alternate theory stands out that could support the alternate conclusion of an increase in mobility being correlated with a decrease in cases: some cities, over time, have become more adept at allowing residents to return to some facets of life pre-pandemic, such as eating in restaurants or working in an office, while limiting the number of cases through technology or mask mandates.

Table 1: Small Business Revenues 1 to 270 Days After First COVID-19 Case

Dependent Variable: *Small Business Revenue 1 to 270 Days After First Case (1)*

Independent Variables	Model 1	Model 2	Model 3
constant	-0.31***	-0.31***	-0.31***
	(0.01)	(0.01)	(0.01)
Case Rate 1 to 270 Days (2)	1.20		-0.11
	(0.74)		(0.66)
Average Mobility 1-270 Days After First COVID-19 Case (3)		1.69***	1.71***
		(0.32)	(0.35)
Obs.	52	52	52
R^2	0.05	0.36	0.36

1: This refers to the average change in small business revenue in a city 210-270 days after the city registered its first positive COVID-19 case

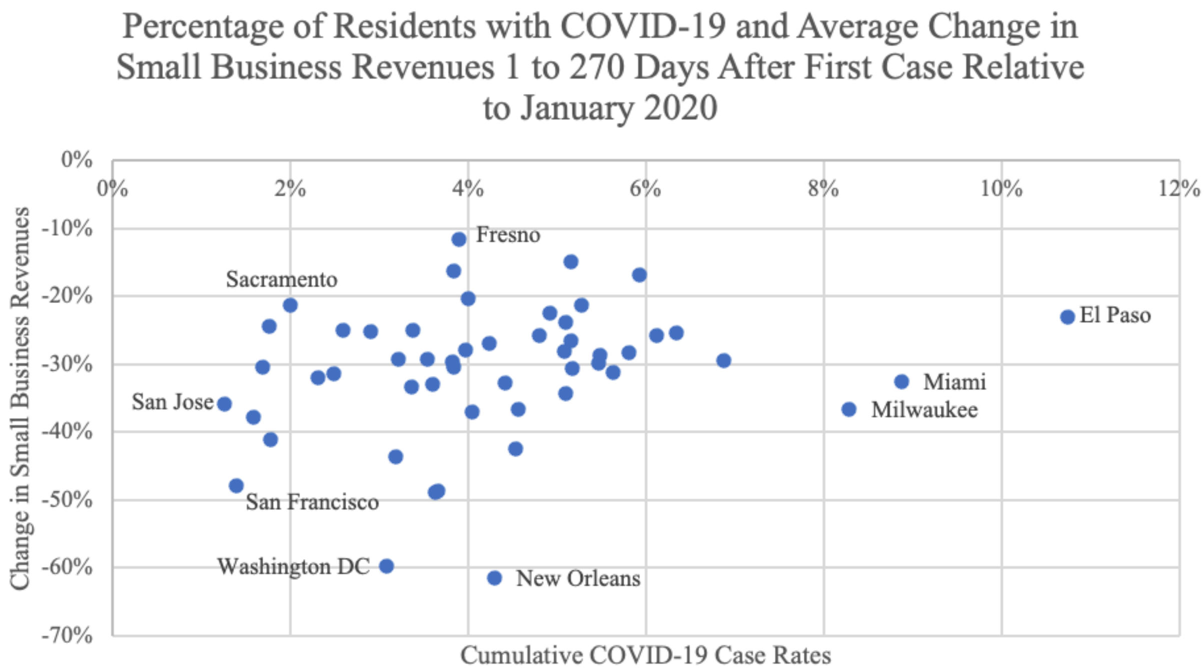
2: This refers to the percentage of the population that tested positive for COVID-19 in the first 270 days after the first positive COVID-19 case was recorded in the city

3: Google Community Mobility tracks time spent away from home, estimated using cellphone location data, and these values are indexed to January 2020 then averaged over the time period (not seasonally adjusted).

Please note that these results are robust for 151 to 210 days after the first recorded COVID-19 case in the city and also after the city reaches a 0.1% case rate threshold (instead of using the date of the first confirmed COVID-19). These results for small business revenues, low-preparation job vacancies, and high-preparation job vacancies can be found in the appendix.

Below, Figure 3 shows the variation in case rates and the average level of small business revenues relative to January 2020. This figure illustrates that some cities, such as Sacramento, have been able to preserve local small business revenues while also limiting the spread of COVID-19. This figure provides visual support that city-level differences in COVID-19 case rates are not the primary driver of small business revenues; instead, other variables explored in Tables 2, 3, and 4 could be the source of these different outcomes.

Figure 3



Source: Opportunity Insights

The lack of correlation between the rate of COVID-19 cases and local revenues is puzzling until the decisions of government officials and risk-averse individuals are considered. For government officials, the decision to save lives and reduce the rate of infection necessitates stay-at-home orders, and these can remain in place to prevent future cases regardless of current case rates. Additionally, residents who are rightfully concerned about the virus will restrict their activities on their own as much as possible, especially wealthier residents who can afford to shelter in place or leave densely populated areas (more on this in the conclusion). COVID-19 is highly infectious, and many infected individuals are asymptomatic; therefore, whether there is one novel case in a city or ten thousand, residents will generally restrict movement and take additional precautions regardless of the actual case rate.

Table 2 examines the resiliency of metro economies during COVID-19. As there is no vaccine readily available during this period, cities must balance maintaining their economies and the health of residents. This analysis extends in discrete periods up to 270 days (roughly nine months) after each city in the sample experienced its first COVID-19 case. In Table 2, it is clear that accommodation spending and average mobility are highly significant. This analysis finds that a 1% increase in average mobility of residents relative to January 2020 leads to a greater than 1% increase in small business revenues up to 210 after the first COVID-19 case in a city.

Conversely, 2012 levels of accommodation spending (the annual spending on hotels and restaurants in the metro area divided by the metro area population) do have a significant negative effect on small business revenues after the first COVID-19 case. This analysis shows that a 1% increase in tourism spending per person is correlated with a 0.09% decrease in small business revenues up to 270 days after the pandemic began.

Table 2: Small Business Revenues after First COVID-19 Case

Dependent Variable: *Small Business Revenues after First Case (1)*

Independent Variables	1 to 30 Days	31 to 90 Days	91 to 150 Days	151 to 210 Days	211 to 270 Days
Constant	-0.26***	-0.35***	-0.25***	-0.30***	-0.24***
	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)
Mobility Index After COVID-19 (2)	2.37***	1.90***	1.14***	1.26**	0.33
	(0.14)	(0.31)	(0.32)	(0.40)	(0.65)
Accommodation Spending (3)	-0.04**	-0.07***	-0.09***	-0.09***	-0.09***
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Share of Trump Votes 2016 (4)	-0.09	0.01	0.20	-0.02	0.18
	(0.08)	(0.12)	(0.14)	(0.15)	(0.21)
Obs.	50	50	50	50	50
R^2	0.88	0.74	0.70	0.56	0.38

1: This represents the seasonally adjusted average change in small business revenue in a city indexed to January 2020 during the specified time period after the first COVID-19 case in the same city.
2: Google Community Mobility tracks time spent away from home, estimated using cellphone location data, and these values are indexed to January 2020 then averaged over the time period (not seasonally adjusted).
3: The log of the quantity of money spent on accommodation, the combination of lodging and dining, in a city per resident in 2012 in thousands of dollars, per the US Census.
4: The percentage of votes in the metro area for Donald Trump in the 2020 Presidential Election

The positive effect of mobility on small business revenues does attenuate as the periods extend farther from the date of the first case, and during the last 60 days of the analysis average mobility is no longer significant. Average mobility across all cities in the sample between 1 and 60 days after each metro's first COVID-19 case is 16% below January 2020 levels, and between 211 and 270 days after the first COVID-19 case it has risen on average to only 12% below January 2020 levels. Additionally, the sample standard deviation of mobility during the first sixty days (5.4%) is higher than the sample standard deviation of mobility during the period of 211 to 270 days (3.8%) after the first case in each respective metro. These variances are also significantly different at the 1% level when compared using an F-test. This suggests that city-level differences in mobility are decreasing and nationally, mobility of metro residents appears to be converging.

Although this effect of accommodation spending appears small, it is persistently significant for every period and after controlling for the mobility of metro residents. Additionally, there is wide variation in accommodation spending: 2012 per-capita accommodation spending in Oakland, California was $499, compared to $7,229 in Washington DC. Therefore, cities that rely heavily on tourism, such as Miami and New Orleans, were particularly devastated by the pandemic, as visitors account for the bulk of restaurant and hotel spending. This likely explains why accommodation spending has a highly significant negative coefficient for small business revenues. This suggests that cities that rely heavily on tourism and do not have diversified economies, such as Miami and New Orleans, are struggling more during the COVID-19 recession. It is also important to note that this effect appears to become even stronger during later periods even though the revenues are seasonally adjusted.

Table 3 examines the effect of pre-pandemic economic variables on average small business revenues between 1 and 90 days after the first metro-area COVID-19 case relative to the revenues of the respective metro area in January 2020. On average, for all cities across the sample, the first COVID-19 case occurred on the 61st day of the calendar year. This means for the average city in the sample, Table 3 examines the days between March 2nd and June 1st, 2020.

Models 1-5 contain univariate regressions of a single pre-pandemic variable, and Model 6 shows the multivariate regression with every variable included. Across the sample, small business revenues were 33% below January 2020 levels during the period, on average. The 2016 share of Trump votes is significant at the 5% level, and its coefficient implies that a 1% increase in the share of votes cast for Trump in the metro area corresponded with a 0.28% increase in small business revenues relative to January 2020 over the first 90 days of the pandemic. The accommodation spending coefficient suggests that a 1% increase in 2012 levels of per-capita accommodation spending led to a 0.10% decrease in average small business revenues relative to January 2020 over the first 90 days of the pandemic.

Table 3: Small Business Revenues 1 to 90 Days after First COVID-19 Case

Dependent Variable: *Small Business Revenues 1 to 90 Days after First Case (1)*

Independent Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Constant	-0.33***	-0.33***	-0.33***	-0.33***	-0.33***	-0.33***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Share of Trump Votes 2016 (2)	0.28*					0.18
	(0.13)					(0.19)
Accommodation Spending (3)		-0.10***				-0.10***
		(0.02)				(0.02)
Median Household Income (4)			-0.02			0.10
			(0.06)			(0.06)
Share of High Digital Skill Jobs (5)				-0.23		-0.12
				(0.39)		(0.40)
Density (6)					-0.05	-0.02
					(0.03)	(0.03)
Obs.	52	50	52	52	52	50
R^2	0.09	0.32	0.00	0.01	0.07	0.40

1: This represents the seasonally adjusted average change in small business revenue in a city indexed to January 2020 during the specified time period after the first COVID-19 case in the same city.
2: The percentage of votes in the metro area for Donald Trump in the 2020 Presidential Election
3: The log of the quantity of money spent on accommodation, the combination of lodging and dining, in a city per resident in 2012 in thousands of dollars, per the US Census.
4: The log of the median household income for a city between 2014-2018, per the US Census Bureau.
5: The percentage of jobs in the metro area that require high digital skills, as defined by Muro et al. (2017)
6: The log of 2010 population-weighted density from the US Census Bureau

Even during the first three months of the pandemic, the effect of higher levels of historical accommodation spending on local businesses is highly significant and explains 32% of the variation in small business revenues between metros. Although the share of Trump votes is significant at the 5% level, this variable has significantly lower explanatory power than the accommodation spending. This suggests that, during the first 90 days of the pandemic, political differences between metro areas do not explain the differences in small business revenues between cities.

Table 4 examines the effect of pre-pandemic economic variables on average small business revenues between 1 and 270 days after the first metro-area COVID-19 case relative to the revenues of the respective metro area in January 2020. On average, for all cities across the sample, this period occurs between March 2nd and November 17th, 2020. On average, small business revenues were 31% lower than January 2020 levels during the 270-day period. Models 1-5 contain univariate regressions of a single pre-pandemic variable, and Model 6 shows the multivariate regression with every variable included. Model 1 shows that a 1% increase in the share of votes for Trump in the metro area corresponds with a 0.38% increase in average small business revenues over the 270-day period relative to January 2020. However, a 1% increase in accommodation spending leads to a 0.10% decrease in average small business revenues over the same period. The percentage share of jobs that require high digital skills in the metro area and the population-weighted density also have a significant negative effect on small business revenues over the 270-day period.

Table 4: Small Business Revenues 1 to 270 Days after First COVID-19 Case

Dependent Variable: *Small Business Revenues 1 to 270 Days after First Case (1)*

Independent Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Constant	-0.31***	-0.31***	-0.31***	-0.31***	-0.31***	-0.31***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Share of Trump Votes 2016 (2)	0.38**					0.05
	(0.11)					(0.14)
Accommodation Spending (3)		-0.10***				-0.10***
		(0.02)				(0.02)
Median Household Income (4)			-0.10			0.06
			(0.05)			(0.05)
Share of High Digital Skill Jobs (5)				-0.80*		-0.61*
				(0.34)		(0.29)
Density (6)					-0.07**	-0.06*
					(0.02)	(0.03)
Obs.	52	50	52	52	52	50
R^2	0.19	0.43	0.07	0.10	0.19	0.62

1: This represents the seasonally adjusted average change in small business revenue in a city indexed to January 2020 during the specified time period after the first COVID-19 case in the same city.
2: The percentage of votes in the metro area for Donald Trump in the 2020 Presidential Election
3: The log of the quantity of money spent on accommodation, the combination of lodging and dining, in a city per resident in 2012 in thousands of dollars, per the US Census.
4: The log of the median household income for a city between 2014-2018, per the US Census Bureau.
5: The percentage of jobs in the metro area that require high digital skills, as defined by Muro et al. (2017)
6: The log of 2010 population-weighted density from the US Census Bureau

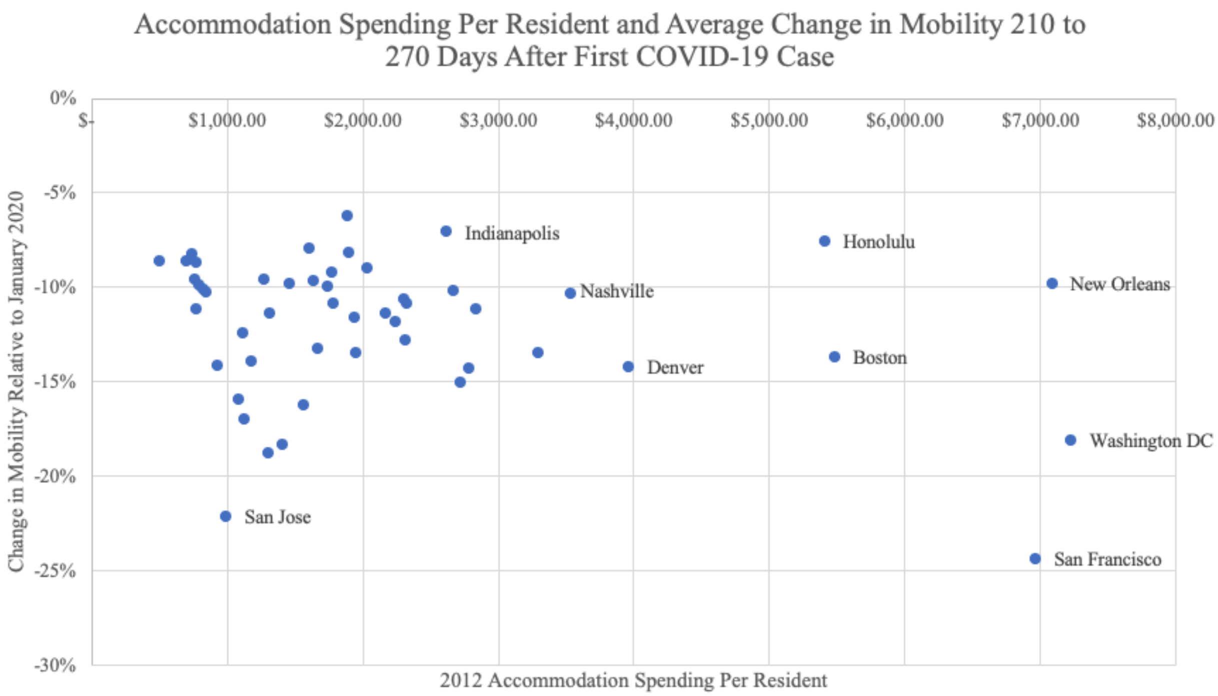
The share of jobs in the metro area that require high levels of digital skills is negatively correlated with average mobility over the 270-day period (-0.55), and this may be explained by high skill (and generally high wage) workers better able to shelter in place and work remotely. As mobility and small business revenues are highly correlated, this means that a large share of technically skilled workers in a metro area should result in lower small business revenues due to an increased propensity to shelter in place. Density is also negatively correlated with average mobility during the time period, and this is likely due to residents of dense, urban cities feeling less comfortable visiting local businesses or using public transportation such as subways and buses.

Model 6 shows that a multivariate regression of small business revenue on these five pre-pandemic variables has a coefficient of determination of 0.62. This implies that these variables together can explain 62% of the variation in revenues between cities during the first roughly nine months of the pandemic. Although the share of Trump voters in the 2016 Presidential election is not significant in the multivariate regression, a regression of small business revenue on accommodation spending and the share of Trump voters results in both variables having coefficients that are significant at the 1% level. The coefficient of Trump votes is 0.33 while the coefficient of accommodation is -0.10. This regression has a coefficient of determination of 0.56 which implies that 56% of the variation in small business revenues between cities can be explained solely by 2016 election results and 2012 per-capita accommodation spending.

One interpretation of this model is that, after controlling for accommodation spending between cities, the share of Trump voters in the 2016 election has a highly significant positive effect on small business revenues during the first 270 days of the pandemic. This implies that metro areas with high levels of tourism and more liberal voting bases, such as New York and San Francisco have been justly more restrictive on residents and small businesses during the COVID-19 pandemic to keep residents safe and prevent the spread of the virus. Additionally, the COVID-19 pandemic has such a devastating impact on the accommodation sector that the Trump votes may only explain city-level differences after controlling for the highly significant effect of accommodation spending.

Below is a figure which shows how cities that experience historically higher levels of tourism have been somewhat more restrictive on the movement of residents during the pandemic. The two variables are negatively correlated: average mobility between 1 and 270 days after the first case and accommodation spending have a correlation coefficient of -0.43. Likely, that ‘destination’ cities have generally stricter “lockdowns” to discourage tourism.

Figure 4



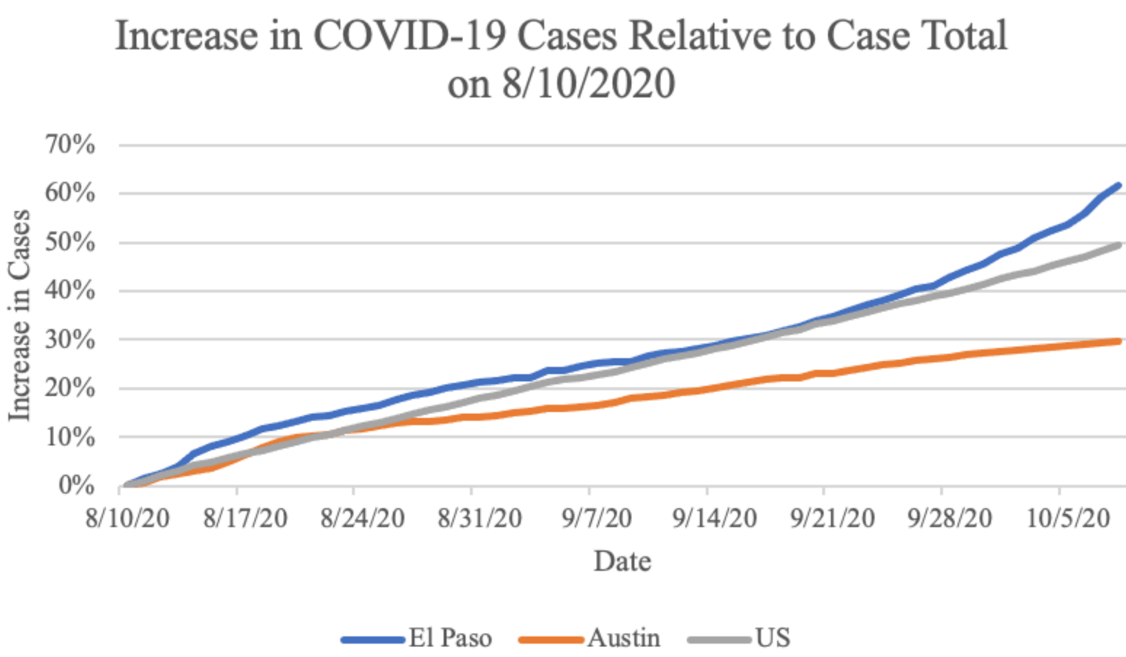
Source: US Census Bureau and Opportunity Insights

One potential reason why the consistently lower revenues of small businesses persist through 2020 is that 'sticky' habits were formed and these led to persistent revenue declines. With public transit largely avoided or closed during the pandemic, this could cause some cities to remain at lower levels of mobility and, as a result, small business revenues. A popular storyline throughout the pandemic has been the 'exodus' from dense cities, such as New York, aided by the ability to work remotely. An exodus from dense cities would result in lower small business revenues relative to January 2020 as the data are not adjusted for changes in population during the pandemic. However, data from *Bloomberg CityLab* do not support this story of 'mass exodus' from highly populated urban areas due to COVID-19. A thorough study of public transit and the relocation of city residents is needed to understand these potentially confounding variables.

To further explore these relationships, it is useful to directly compare two cities: El Paso and Austin. The cities are roughly seven hours apart by car and are both in Texas. Austin is wealthier in terms of median household income ($67,462 compared to $45,465) and Austin is more educated with 50.4% of residents have a college degree versus El Paso's 24.7%. Austin residents were also more likely to vote for Donald Trump in the 2016 Presidential election, as he captured 38% of total votes compared to 26% in El Paso.

Austin has roughly 50% more residents than El Paso but is slightly less dense. However, neither have the high density associated with New York City or San Francisco. Accommodation spending is almost twice as high in Austin versus El Paso: $2,727 and $1,562, in order. However, the accommodation data dates back to 2012 and, given Austin's recent growth, the magnitude of accommodation spending is likely significantly higher. Through their first 150 days with COVID-19 (both cities received their first case on March 13th) the case rates are almost identical: 1.8% of Austin's population contracted COVID-19 and 1.95% of El Paso's population had been infected. However, between 150 and 210 days after their first cases, the infection rate in El Paso spiked, and this can be seen in Figure 5.

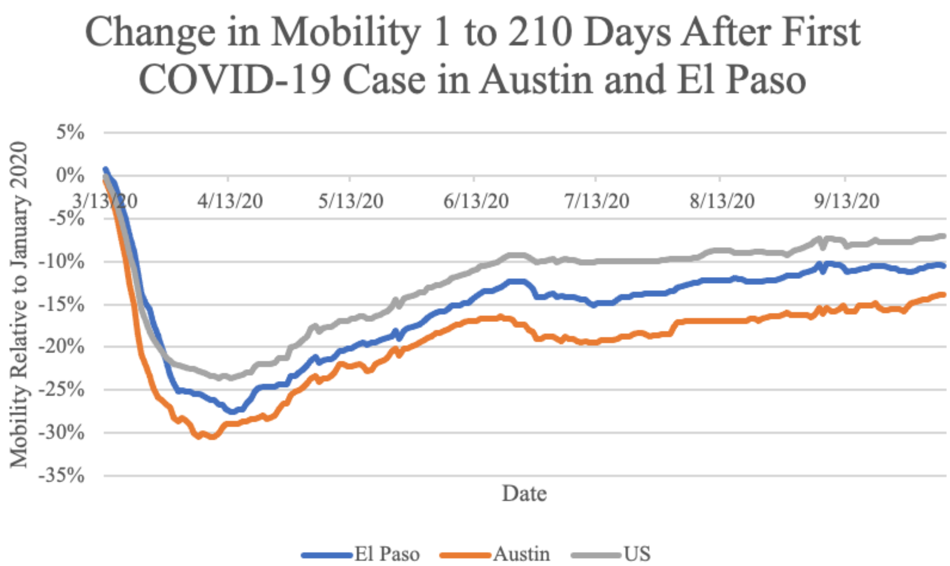
Figure 5



Source: Opportunity Insights

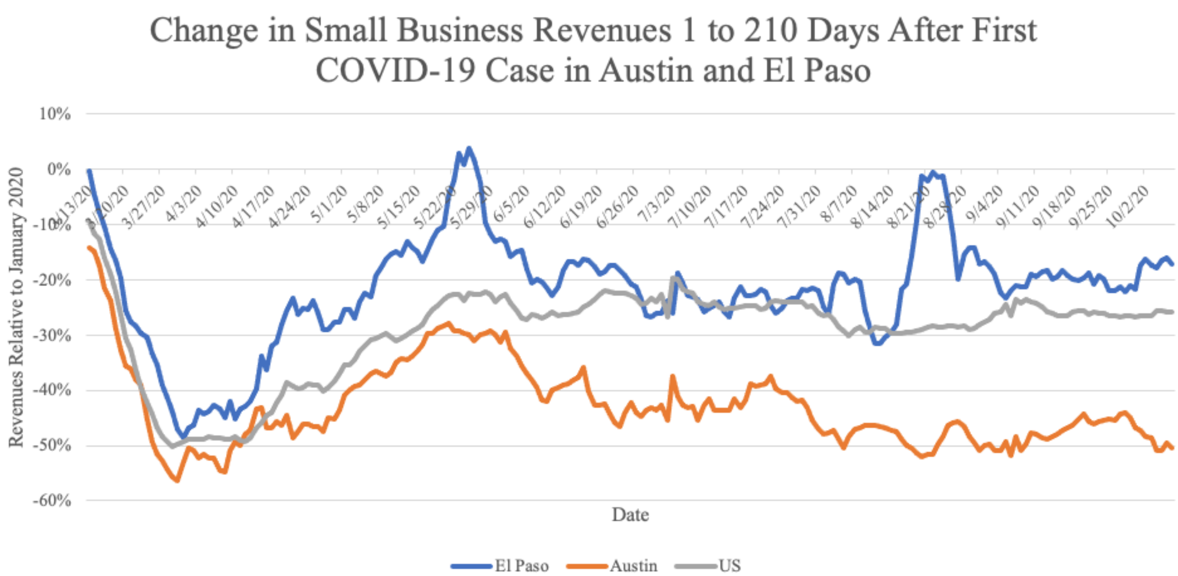
El Paso had higher levels of average mobility during the COVID-19 recession, as seen in Figure 6, and its local economy relies far less on tourism and accommodation spending. This can be viewed in Figure 7.

Figure 6



Source: Opportunity Insights

Figure 7



Source: Opportunity Insights

Although the COVID-19 case rate accelerates in El Paso after August 10th, this does not appear to cause significant downward pressure on small business revenues in the city. This further supports the hypothesis that case rates are not directly correlated with small business revenues; instead, the more mobile El Paso population is driving these revenue increases. One confounding variable in this analysis is the number of residents who remain in El Paso and Austin during the pandemic. If Austin residents have left the city to work remotely elsewhere, then the differences in small business revenues could be explained by the missing residents and not the mobility of those who remain.

5.2 Low-Preparation Job Vacancies

Figure 8 provides further support for the hypothesis that city-level differences are driving different economic outcomes. As in Figure 2, San Francisco and Fresno are used to illustrate the persistent differences in economic outcomes during the COVID-19 pandemic. Metro small business revenues and low-preparation job vacancies are highly correlated (0.67) over the 270-day period, and therefore it is unsurprising that persistently lower small business revenues in San Francisco are also connected with lower levels of low-preparation job vacancies than in Fresno.

Figure 8

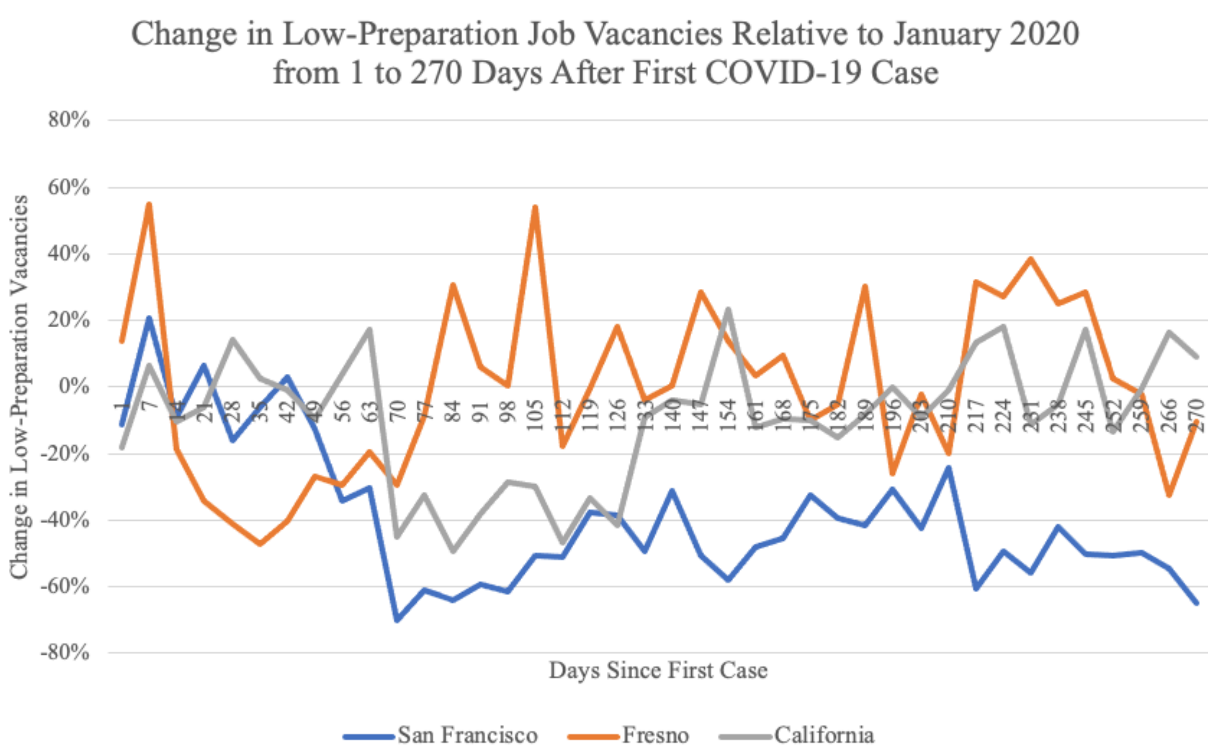


Table 5 contains regressions of low-preparation job vacancies on COVID-19 variables and mobility to understand the connection between positive cases and the hiring needs of businesses in a metro area. Mobility is highly significant in explaining the low-preparation job vacancies; this multivariate regression suggests that, without controlling for metro-level rates of COVID-19, a 1% increase in mobility in the metro over the period relative to the same metro in January 2020 leads to a 2% increase in low-preparation job vacancies over the same period.

Table 5: Low-Preparation Job Vacancies 1 to 270 Days After First COVID-19 Case

Dependent Variable: *Low-Preparation Job Vacancies 1 to 270 Days After First Case (1)*

Independent Variables	Model 1	Model 2	Model 3
constant	-0.16***	-0.16***	-0.16***
	(0.02)	(0.02)	(0.02)
Case Rate 1 to 270 Days (2)	0.73		-0.97
	(0.85)		(0.71)
Average Mobility 1-270 Days After First COVID-19 Case (3)		2.01***	2.22***
		(0.34)	(0.37)
Obs.	52	52	52
R^2	0.01	0.41	0.43

1: This refers to the average change in low-preparation job vacancies in a city 211-270 days after the city registered its first positive COVID-19 case

2: This refers to the percentage of the population that tested positive for COVID-19 in the first 270 days after the first positive COVID-19 case was recorded in the city

3: Google Community Mobility tracks time spent away from home, estimated using cellphone location data, and these values are indexed to January 2020 then averaged over the time period (not seasonally adjusted).

Just as with metro-level small business revenues, I find that case rates of COVID-19 alone do not have a significant effect on the level of low-preparation job vacancies during the first 270 days of the 2020 pandemic.

Table 6 regresses low-preparation vacancies on pre-pandemic variables and mobility over several periods after each metro area’s first respective COVID-19 case to determine the effect of the mobility on low-preparation job vacancies. The coefficient on average mobility is highly positive and is largest between 91 and 150 days after the first COVID-19 case in each city. During this period, a 1% increase in mobility relative to January 2020 implies a 2.19% increase in low-preparation job vacancies. However, just as in Table 2, the average mobility during the last period (211 to 270 days) is not significant. Meanwhile, the effect of accommodation spending continues to strengthen and become more significant every period: over the last sixty days in the sample, a 1% increase in accommodation spending, on average, corresponds to a 0.14% decrease in low-preparation job vacancies in the same metro.

Table 6: Low-Preparation Job Vacancies after First COVID-19 Case

Dependent Variable: *Low-Preparation Job Vacancies After First Case (1)*

Independent Variables	1 to 30 Days	31 to 90 Days	91 to 150 Days	151 to 210 Days	211 to 270 Days
Constant	-0.08***	-0.30***	-0.10***	-0.11***	-0.14***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Mobility Index After COVID-19 (2)	1.17***	1.62***	2.19***	2.03***	1.31
	(0.18)	(0.37)	(0.38)	(0.53)	(0.75)
Accommodation Spending (3)	-0.00	-0.02	-0.06**	-0.11***	-0.14***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Share of Trump Votes 2016 (4)	0.08	-0.13	0.07	-0.25	-0.11
	(0.11)	(0.15)	(0.17)	(0.20)	(0.25)
Obs.	50	50	50	50	50
R^2	0.48	0.45	0.71	0.54	0.50

1: This represents the average change in new low-preparation job postings on online job boards for each city during the specified time period, indexed to January 2020 and not seasonally adjusted

2: Google Community Mobility tracks time spent away from home, estimated using cellphone location data, and these values are indexed to January 2020 then averaged over the time period (not seasonally adjusted).

3: The log of the quantity of money spent on accommodation, the combination of lodging and dining, in a city per resident in 2012 in thousands of dollars, per the US Census.

4: The percentage of votes in the metro area for Donald Trump in the 2020 Presidential Election

Again, I find a significantly persistent negative effect of accommodation spending on a dependent economic variable. This likely implies that cities in the sample more heavily reliant on tourism, such as Miami or Virginia Beach, have not seen job vacancies recover to pre-pandemic levels.

Table 7 shows the results of regressing low-preparation job vacancies over the first 90 days of the pandemic on several pre-pandemic economic variables in the respective metro area. Models 1-5 contain univariate regressions of a single pre-pandemic variable, and Model 6 shows the multivariate regression with every variable included. Across the sample, low-preparation vacancies were, on average, 24% below January 2020 levels during the period.

Table 7: Low-Preparation Job Vacancies 1 to 90 Days after First COVID-19 Case

Dependent Variable: *Low-Preparation Job Vacancies 1 to 90 Days after First Case (1)*

Independent Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Constant	-0.24***	-0.24***	-0.24***	-0.24***	-0.24***	-0.24***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Share of Trump Votes 2016 (2)	0.21					0.25
	(0.11)					(0.20)
Accommodation Spending (3)		-0.03				-0.04
		(0.02)				(0.02)
Median Household Income (4)			-0.02			0.05
			(0.05)			(0.06)
Share of High Digital Skill Jobs (5)				-0.09		0.12
				(0.33)		(0.41)
Density (6)					-0.03	0.00
					(0.02)	(0.03)
Obs.	52	50	52	52	52	50
R^2	0.07	0.06	0.09	0.00	0.03	0.13

1: This represents the average change in new low-preparation job postings on online job boards for each city during the specified time period, indexed to January 2020 and not seasonally adjusted
2: The percentage of votes in the metro area for Donald Trump in the 2020 Presidential Election
3: The log of the quantity of money spent on accommodation, the combination of lodging and dining, in a city per resident in 2012 in thousands of dollars, per the US Census.
4: The log of the median household income for a city between 2014-2018, per the US Census Bureau.
5: The percentage of jobs in the metro area that require high digital skills, as defined by Muro et al. (2017)
6: The log of 2010 population-weighted density from the US Census Bureau

The table above shows that none of the pre-pandemic variables have a significant effect on low-preparation vacancies during the first 90 days of the COVID-19 pandemic. Unlike the revenues analyzed in section 5.1, the low-preparation vacancies also include postings from national firms such as fast-food restaurants and department stores. These large firms may have frozen hiring and taken down postings for all of their locations, and so the low-preparation vacancies do not reflect city-level differences to the same extent as small business revenues. This is supported by the average small business revenues during the first 90 days of the pandemic having a larger sample standard deviation and range than the low-preparation job vacancies. Additionally, unlike in Table 3, accommodation spending is not a significant variable over the first 90 days of the pandemic. This is likely due to firms reducing vacancies uniformly across all industries during the early days of the pandemic due to uncertainty about tourism and indoor dining. In later periods the effect of accommodation spending will strengthen (as seen in Table 6) as employers in accommodation-related sectors continue to delay hiring.

Table 8 shows the results of regressing low-preparation job vacancies over the first 270 days of the pandemic on several pre-pandemic economic variables in the respective metro area. Models 1-5 contain univariate regressions of a single pre-pandemic variable, and Model 6 shows the multivariate regression with every variable included. The results of the multivariate regression imply that a 1% increase in accommodation spending in a metro area is correlated with a 0.09% decrease in low-preparation job vacancies up to 270 days after the first local COVID-19 case. In Model 1 I find that a 1% increase in the share of voters for Trump in the 2016 Presidential election is correlated with a 0.42% increase in low-preparation job vacancies over the period. In Model 3 I find that a 1% increase in median household income corresponds to a 0.13% decrease in low-preparation vacancies in the same metro, while in Model 5 I find that a 1% increase in population-weighted density leads to a 0.07% decrease in low-preparation vacancies.

Table 8: Low-Preparation Job Vacancies 1 to 270 Days after First COVID-19 Case

Dependent Variable: *Low-Preparation Job Vacancies 1 to 270 Days after First Case (1)*

Independent Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Constant	-0.16***	-0.16***	-0.16***	-0.16***	-0.16***	-0.16***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Share of Trump Votes 2016 (2)	0.42**					0.30
	(0.13)					(0.20)
Accommodation Spending (3)		-0.10***				-0.09***
		(0.02)				(0.02)
Median Household Income (4)			-0.13*			0.01
			(0.06)			(0.06)
Share of High Digital Skill Jobs (5)				-0.70		-0.19
				(0.39)		(0.41)
Density (6)					-0.07*	-0.01
					(0.03)	(0.03)
Obs.	52	50	52	52	52	50
R^2	0.19	0.29	0.08	0.06	0.12	0.43

1: This represents the average change in new low-preparation job postings on online job boards for each city during the specified time period, indexed to January 2020 and not seasonally adjusted
2: The percentage of votes in the metro area for Donald Trump in the 2020 Presidential Election
3: The log of the quantity of money spent on accommodation, the combination of lodging and dining, in a city per resident in 2012 in thousands of dollars, per the US Census.
4: The log of the median household income for a city between 2014-2018, per the US Census Bureau.
5: The percentage of jobs in the metro area that require high digital skills, as defined by Muro et al. (2017)
6: The log of 2010 population-weighted density from the US Census Bureau

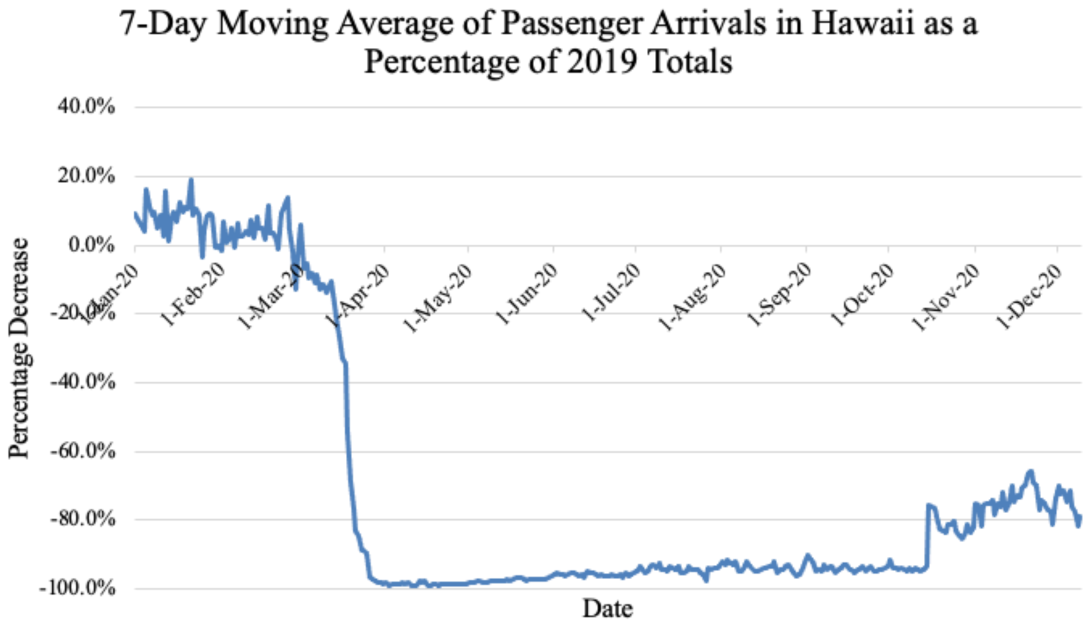
Just as in Table 4 (which examined small business revenues up to 270 days after the first case), the share of Trump votes, accommodation spending, and density are significant in the simple regression and their coefficients have similar magnitudes. This is likely due to the high correlation (0.67) between low-preparation vacancies and small business revenues. However, for low-preparation vacancies, the effect of metro median household income is also significant (albeit at the 5% level) and negative. Similar to the share of high digital skill jobs, median household incomes and average mobility over the first 270 days of the pandemic are also highly correlated (-0.70), and this likely means wealthier communities are more likely to shelter in place and enact more restrictive measures to prevent the spread of the virus. Importantly, low-preparation job vacancies include roles such as receptionists, customer service representatives, and upholsterers, which involve servicing wealthier clientele. However, during the pandemic, demand for these services has decreased due to sheltering in place and transactions moving online. This may explain why wealthier cities are experiencing persistently lower low-preparation vacancies.

Just as with small business revenues (in Table 4), the share of Trump votes in 2016 is not significant in the final multivariate regression. However, a regression of low-preparation vacancies on the share of Trump votes and accommodation spending results in a coefficient of determination of 0.42 (almost as high as in Model 6!) and the coefficients of both independent variables significant at the 1% level. The coefficient of the share of Trump votes is 0.37 which can be interpreted as, after controlling for COVID-19, a 1% increase in the share of voters for Trump leading to a 0.37% increase in the average low-preparation job vacancies during the first 270 days after the pandemic. COVID-19 has such a devastating impact on the accommodation sector that without controlling for the highly significant effect of accommodation spending on local low-preparation vacancies the full effect of the share of voters for Trump in the 2016 election can be seen.

For a second case study, two 'destination' cities will be compared that have economies heavily reliant on tourism. Throughout the COVID-19 pandemic, both small business revenues and low-preparation job vacancies appear to be significantly correlated with accommodation spending. Honolulu is a particular outlier due to its highly restrictive travel policy (a 14-day quarantine period) and physical location on an island far removed from the continental United States. For the first several months of the COVID-19 pandemic, the 7-day moving average of passengers arriving in Hawaii was down 99% year over year.

As evidenced by Figure 9, passenger arrivals only started to rebound in October (when the policy became less restrictive) and have not surpassed 40% of the previous year-over-year totals since the pandemic started. In terms of absolute numbers, roughly 30,000 fewer daily passengers are traveling to Hawaii (for reference, more than ten million tourists visited the state in 2019). Although not all of these tourists visit Honolulu, this decrease is still crippling for the local economy.

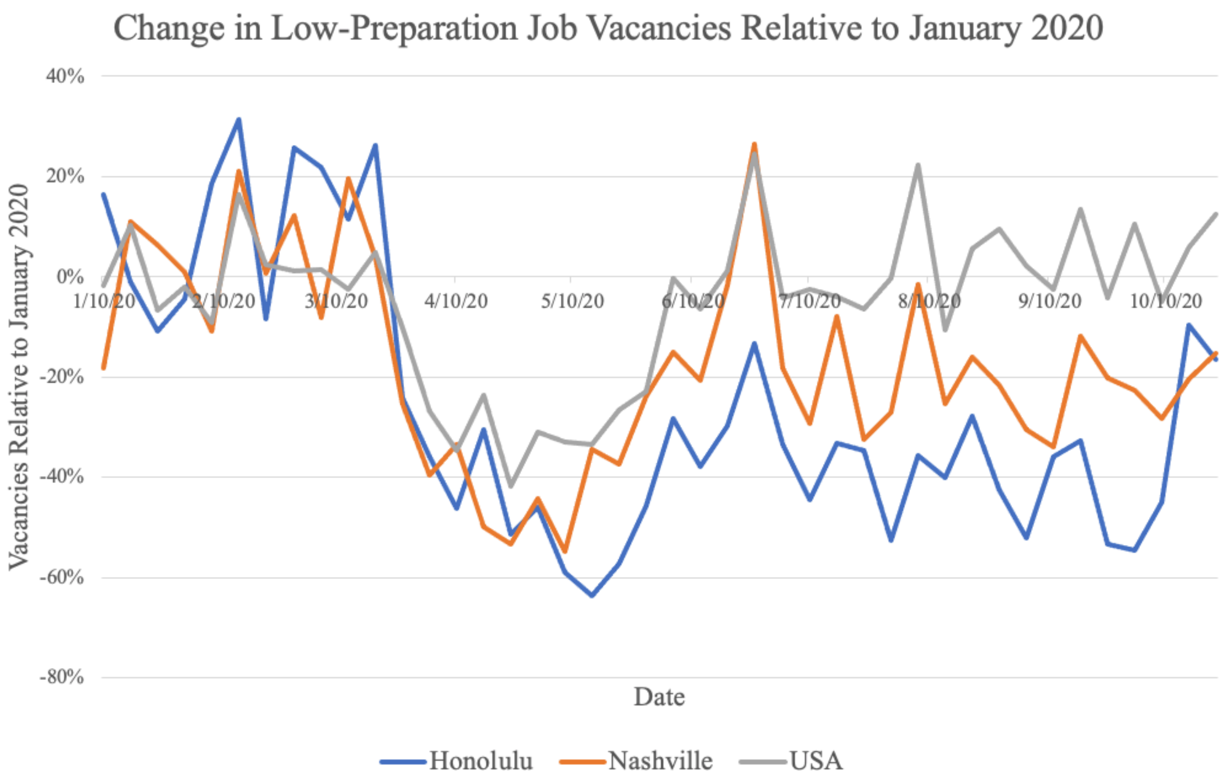
Figure 9



Source: Opportunity Insights

The practical elimination of tourism in Hawaii is visually apparent when comparing Honolulu and Nashville, two similarly sized cities whose economies are heavily dependent on tourism dollars. Not to be outdone by the state of Hawaii, Nashville alone received over 16 million visitors in 2019. Nashville has a slightly smaller population than Honolulu and received slightly less tourism spending: $3,537 per capita in Nashville compared to $5,411 in Honolulu. Nashville has a roughly 5 percentage point higher number of college graduates per capita but Honolulu is significantly wealthier, with a median household income that is nearly $27,000 higher. Neither Honolulu nor Nashville has a particularly large share of high-tech jobs, as jobs requiring high digital skill only account for 21.3% and 23.9% of all occupations, respectively. One important distinction is that Honolulu is much denser than Nashville due to constrained space on the island. As expected from the above regressions, low-preparation job vacancies are lower in Honolulu than in Nashville and the rest of the US (included for comparison below).

Figure 10



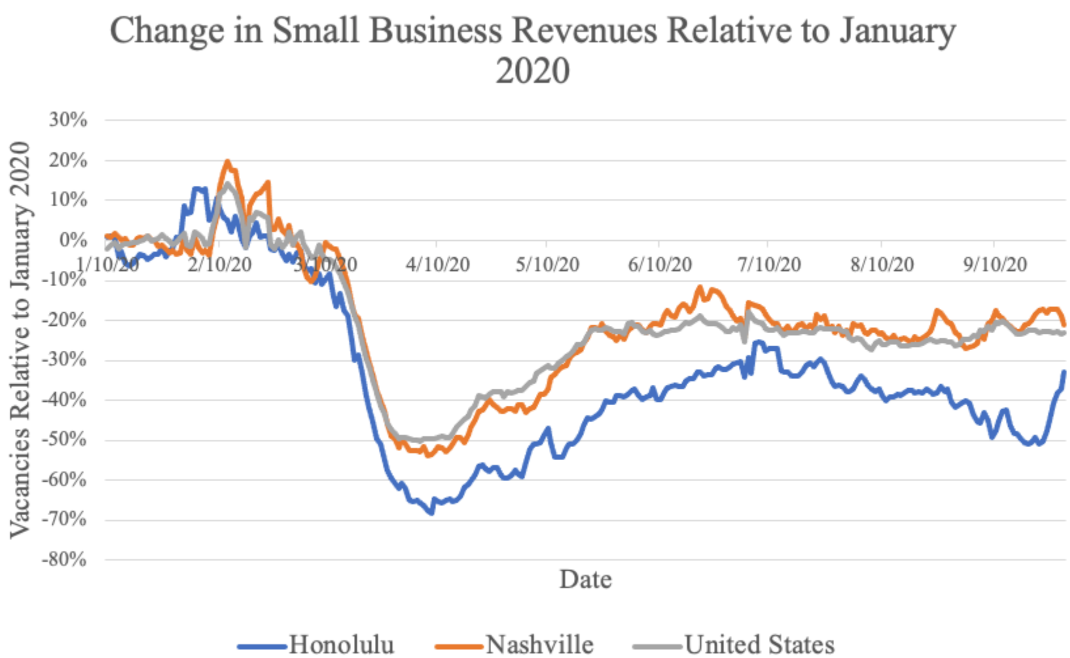
Source: Opportunity Insights. Low-Preparation Job Vacancies are comprised of vacancies in O*NET Zones 1 and 2.

For Honolulu, the loss of tourism jobs and business income is stark, although it is perhaps not as steep as expected considering that the total number of visitors to the islands during a typical year is seven times greater than the local population. Interestingly, in the month of October, there appears to be an uptick in low-preparation job vacancies. This increase in vacancies is likely due to an increased need to hire local workers to serve the tourists who are now traveling to the island. These vacancies could be considered a leading indicator as businesses need to hire and train local workers before tourists arrive to ensure their operations will run smoothly.

Although small business revenues also increase significantly in September, they are only rising back to their previous level from the summer months. The dip in small business revenues in July and August may be due to a spike in COVID-19 cases in Honolulu, which occurred in July and August before leveling off in October. However, Nashville has not seen a commensurate dip in small business revenue despite the case rate being almost four times greater than Honolulu and also twice the national average. More analysis is needed here to understand the changes in

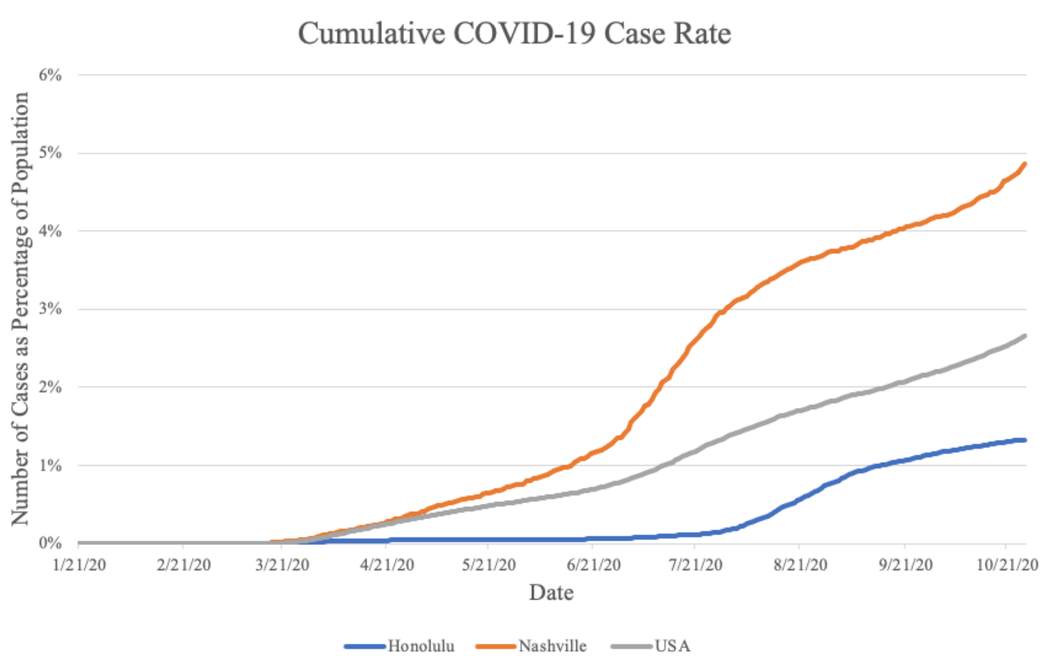
Honolulu's small business revenues, which can be seen below along with the cumulative case rates for both cities and the United States.

Figure 11



Source: Opportunity Insights

Figure 12



Source: Opportunity Insights

Low-preparation job vacancies are highly correlated with small business revenues, as evidenced above, and density is highly significant with a negative coefficient. Chetty et al. write about small businesses in large cities, such as sandwich shops and dry cleaners, being most affected by the pandemic and a lack of commuters, and this result generally supports that finding. Unlike small business revenues, however, adding density and median household income to the regression causes accommodation spending to lose its significance. Low-preparation job vacancies may not be as affected by accommodation spending as small business revenues because low-preparation vacancies, by nature, require less training and workers can easily shift to where they are needed most. For example, a laid-off bartender may find work stocking grocery shelves or delivering food. The pandemic, especially at the onset, shifted some of the need for workers to other industries; however, small businesses are generally not as flexible: a boutique clothing store cannot quickly adapt to supply personal protective equipment.

Findings from Table 6 show that accommodation spending in a city has a significantly negative and persistent effect on the rate of low-preparation job vacancies in a metro area relative to January 2020. This finding is confirmed by a February 2021 analysis by the *Wall Street Journal* which shows that cities with less reliance on tourism and lower population densities are recovering faster from the COVID-19 recession. Minneapolis and Indianapolis (both included in the Opportunity Insights sample) in addition to Cincinnati and Columbus (both not in the sample) have the lowest unemployment rates of 51 major metro areas in February based on Labor Department data, which implies a much tighter labor market than in coastal cities such as San Francisco and Boston. The *Journal* article also connects the success of these cities to their diversified economies which are not overly reliant on tourism. These findings support the

5.3 High-Preparation Job Vacancies

Table 9 seeks to understand the effect of COVID-19 cases and mobility on high-preparation job vacancies between 1 and 270 days after the first COVID-19 case in a metro area. Unlike small business revenues and low-preparation vacancies, average mobility and the COVID-19 case rate have no significant effect on high-preparation vacancies.

Table 9: High-Preparation Job Vacancies 1 to 270 Days After First COVID-19 Case

Dependent Variable: *High-Preparation Job Vacancies 1 to 270 Days After First Case (1)*

Independent Variables	Model 1	Model 2	Model 3
constant	-0.23***	-0.23***	-0.23***
	(0.01)	(0.01)	(0.01)
Case Rate 1 to 270 Days (2)	-0.14		-0.65
	(0.63)		(0.67)
Average Mobility 1-270 Days After First COVID-19 Case (3)		0.52	0.65
		(0.32)	(0.35)
Obs.	52	52	52
R^2	0.00	0.05	0.07

1: This refers to the average change in high-preparation job vacancies in a city 211-270 days after the city registered its first positive COVID-19 case

2: This refers to the percentage of the population that tested positive for COVID-19 in the first 270 days after the first positive COVID-19 case was recorded in the city

3: Google Community Mobility tracks time spent away from home, estimated using cellphone location data, and these values are indexed to January 2020 then averaged over the time period (not seasonally adjusted).

Although high-preparation job vacancies are, on average across the sample, 23% lower than January 2020 levels, neither average mobility nor the COVID-19 case rate can explain the variations in high-preparation vacancies between metro areas in the sample. Although many high-preparation jobs are dependent on in-person services (consider a dental technician or barber), it is unlikely that the general movement of residents around the metro area would stimulate demand for services which would lead to the hiring of new high-preparation workers. Also, many high-preparation jobs can be done remotely and remain in demand regardless of variations in metro COVID-19 case rates.

Table 10 regresses high-preparation job vacancies on average mobility of residents in the metro area relative to January 2020, per-capita 2012 accommodation spending, and the share of Trump voters in the 2016 Presidential election in the metro area. Compared to small business revenues and low-preparation vacancies (Table 2 and Table 6, respectively), the effect of mobility attenuates more rapidly and then flips from positive to negative for the last two periods. In the first 30 days of the pandemic, a 1% increase in average mobility is correlated with a 0.86% increase in high-preparation vacancies in the same metro area.

Table 10: High-Preparation Job Vacancies after First COVID-19 Case

Dependent Variable: *High-Preparation Job Vacancies After First Case (1)*

Independent Variables	1 to 30 Days	31 to 90 Days	91 to 150 Days	151 to 210 Days	211 to 270 Days
Constant	-0.05***	-0.29***	-0.21***	-0.27***	-0.17***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Mobility Index After COVID-19 (2)	0.86***	0.98*	0.23	-0.32	-0.33
	(0.17)	(0.43)	(0.37)	(0.40)	(0.81)
Accommodation Spending (3)	0.04*	0.04	0.01	-0.01	0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Share of Trump Votes 2016 (4)	-0.05	-0.39*	0.23	0.41**	-0.27
	(0.10)	(0.17)	(0.17)	(0.15)	(0.27)
Obs.	50	50	50	50	50
R^2	0.41	0.14	0.16	0.20	0.13

1: This represents the average change in new high-preparation job postings on online job boards for each city during the specified time period, indexed to January 2020 and not seasonally adjusted

2: Google Community Mobility tracks time spent away from home, estimated using cellphone location data, and these values are indexed to January 2020 then averaged over the time period (not seasonally adjusted).

3: The log of the quantity of money spent on accommodation, the combination of lodging and dining, in a city per resident in 2012 in thousands of dollars, per the US Census.

4: The percentage of votes in the metro area for Donald Trump in the 2020 Presidential Election

Average mobility does not have any persistent effect on metro-level high-preparation vacancies beyond the first 90 days of the pandemic. Unlike low-skill job vacancies, there appears to be no significant link between high-skill vacancies and the mobility of residents in the metro area. This is likely because most high-skill professionals, such as lawyers and accountants, work at businesses that do not depend on local foot traffic or tourism. These results suggest that other variables besides mobility are responsible for the metro-area differences in high-preparation vacancies.

Table 11 shows the results of regressing high-preparation job vacancies over the first 90 days of the pandemic on several pre-pandemic economic variables in the respective metro area. Models 1-5 contain univariate regressions of a single pre-pandemic variable, and Model 6 shows the multivariate regression with every variable included.

Across the sample, high-preparation vacancies were, on average, 21% below January 2020 levels during the first 90 days. Model 3 finds that metro median household income has a significantly positive effect on high-preparation vacancies. This regression shows that a 1% increase in median household income is associated with a 0.17% increase in high-preparation vacancies.

Table 11: High-Preparation Job Vacancies 1 to 90 Days after First COVID-19 Case

Dependent Variable: *High-Preparation Job Vacancies 1 to 90 Days after First Case (1)*

Independent Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Constant	-0.21***	-0.21***	-0.21***	-0.21***	-0.21***	-0.21***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Share of Trump Votes 2016 (2)	-0.17					0.13
	(0.12)					(0.20)
Accommodation Spending (3)		0.02				0.01
		(0.02)				(0.02)
Median Household Income (4)			0.17***			0.16
			(0.05)			(0.06)
Share of High Digital Skill Jobs (5)				0.55		0.09
				(0.033)		(0.40)
Density (6)					0.04	0.03
					(0.02)	(0.03)
Obs.	52	50	52	52	52	50
R^2	0.04	0.02	0.21	0.05	0.06	0.22

1: This represents the average change in new high-preparation job postings on online job boards for each city during the specified time period, indexed to January 2020 and not seasonally adjusted
2: The percentage of votes in the metro area for Donald Trump in the 2020 Presidential Election
3: The log of the quantity of money spent on accommodation, the combination of lodging and dining, in a city per resident in 2012 in thousands of dollars, per the US Census.
4: The log of the median household income for a city between 2014-2018, per the US Census Bureau.
5: The percentage of jobs in the metro area that require high digital skills, as defined by Muro et al. (2017)
6: The log of 2010 population-weighted density from the US Census Bureau

Although the coefficient is small, the total effect of median household income on high-preparation vacancies may be quite large as there is a significant amount of variation in median household income in the sample. For example, household income is over three times higher in San Francisco than in Cleveland or Detroit, and the sample standard deviation is $14,900. Therefore, median household income may be critical to understanding the variations in high-preparation vacancies between cities in the sample. High-preparation vacancies may be higher in wealthier cities in the sample because high-income individuals are still demanding individualized local services during the pandemic, such as home maintenance or medical care, with their accumulated savings or higher-paying work that can be done remotely. Further analysis is needed to fully understand this relationship.

Table 12 shows the results of regressing high-preparation job vacancies over the first 270 days of the pandemic on several pre-pandemic economic variables in the respective metro area. On average, high-preparation vacancies were 23% lower than January 2020 levels for all metros in the sample. In Model 6, median household income is significant, and its coefficient implies that a 1% increase in metro-area median household income is correlated with a 0.15% increase in high-preparation vacancies.

Table 12: High-Preparation Job Vacancies 1 to 270 Days after First COVID-19 Case

Dependent Variable: *High-Preparation Job Vacancies 1 to 270 Days after First Case (1)*

Independent Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Constant	-0.23***	-0.23***	-0.23***	-0.23***	-0.23***	-0.23***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Share of Trump Votes 2016 (2)	0.18					0.28
	(0.10)					(0.17)
Accommodation Spending (3)		-0.00				-0.01
		(0.02)				(0.02)
Median Household Income (4)			0.06			0.15*
			(0.05)			(0.06)
Share of High Digital Skill Jobs (5)				-0.30		-0.42
				(0.30)		(0.35)
Density (6)					-0.02	0.01
					(0.02)	(0.03)
Obs.	52	50	52	52	52	50
R^2	0.06	0.00	0.04	0.02	0.02	0.20

1: This represents the average change in new high-preparation job postings on online job boards for each city during the specified time period, indexed to January 2020 and not seasonally adjusted
2: The percentage of votes in the metro area for Donald Trump in the 2020 Presidential Election
3: The log of the quantity of money spent on accommodation, the combination of lodging and dining, in a city per resident in 2012 in thousands of dollars, per the US Census.
4: The log of the median household income for a city between 2014-2018, per the US Census Bureau.
5: The percentage of jobs in the metro area that require high digital skills, as defined by Muro et al. (2017)
6: The log of 2010 population-weighted density from the US Census Bureau

One interesting result from Tables 11 and 12 is that the effect of median household income on high-preparation vacancies over both periods is positive; however, the effect of median household income on low-preparation vacancies (in Tables 7 and 8) is negative. This suggests that residents of wealthier cities are continuing to demand local high-skill, but not low-skill, services during the pandemic because their accumulated wealth allows them to maintain their standard of living during the pandemic. This relationship is currently tenuous, and more information will be needed to support this hypothesis.

The metro-level variations of high-preparation vacancies remain difficult to explain, and generally, the regressions in Tables 9 through Table 12 have much lower coefficients of determination than the tables analyzing low-preparation vacancies and small business revenues. Over the 270-day period, high-preparation vacancies (23% below January 2020 levels, on average) are lower than low-preparation vacancies (16% below January 2020 levels, on average) and have a smaller sample standard deviation. Therefore, the city-level variations in high-preparation vacancies may be difficult to analyze as they are a result of the uncertainties businesses face when hiring employees. High-skill employees are expensive, and firms generally seek to retain and develop workers for much longer than low-skill workers. For example, a law firm may employ an attorney for several decades (if she is on a partner track); however, low-skill workers generally do not remain in the same role for extended periods, especially if the work is seasonal. The COVID-19 pandemic has made forecasting future demand for workers particularly difficult regardless of locale, and this national uncertainty may be crowding out local variations in high-preparation vacancies.

Finally, it is unclear whether the recent surge of remote work is confounding some of the analysis on high-preparation job vacancies (which are more likely to have a remote option, as evidenced by Dingel and Neiman, 2020). An Upwork survey from December 2020 found that 41.8% of workers are working remotely, and their analysis suggests that, by 2025, 16.8 million additional jobs will be added that are fully remote. According to Owl Labs, remote workers earn salaries greater than one hundred thousand dollars twice as often as in-person workers. Therefore, a large share of these new remote jobs added over the next five years will likely be high-skill positions. However, this can create difficulty with measuring city-level differences in job vacancy rates. It is important to establish how to interpret these roles as they quickly become a larger share of high-preparation vacancies.

5.4 Labor Economic Theory and the COVID-19 Recession

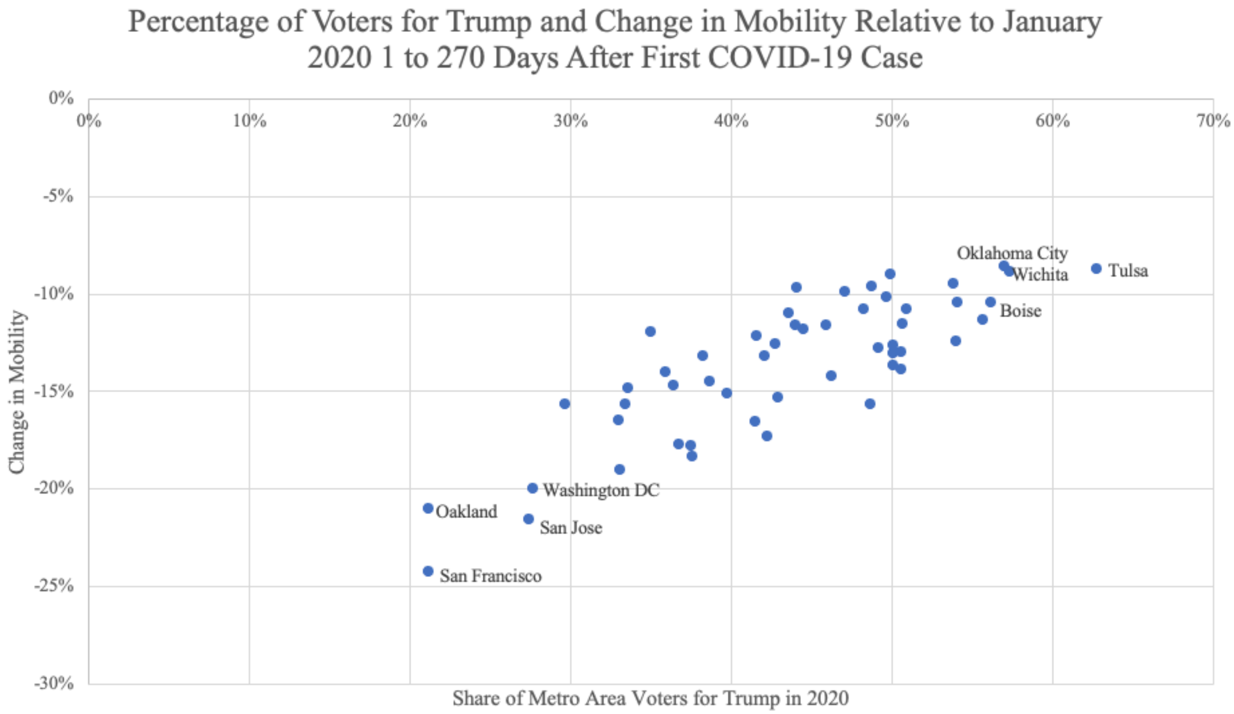
In Section 2.1 three fundamental views of the labor market from Karanassou et al. (2006) were outlined: the frictionless equilibrium view, the prolonged adjustment view, and the hysteresis view. The frictionless equilibrium view states that the labor market quickly adjusts to equilibrium in the presence of external shocks in contrast to the prolonged adjustment view, which theorizes that the labor market adjusts slowly to external stocks due to adjustment costs and sticky variables. Based on the rapid collapse in vacancies and the sharp spike in the unemployment rate across the United States, it appears that the labor market reacted rapidly to the COVID-19 pandemic as expected in the frictionless equilibrium view.

Interestingly, as visualized above in Figures 10 and 17, there appear to be persistent differences in the rates of both low and high-preparation job vacancies between cities up to 210 days after the first COVID-19 case. Although this roughly seven-month period cannot be viewed as the “long-run”, this persistence in levels of vacancies is supported by the hysteresis view, which purports that “short-run fluctuations in the unemployment rate turn into long-run changes”, and business cycle fluctuations can cause permanent changes. More data is needed to corroborate this theory, but the view of many pundits that COVID-19 will cause “permanent” changes to cities such as New York and San Francisco are supported by this hysteresis view.

5.5 The 2016 Presidential Election and 2020 COVID-19 Pandemic Outcomes

During the COVID-19 recession, and especially leading up to the November 2020 US Presidential Elections, the pandemic and public health measures such as face masks were highly politicized and polarizing. For example, a study found that the political party of a state’s governor is the most important predictor of whether a state has a mask mandate (Adolph et al. 2020). Therefore, it may not be surprising that the share of voters for Trump in 2016 had a highly significant positive effect in regressions of small business revenues and low-preparation vacancies (as seen in Table 4 and Table 8) even though the votes were cast almost four years before the COVID-19 pandemic began. Much of this relationship is due to a high correlation (0.80) between average mobility and the share of Trump voters in the metro area which can be seen in Figure 13.

Figure 13



Source: Opportunity Insights and *The New York Times*

Table 13 shows that metro areas with higher shares of Trump voters in the 2016 election had significantly higher levels of mobility even when controlling for COVID-19 case rates between metro areas. These results suggest that a 1% increase in the share of Trump voters leads to a 0.25% increase in the average mobility of the residents of a metro area compared to another metro area with the same rate of COVID-19. This may imply that officials in cities with higher shares of Trump voters (who were elected by many of the same local voters as in 2016) are enacting more relaxed 'stay-at-home orders', or that areas with higher shares of Trump voters contain residents less concerned about the COVID-19 pandemic. These results support some of the reports of 'politicization' of the virus and show that some city-level differences in experiences during the COVID-19 pandemic can be explained by political affiliations.

Table 13: Average Mobility 1 to 270 Days After First COVID-19 Case

Dependent Variable: *Average Mobility 1 to 270 Days After First COVID-19 Case (1)*

Independent Variables	Model 1	Model 2	Model 3
Constant	-0.14***	-0.14***	-0.14***
	(0.00)	(0.00)	(0.00)
COVID-19 Case Rate (2)	0.77**		0.21
	(0.25)		(0.17)
Metro Trump Vote 2016 (3)		0.25***	0.24***
		(0.03)	(0.03)
Obs.	52	52	52
R^2	0.16	0.66	0.67

1: Google Community Mobility tracks time spent away from home, estimated using cellphone location data, and these values are indexed to January 2020 then averaged over the time period (not seasonally adjusted).
2: The demeaned cumulative COVID-19 case rate in the metro area between 1 and 270 days after the first recorded COVID-19 case in the metro area
3: The demeaned share of votes in the metro area for Trump in the 2016 Presidential Election

Importantly, as can be seen in Table 13B in the appendix, the state share of Trump voters does not have as high of a coefficient of determination (0.32), and the effect of an increasing share of Trump voters at the state level is smaller than at the city level. This further supports the idea that cross-sectional city-level differences are driving outcomes even if the policy is being determined at the state level (as evidenced by the state-wide lockdowns in California and Michigan, among others).

As shown in Tables 1 and 5 above, increases in the mobility of metro residents have a strongly positive effect on low-preparation vacancies and small business revenues in the same metro area. This implies that highly Republican cities during the 2016 election have stronger local economies during the first nine months of the pandemic. However, this relationship is also deeply problematic because these metro areas also have higher rates of COVID-19.

In the sample, the average share of metro voters for Trump in 2016 was 42%. Of the 52 cities in the sample, 28 voted for Donald Trump at a higher share than the sample average, and in these cities, 4.8% of residents have contracted COVID-19 over the first 270 days of the pandemic. Comparatively, the 24 cities whose voters chose Donald Trump less than the sample average have an average cumulative case rate of only 3.7%. These case rates are significantly different at the 5% level using a two-sample T-test assuming unequal variances. Furthermore, running a simple regression of cumulative COVID-19 case rates over the 270-day period on the share of

Trump voters in 2016 shows that a 1% increase in the share of Trump voters is associated with a 0.06% increase in the cumulative rate of COVID-19. This is significant at the 1% level with a coefficient of determination of 0.14.

Although it could appear that cities that voted more often in favor of Donald Trump in 2016 fared better during the first nine months of the COVID-19 pandemic, human health and containing the spread of COVID-19 is of paramount importance and must not be put aside in favor of economic well-being. Additionally, as seen in Tables 2 and 6, the effect of mobility is attenuating in later periods for small business revenues and low-preparation vacancies. Therefore, data further into the pandemic may likely reveal that these cities that favored Donald Trump in 2016 are no longer faring better economically but still have higher local rates of COVID-19.

5.6 COVID-19 and the Great Recession of 2008

Arias et al. (2016) concluded that cities with higher levels of education experienced less severe effects of the Great Recession. However, the COVID-19 recession is far different in cause and nature than the Great Recession, and tables in the appendix show that, so far, higher levels of college-educated residents have not led to higher levels of small business revenues or job vacancies. The share of high digital skill roles and the rate of college graduates in a city are positively correlated (0.60), but over the first 270 days of the pandemic, the share of high digital skill jobs has a significantly negative effect on small business revenues (as seen in Table 4). Measuring up to 270 days after the first COVID-19 cases in cities may not be long enough to pick up if education or other variables will have long-term significance in economic recovery. Further analysis up to a later date could confirm or deny this hypothesis.

Arias et al (2016) found that cities with more elastic housing supplies recovered faster from the Great Recession. If fears over infectious diseases and the pivot to remote work led to a mass relocation of Americans housing elasticity in less dense cities, such as Boise or Colorado Springs, housing prices become a significant factor in the late stages of the COVID-19 recession. However, to date, there is no reason that pre-pandemic housing elasticity is causing differences in economic outcomes between cities.

Additional relevant research on small businesses and the labor market during the Great Recession include Bivens (2016), Chernick et al. (2011), and Sahin et al. (2011). Chernick et al. (2011) empirically examines businesses during the Great Recession and finds that small businesses, in particular, were disproportionately affected by the decline in output. Additionally, small firms faced a more constrained credit supply and more uncertainty due to the recession. Although the two recessions have completely unrelated causes, this analysis of small businesses appears to apply strongly to both situations. In particular, while large firms have had access to cheap lines of credit (at real interest rates close to zero) and the stock market has soared to record highs, millions of small businesses remain devastated due to a disease beyond their control. If local or state governments could allow small businesses to have access to more lending and other funding opportunities this could drive positive economic outcomes for local businesses and workers.

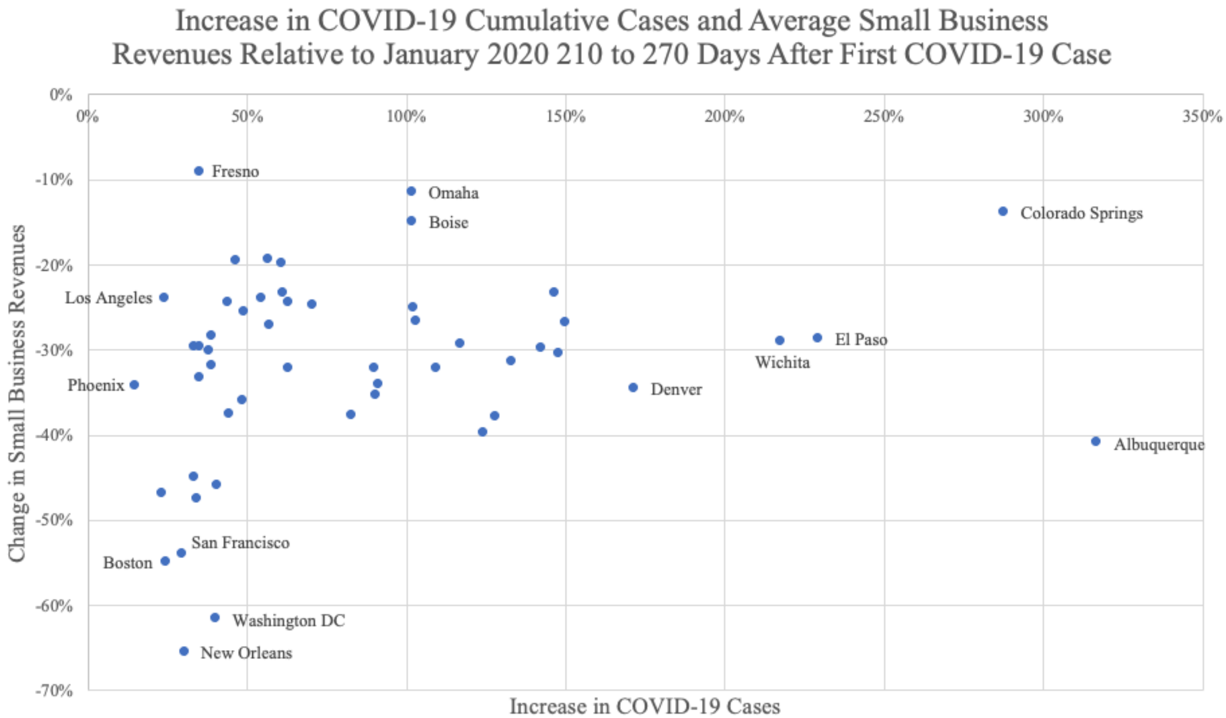
6 Conclusion

As the COVID-19 pandemic continues in the US, it will be impossible to fully understand which cities will fully recover until vaccines are widely available. American cities, historically beacons of innovation and progress, have struggled mightily to contain the virus and balance economic factors with human health. As the pandemic progresses, a more complete decoupling of COVID-19 infections from mobility could represent a path forward without sacrificing physical or economic well-being. However, the necessary public health measures to contain the virus have become politicized, and sharp lines were drawn about the optimal course of action.

There are also likely biases in the data and missing variables that are preventing a complete understanding of the economic situation in cities. The pandemic has changed the nature of work for many (perhaps permanently) to remote, as discussed in 5.4. Employees no longer have to reside close to their work and can reside anywhere with an internet connection. Google mobility data only tracks the mobility of residents who remain in the metro area and does not reveal what percentage of residents currently remain in a city. Data from *Bloomberg CityLab* suggests that anecdotal stories of residents leaving dense, expensive cities such as New York and San Francisco in droves are largely overplayed, but certainly, some fraction of residents have permanently moved or are temporarily residing elsewhere. The inclusion of this data, or a suitable proxy, will reveal more about the situation in cities. For example, USPS data from San Francisco presented by the *San Francisco Chronicle* revealed that the majority of residents moved from the city to surrounding counties and not Texas or Utah, two areas widely regarded as destination cities for ‘California flight’.

Although outside the scope of this paper, it remains an open question of what cities themselves can do during the pandemic to improve their economic situation while maintaining public health and safety. For example, according to *Bloomberg Cities*, Seattle had a specialized innovative team design its testing program to maximize results. However, it remains to be seen if any innovations will be adopted at scale to yield significantly improved outcomes during the pandemic. Successful vaccine trials hopefully signal the end of the pandemic by the summer of 2021, and cities will need to be adaptable and innovative in ensuring that their residents are vaccinated as quickly as possible. Until then, cities should try their best to reach the ‘top left’ corner of Figure 14, in which small business revenues remain similar to January 2020 levels but the growth in cases remains low as well. Although public health should outweigh economic vitality during this pandemic, it can be said that neither the ‘top right’ nor ‘bottom left’ quadrants are ideal for cities.

Figure 14



Source: Opportunity Insights

Although it is tempting to praise the cities that have low COVID-19 case growth and relatively high small business revenues (such as Fresno, Colorado Springs, Charlotte, and Omaha), many of these cities have already experienced large COVID-19 outbreaks and therefore their case growth is relatively smaller. In contrast, Honolulu had almost contained the virus before opening back up for tourism, so this large growth in cases is from a very low base.

For every city, achieving economic stability without accelerating the spread of the virus will be difficult, and there is no 'one size fits all' approach. Although COVID-19 should always be the top concern of local officials, there is evidence that the depth of a recession is correlated with the length of time until the economy is returned to pre-recession levels. Therefore, cities should consider experimenting with policies that may keep cases low and their economies intact to maximize public health during the pandemic and economic health post-pandemic. Also, now that it is clear that city-level differences are creating some of the variation in economic outcomes, government assistance such as infrastructure spending or lending programs should be directed at cities that are of the greatest need to ensure an equitable recovery.

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Appendix

Summary Tables

Table A.1

Independent Variables

Variable	Definition
Cumulative Case Rate 0 to 150	the percentage of the population in the city that contracted COVID-19 between 0 and 150 days after the first recorded COVID-19 case
Cumulative Case Rate 0 to 210	the percentage of the population in the city that contracted COVID-19 between 0 and 210 days after the first recorded COVID-19 case
Increase in Cases 151 to 210 Days	the number of COVID-19 cases that occurred between 151 and 210 days after the first registered case in a city divided by the number of cases that occurred between 0 and 150 days after the first registered case in a city
Days To First Case	the number of days between January 1st, 2020 and the first registered COVID-19 case in a city
Average Mobility 1 to 30 Days After First Case	the average mobility of residents relative to January 2020 outside of their homes in a city between 1 and 30 days after the first COVID-19 case is recorded
Average Mobility 31 to 90 Days After First Case	the average mobility of residents relative to January 2020 outside of their homes in a city between 31 and 90 days after the first COVID-19 case is recorded
Average Mobility 91 to 150 Days After First Case	the average mobility of residents relative to January 2020 outside of their homes in a city between 91 and 150 days after the first COVID-19 case is recorded
Average Mobility 151 to 210 Days After First Case	the average mobility of residents relative to January 2020 outside of their homes in a city between 151 and 210 days after the first COVID-19 case is recorded
Average Mobility 1 to 150 Days After Revenue Trough	the average mobility of residents in a city relative to January 2020 between 1 and 150 days after the maximum decrease (trough) is reached in small business revenue
Average Mobility 1 to 150 Days After Low-Preparation Trough	the average mobility of residents in a city relative to January 2020 between 1 and 150 days after the maximum decrease (trough) is reached in job vacancies for O*NET Job Zones 1-2
Average Mobility 1 to 150 Days After High-Preparation Trough	the average mobility of residents in a city relative to January 2020 between 1 and 150 days after the maximum decrease (trough) is reached in job vacancies for O*NET Job Zones 3-5
Days to Revenue Trough	the number of days between January 1st, 2020 and the maximum decrease in small business revenue in a city in 2020

Days to Low-Preparation Trough	the number of days between January 1st, 2020 and the maximum decrease in job vacancies in O*NET Zones 1-2 in a city in 2020
Days to High-Preparation Trough	the number of days between January 1st, 2020 and the maximum decrease in job vacancies in O*NET Zones 3-5 in a city in 2020
Accommodation	the amount of money spent on accommodation, the combination of lodging and dining, in a city per resident in 2012 in thousands of dollars, per the US Census
Median Household Income	the median household income for a city between 2014-2018, per the US Census Bureau
College	the percentage of residents ages 25+ who have obtained a bachelor's degree or equivalent
Paycheck Protection Program	the log of the quantity of dollars per state resident that the state in which the city resides in received in PPP loans
City Population	the population that lives within city limits
Density	US Census Bureau 2010 population-weighted density
Share of High Digital Skill Jobs	the share of jobs in the community that require high digital skills, as defined by Brookings' Muro et al. (2017)

Table A.2

Dependent Variables	
Variable	Definition
Small Business Revenue 0 to 30 Days After First Case	the average change in seasonally-adjusted small business revenue relative to January 4-31 2020 in a city between 1 and 30 days after the first local COVID-19 case
Small Business Revenue 31 to 90 Days After First Case	the average change in seasonally-adjusted small business revenue relative to January 4-31 2020 in a city between 31 and 90 days after the first local COVID-19 case
Small Business Revenue 91 to 150 Days After First Case	the average change in seasonally-adjusted small business revenue relative to January 4-31 2020 in a city between 91 and 150 days after the first local COVID-19 case
Small Business Revenue 151 to 210 Days After First Case	the average change in seasonally-adjusted small business revenue relative to January 4-31 2020 in a city between 151 and 210 days after the first local COVID-19 case
Low-Preparation Vacancies 0 to 30 Days After First Case	the average change in job vacancies in O*NET Zones 1-2 relative to January 4-31 2020 in a city between 1 and 30 days after the first local COVID-19 case
Low-Preparation Vacancies 31 to 90 Days After First Case	the average change in job vacancies in O*NET Zones 1-2 relative to January 4-31 2020 in a city between 31 and 90 days after the first local COVID-19 case
Low-Preparation Vacancies 91 to 150 Days After First Case	the average change in job vacancies in O*NET Zones 1-2 relative to January 4-31 2020 in a city between 91 and 150 days after the first local COVID-19 case
Low-Preparation Vacancies 151 to 210 Days After First Case	the average change in job vacancies in O*NET Zones 1-2 relative to January 4-31 2020 in a city between 151 and 210 days after the first local COVID-19 case
High-Preparation Vacancies 0 to 30 Days After First Case	the average change in job vacancies in O*NET Zones 3-5 relative to January 4-31 2020 in a city between 1 and 30 days after the first local COVID-19 case
High-Preparation Vacancies 31 to 90 Days After First Case	the average change in job vacancies in O*NET Zones 3-5 relative to January 4-31 2020 in a city between 31 and 90 days after the first local COVID-19 case
High-Preparation Vacancies 91 to 150 Days After First Case	the average change in job vacancies in O*NET Zones 3-5 relative to January 4-31 2020 in a city between 91 and 150 days after the first local COVID-19 case
High-Preparation Vacancies 151 to 210 Days After First Case	the average change in job vacancies in O*NET Zones 3-5 relative to January 4-31 2020 in a city between 151 and 210 days after the first local COVID-19 case

Maximum Decrease in Revenue	the maximum decrease in revenue between January 1st and August 28th, 2020
Maximum Decrease in Low-Preparation Vacancies	the maximum decrease in job vacancies in O*NET Zones 1-2 between January 1st and August 28th, 2020
Maximum Decrease in High-Preparation Vacancies	the maximum decrease in job vacancies in O*NET Zones 3-5 between January 1st and August 28th, 2020
Revenue 1 to 150 Days After Maximum Decline	the average index of small business revenue between 1 and 150 days after the trough
Low-Preparation Vacancies 1 to 150 Days After Maximum Decline	the average index of job vacancies in O*NET Zones 1-2 between 1 and 150 days after the trough
High-Preparation Vacancies 1 to 150 Days After Maximum Decline	the average index of job vacancies in O*NET Zones 3-5 between 1 and 150 days after the trough

Table A.3

Summary Table: Independent Variables							
Variable	Obs	Min	1st Quartile	Mean	3rd Quartile	Max	St. Dev
caserate_0to150	52	0.0021	0.0098	0.0156	0.0195	0.0482	0.0084
caserate_0to210	52	0.0087	0.0180	0.0240	0.0293	0.0637	0.0096
increase_in_cases	52	0.0719	0.3457	0.7590	0.8031	4.4896	0.7772
days_to_first_case	52	23.00	59.75	61.21	70.00	79.00	14.48
avgmob_covid_1to30	52	-0.2277	-0.1674	-0.1172	-0.1021	0.0091	0.0668
avgmob_covid_31to90	52	-0.3022	-0.225	-0.1954	-0.1678	-0.1124	0. 0465
avgmob_covid_91to150	52	-0.3067	-0.1529	-0.1337	-0.0900	-0.0668	0.0518
avgmob_covid_151to210	52	-0.2574	-0.1390	-0.1135	-0.0802	-0.0507	0.0434
avgmob_trough_rev	52	-0.3077	-0.1746	-0.1573	-0.1225	-0.0910	0.0444
avgmob_trough_jz12	52	-0.29	-0.18	-0.15	-0.11	-0.08	0.04
avgmob_trough_jz345	52	-0.25	-0.16	-0.13	-0.11	-0.07	0.04
travel	50	0.4988	1.1157	2.1879	2.5481	7.2286	1.69
houseinc	52	29008	49820	57478	62703	104552	14896
college	52	0.146	0.281	0.356	0.429	0.628	0.109
ppp	52	504	659.2	766.7	853	1647	175.6
city_pop	52	390144	789765	1710865	1793970	1003911	1848003
density	52	1695	2962	5234	5674	31251	4593
digital_skill	52	16.10	22.57	24.45	26.05	38.20	3.93
days_to_trough_rev	52	82	89	93.52	98	103	4.96
days_to_trough_jz12	52	100	114	126.4	128	282	38.9
days_to_trough_jz345	52	107	128	152.4	142	275	50.6
trump_2016	52	0.141	0.349	0.419	0.495	0.633	0.115

Table A.4

Summary Table: Dependent Variables

Variable	Obs	Min	1st Quartile	Mean	3rd Quartile	Max	St. Dev
rev_covid_1to30	52	-0.6213	-0.3599	-0.2583	-0.1834	0.0679	0.1765
rev_covid_31to90	52	-0.6636	-0.4159	-0.3459	-0.2359	-0.1321	0.1281
rev_covid_91to150	52	-0.5992	-0.2945	-0.2482	-0.1848	-0.0164	0.1264
rev_covid_151to210	52	-0.6141	-0.3427	-0.3002	-0.2358	-0.0534	0.1159
jz12_covid_1to30	52	-0.2859	-0.1674	-0.0800	-0.0151	0.2555	0.1115
jz12_covid_31to90	52	-0.5000	-0.3687	-0.3021	-0.2303	-0.0564	0.1020
jz12_covid_91to150	52	-0.4823	-0.1961	-0.1048	0.0023	0.2402	0.1532
jz12_covid_151to210	52	-0.4407	0.1919	-0.1154	-0.0264	0.2017	0.1485
jz345_covid_1to30	52	-0.3680	-0.1183	-0.0460	0.0138	0.2348	0.0967
jz345_covid_31to90	52	-0.5287	-0.3530	-0.2882	-0.2283	-0.0894	0.0947
jz345_covid_91to150	52	-0.4454	-0.2921	-0.2161	-0.1474	-0.0469	0.0888
jz345_covid_151to210	52	-0.5217	-0.3261	-0.2673	-0.2042	-0.0525	0.0862
rev_trough	52	-0.8190	-0.6035	-0.5494	-0.4800	-0.3440	0.0958
jz12_trough	52	-0.70	-0.57	-0.53	-0.48	-0.36	0.07
jz345_trough	52	-0.66	-0.51	-0.46	-0.42	-0.31	0.07
rev_after_trough	52	-0.6181	-0.3529	-0.3105	-0.2379	-0.0811	0.1196
jz12_after_trough	49	-0.48	-0.24	-0.17	-0.08	0.07	0.13
jz345_after_trough	42	-0.49	-0.33	-0.26	-0.20	-0.05	0.08

Using a 0.1% COVID-19 Case Rate as a Threshold

Table 1B: Small Business Revenues 151 to 210 Days After 0.1% COVID-19 Threshold

Dependent Variable: *Small Business Revenue 151 to 210 Days After 0.1% Threshold (1)*

Independent Variables	Model 1	Model 2	Model 3	Model 4
constant	-0.37***	-0.37***	-0.46***	-0.32*
	(0.04)	(0.04)	(0.07)	(0.12)
Case Rate 0 to 210 Days (2)	1.63	0.93	0.73	-0.11
	(1.10)	(1.22)	(1.21)	(1.17)
Increase in Cases (3)		0.04	0.03	0.03
		(0.03)	(0.03)	(0.03)
Days to 0.1% Threshold (4)			0.00	0.00
			(0.00)	(0.00)
Average Mobility Post-COVID 151-210 Days (5)				1.15**
				(0.46)
Obs.	51	51	51	51
R^2	0.04	0.08	0.12	0.25

1: This refers to the average change in small business revenue in a city 151-210 days after the city registered its first positive COVID-19 case

2: This refers to the percentage of the population that tested positive for COVID-19 in the first 210 days after the first positive COVID-19 case was recorded in the city

3: This refers to the percentage increase in total cases 151 to 210 days after first COVID-19 case

4: This refers to the number of days between January 1st, 2020 and the case rate reaching 0.1% in the same city

5: This refers to the average Google mobility index 151-210 days after the first positive COVID-19 case in a city

Table 5B: Low-Preparation Job Vacancies 151 to 210 Days After 0.1% COVID-19 Case Rate

Dependent Variable: *Low-Preparation Job Vacancies Zones 151 to 210 Days After 0.1% Threshold (1)*

Independent Variables	Model 1	Model 2	Model 3	Model 4
constant	-0.19**	-0.19**	-0.29	0.92
	(0.06)	(0.06)	(0.16)	(0.14)
Case Rate 0 to 210 Days (2)	1.96	1.90	1.86	-0.05
	(1.47)	(1.65)	(1.66)	(1.44)
Increase in Cases (3)		0.00	-0.01	-0.00
		(0.04)	(0.05)	(0.04)
Days to 0.1% Threshold (4)			0.00	-0.00
			(0.00)	(0.00)
Average Mobility Post-COVID 151-210 Days (5)				2.38***
				(0.50)
Obs.	51	51	51	51
R^2	0.04	0.04	0.04	0.36

1: This refers to the average change in small business revenue in a city 151-210 days after the city registered its first positive COVID-19 case

2: This refers to the percentage of the population that tested positive for COVID-19 in the first 210 days after the first positive COVID-19 case was recorded in the city

3: This refers to the percentage increase in total cases 151 to 210 days after first COVID-19 case

4: This refers to the number of days between January 1st, 2020 and the case rate reaching 0.1% in the same city

5: This refers to the average Google mobility index 151-210 days after the first positive COVID-19 case in a city

Table 9B: High-Preparation Job Vacancies 151 to 210 Days After 0.1% COVID-19 Case Rate

Dependent Variable: *High-Preparation Job Vacancies 151 to 210 Days After 0.1% Threshold (1)*

Independent Variables	Model 1	Model 2	Model 3	Model 4
constant	-0.35***	-0.35***	-0.53***	-0.42***
	(0.04)	(0.04)	(0.10)	(0.10)
Case Rate 0 to 210 Days (2)	2.96**	2.17*	2.08*	1.35
	(0.96)	(1.05)	(1.02)	(1.00)
Increase in Cases (3)		0.05	0.02	0.02
		(0.03)	(0.03)	(0.03)
Days to 0.1% Threshold (4)			0.00	0.00*
			(0.00)	(0.00)
Average Mobility Post-COVID 151-210 Days (5)				0.91*
				0.35
Obs.	51	51	51	51
R^2	0.16	0.21	0.27	0.37

1: This refers to the average change in small business revenue in a city 151-210 days after the city registered its first positive COVID-19 case

2: This refers to the percentage of the population that tested positive for COVID-19 in the first 210 days after the first positive COVID-19 case was recorded in the city

3: This refers to the percentage increase in total cases 151 to 210 days after first COVID-19 case

4: This refers to the number of days between January 1st, 2020 and the case rate reaching 0.1% in the same city

5: This refers to the average Google mobility index 151-210 days after the first positive COVID-19 case in a city

Further Analysis of Small Business Revenues

Table 1C: Small Business Revenues 151 to 210 Days After First COVID-19 Case

Dependent Variable: *Small Business Revenue 151 to 210 Days After First Case (1)*

Independent Variables	Model 1	Model 2	Model 3	Model 4
constant	-0.30***	-0.30***	-0.30***	-0.30***
	(0.02)	(0.02)	(0.02)	(0.02)
Case Rate 0 to 210 Days (2)	0.77	0.51	0.22	-0.29
	(1.66)	(1.78)	(1.77)	(1.45)
Increase in Cases (3)		-0.01	-0.00	0.03
		(0.02)	(0.02)	(0.02)
Days to First Case (4)			0.00	-0.00
			(0.00)	(0.00)
Average Mobility Post-COVID-19 151-210 Days (5)				1.81***
				(0.40)
Obs.	52	52	52	52
R^2	0.00	0.01	0.05	0.37

1: This refers to the average change in small business revenue in a city 151-210 days after the city registered its first positive COVID-19 case

2: This refers to the percentage of the population that tested positive for COVID-19 in the first 210 days after the first positive COVID-19 case was recorded in the city

3: This refers to the percentage increase in total cases 151 to 210 days after first COVID-19 case

4: This refers to the number of days between January 1st, 2020 and the first positive COVID-19 case in a city

5: This refers to the average Google mobility index 151-210 days after the first positive COVID-19 case in a city

Table 2B: Small Business Revenues after First COVID-19 Case

Dependent Variable: *Small Business Revenues after First Case (1)*

Independent Variables	1 to 30 Days	31 to 90 Days	91 to 150 Days	151 to 210 Days
Constant	-0.97	-0.70	-0.61	-0.61
	(0.69)	(0.75)	(0.78)	(0.90)
De-Meaned Mobility Index After COVID-19 (2)	2.26***	2.10***	1.40***	1.10*
	(0.14)	(0.35)	(0.36)	(0.47)
Accommodation Spending (3)	-0.05**	-0.07**	-0.06***	-0.10***
	(0.02)	(0.03)	(0.02)	(0.02)
Median Household Income (4)	0.03	0.06	0.07	0.09
	(0.05)	(0.05)	(0.06)	(0.08)
Share of High Digital Skill Jobs (5)	0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Paycheck Protection Program Loans (6)	-0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
City Population (7)	0.01	0.02	0.05*	-0.01
	(0.02)	(0.02)	(0.02)	(0.02)
Density (8)	-0.00	-0.01	-0.04	-0.02
	(0.02)	(0.03)	(0.03)	(0.03)
Percentage of Adults with College Degree (9)	0.19	0.15	-0.02	0.05
	(0.13)	(0.17)	(0.15)	(0.18)
Obs.	50	50	50	50
R^2	.90	0.76	0.77	0.62

1: This represents the seasonally adjusted average change in small business revenue in a city indexed to January 2020 during the specified time period after the first COVID-19 case in the same city.
2: Google Community Mobility tracks time spent away from home, estimated using cellphone location data, and these values are indexed to January 2020 then averaged over the time period (not seasonally adjusted).
3: The log of the quantity of money spent on accommodation, the combination of lodging and dining, in a city per resident in 2012 in thousands of dollars, per the US Census.
4: The log of the median household income for a city between 2014-2018, per the US Census Bureau.
5: The percentage of jobs in the metro area that require high digital skills, as defined by Muro et al. (2017)
6: The log of quantity of dollars per state resident that the state in which the city resides in received in PPP loans
7: The log of metro area population
8: The log of 2010 population-weighted density from the US Census Bureau
9: The percentage of residents ages 25+ who have obtained a bachelor's degree or equivalent

Table 2C: Small Business Revenues after First COVID-19 Case

Dependent Variable: *Small Business Revenues after First Case (1)*

Independent Variables	1 to 30 Days	31 to 90 Days	91 to 150 Days	151 to 210 Days
Constant	-0.26***	-0.35***	-0.25***	-0.30***
	(0.02)	(0.01)	(0.01)	(0.01)
Share of Votes for Trump (2)	0.16	0.23	0.16	-0.22
	(0.36)	(0.19)	(0.16)	(0.18)
Accommodation Spending (3)	-0.04	-0.08**	-0.08**	-0.11***
	(0.04)	(0.02)	(0.02)	(0.22)
Median Household Income (4)	0.22	0.08	-0.00	0.04
	(0.14)	(0.08)	(0.07)	(0.08)
Share of High Digital Skill Jobs (5)	0.01	-0.00	-0.01	-0.01
	(0.01)	(0.00)	(0.00)	(0.00)
Paycheck Protection Program Loans (6)	-0.02	-0.02	-0.03	0.02
	(0.15)	(0.08)	(0.07)	(0.08)
City Population (7)	0.08	0.02	0.02	-0.01
	(0.05)	(0.03)	(0.02)	(0.02)
Density (8)	0.01	-0.06	-0.06	-0.07
	(0.08)	(0.04)	(0.04)	(0.04)
Percentage of Adults with College Degree (9)	0.01	-0.22	-0.08	-0.10
	(0.38)	(0.21)	(0.18)	(0.20)
Obs.	50	50	50	50
R^2	.32	0.60	0.71	0.57

1: This represents the seasonally adjusted average change in small business revenue in a city indexed to January 2020 during the specified time period after the first COVID-19 case in the same city.
2: The percentage of votes in the metro area for Donald Trump in the 2016 Presidential Election
3: The log of the quantity of money spent on accommodation, the combination of lodging and dining, in a city per resident in 2012 in thousands of dollars, per the US Census.
4: The log of the median household income for a city between 2014-2018, per the US Census Bureau.
5: The percentage of jobs in the metro area that require high digital skills, as defined by Muro et al. (2017)
6: The log of quantity of dollars per state resident that the state in which the city resides in received in PPP loans
7: The log of metro area population
8: The log of 2010 population-weighted density from the US Census Bureau
9: The percentage of residents ages 25+ who have obtained a bachelor's degree or equivalent

Table 2D: Small Business Revenues after First COVID-19 Case

Dependent Variable: *Small Business Revenues after First Case (1)*

Independent Variables	1 to 30 Days	31 to 90 Days	91 to 150 Days	151 to 210 Days	210 to 270 Days
Constant	-0.26***	-0.35***	-0.25***	-0.30***	-0.32***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Mobility Index After COVID-19 (2)	2.31***	2.15***	1.29***	1.10	0.17
	(0.14)	(0.34)	(0.36)	(0.46)	(0.58)
Accommodation Spending (3)	-0.02***	-0.03***	-0.03**	-0.04***	-0.05***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
Median Household Income (4)	0.03	0.06	0.07	0.09	0.13
	(0.05)	(0.05)	(0.06)	(0.08)	(0.08)
Share of High Digital Skill Jobs (5)	0.01	-0.01	-0.00	-0.01	-0.01
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Paycheck Protection Program Loans (6)	-0.05	-0.05	-0.08	-0.05	0.02
	(0.00)	(0.00)	(0.00)	(0.00)	(0.08)
City Population (7)	0.01	0.02	0.05*	-0.01	-0.03
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Density (8)	-0.00	-0.01	-0.04	-0.02	-0.02
	(0.02)	(0.03)	(0.03)	(0.03)	(0.04)
Percentage of Adults with College Degree (9)	0.19	0.15	-0.02	0.01	0.05
	(0.13)	(0.17)	(0.15)	(0.18)	(0.21)
Obs.	50	50	50	50	50
R^2	.90	0.77	0.77	0.62	0.53

1: This represents the seasonally adjusted average change in small business revenue in a city indexed to January 2020 during the specified time period after the first COVID-19 case in the same city.
2: Google Community Mobility tracks time spent away from home, estimated using cellphone location data, and these values are indexed to January 2020 then averaged over the time period (not seasonally adjusted).
3: The log of the quantity of money spent on accommodation, the combination of lodging and dining, in a city per resident in 2012 in thousands of dollars, per the US Census.
4: The log of the median household income for a city between 2014-2018, per the US Census Bureau.
5: The percentage of jobs in the metro area that require high digital skills, as defined by Muro et al. (2017)
6: The log of quantity of dollars per state resident that the state in which the city resides in received in PPP loans
7: The log of metro area population
8: The log of 2010 population-weighted density from the US Census Bureau
9: The percentage of residents ages 25+ who have obtained a bachelor's degree or equivalent

Table 2E: Small Business Revenues after First COVID-19 Case

Dependent Variable: *Small Business Revenues after First Case (1)*

Independent Variables	1 to 30 Days	31 to 90 Days	91 to 150 Days	151 to 210 Days	211 to 270 Days
Constant	-0.26***	-0.35***	-0.25***	-0.30***	-0.24***
	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)
Share of Trump Votes 2016 (2)	0.17	0.34	0.20	-0.17	-0.08
	(0.34)	(0.18)	(0.15)	(0.16)	(0.18)
Accommodation Spending (3)	-0.03*	-0.04***	-0.04***	-0.05***	-0.05***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Median Household Income (4)	0.23*	0.04	-0.01	0.04	0.13*
	(0.11)	(0.06)	(0.01)	(0.05)	(0.06)
Share of High Digital Skill Jobs (5)	0.01	-0.00	-0.01*	-0.01**	-0.01*
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Density (6)	0.08	-0.02	-0.03	-0.07*	-0.05
	(0.06)	0.03	(0.03)	(0.03)	(0.03)
Obs.	50	50	50	50	50
R^2	0.26	0.58	0.71	0.61	0.56

1: This represents the seasonally adjusted average change in small business revenue in a city indexed to January 2020 during the specified time period after the first COVID-19 case in the same city.
2: The percentage of votes in the metro area for Donald Trump in the 2020 Presidential Election
3: The log of the quantity of money spent on accommodation, the combination of lodging and dining, in a city per resident in 2012 in thousands of dollars, per the US Census.
4: The log of the median household income for a city between 2014-2018, per the US Census Bureau.
5: The percentage of jobs in the metro area that require high digital skills, as defined by Muro et al. (2017)
6: The log of 2010 population-weighted density from the US Census Bureau

Table 3B: Small Business Revenues 1 to 60 Days after First COVID-19 Case

Dependent Variable: *Small Business Revenues 1 to 60 Days after First Case (1)*

Independent Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Constant	-0.34***	-0.34***	-0.34***	-0.34***	-0.34***	-0.34***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Share of Trump Votes 2016 (2)	-0.05					0.16
	(0.17)					(0.27)
Accommodation Spending (3)		-0.08**				-0.10**
		(0.03)				(0.03)
Median Household Income (4)			0.11			0.15
			(0.08)			(0.09)
Share of High Digital Skill Jobs (5)				0.01		0.00
				(0.00)		(0.01)
Density (6)					0.02	0.03
					(0.03)	(0.05)
Obs.	52	50	52	52	52	50
R^2	0.00	0.15	0.04	0.03	0.01	0.25

1: This represents the seasonally adjusted average change in small business revenue in a city indexed to January 2020 during the specified time period after the first COVID-19 case in the same city.
2: The percentage of votes in the metro area for Donald Trump in the 2020 Presidential Election
3: The log of the quantity of money spent on accommodation, the combination of lodging and dining, in a city per resident in 2012 in thousands of dollars, per the US Census.
4: The log of the median household income for a city between 2014-2018, per the US Census Bureau.
5: The percentage of jobs in the metro area that require high digital skills, as defined by Muro et al. (2017)
6: The log of 2010 population-weighted density from the US Census Bureau

Further Analysis of Low-Preparation Job Vacancies

Table 6B: Low-Preparation Job Vacancies after First COVID-19 Case

Dependent Variable: *Low-Preparation Job Vacancies After First Case (1)*

Independent Variables	1 to 30 Days	31 to 90 Days	91 to 150 Days	151 to 210 Days	211 to 270 Days
Constant	-0.08***	-0.30***	-0.10***	-0.12***	-0.14***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Share of Votes for Trump (2)	0.26	0.28	0.41	0.22	0.20
	(0.24)	(0.20)	(0.22)	(0.25)	(0.25)
Accommodation Spending (3)	-0.01	-0.02	-0.03**	-0.05	-0.16***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)
Median Household Income (4)	0.05	0.03	-0.07	-0.04	0.11
	(0.08)	(0.07)	(0.07)	(0.08)	(0.08)
Share of High Digital Skill Jobs (5)	0.01	0.00	-0.01	0.00	-0.01
	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)
Density (6)	0.05	-0.01	-0.05	0.01	-0.01
	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)
Obs.	50	50	50	50	50
R^2	0.07	0.23	0.60	0.42	0.49

1: This represents the average change in new low-preparation job postings on online job boards for each city during the specified time period, indexed to January 2020 and not seasonally adjusted
2: The percentage of votes in the metro area for Donald Trump in the 2020 Presidential Election
3: The log of the quantity of money spent on accommodation, the combination of lodging and dining, in a city per resident in 2012 in thousands of dollars, per the US Census.
4: The log of the median household income for a city between 2014-2018, per the US Census Bureau.
5: The percentage of jobs in the metro area that require high digital skills, as defined by Muro et al. (2017)
6: The log of 2010 population-weighted density from the US Census Bureau

Table 6C: Low-Preparation Job Vacancies after First COVID-19 Case

Dependent Variable: *Low-Preparation Job Vacancies After First Case (1)*

Independent Variables	1 to 30 Days	31 to 90 Days	91 to 150 Days	151 to 210 Days	211 to 270 Days
Constant	-0.08***	-0.30***	-0.10***	-0.12***	-0.14***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
Mobility Index After COVID-19 (2)	1.39***	1.75***	1.94***	2.54***	1.56*
	(0.17)	(0.37)	(0.46)	(0.61)	(0.69)
Accommodation Spending (3)	-0.05*	-0.04*	-0.08**	-0.13***	-0.18***
	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)
Median Household Income (4)	-0.12	0.06	0.03	0.09	0.20*
	(0.07)	(0.07)	(0.08)	(0.10)	(0.09)
Share of High Digital Skill Jobs (5)	0.00	0.00	-0.00	0.01	-0.00
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
Paycheck Protection Program Loans (6)	0.00	0.00	0.00	-0.00	0.18
	(0.00)	(0.00)	(0.00)	(0.00)	(0.10)
City Population (7)	-0.09***	-0.05*	-0.05	-0.03	-0.04
	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)
Density (8)	0.05	0.04	-0.00	0.06	-0.01
	(0.028)	(0.03)	(0.04)	(0.05)	(0.05)
Percentage of Adults with College Degree (9)	0.26	-0.04	-0.10	0.05	-0.16
	(0.16)	(0.19)	(0.20)	(0.24)	(0.24)
Obs.	50	50	50	50	50
R^2	0.66	0.59	0.75	0.59	0.62

1: This represents the average change in new low-preparation job postings on online job boards for each city during the specified time period, indexed to January 2020 and not seasonally adjusted
2: Google Community Mobility tracks time spent away from home, estimated using cellphone location data, and these values are indexed to January 2020 then averaged over the time period (not seasonally adjusted).
3: The log of the quantity of money spent on accommodation, the combination of lodging and dining, in a city per resident in 2012 in thousands of dollars, per the US Census.
4: The log of the median household income for a city between 2014-2018, per the US Census Bureau.
5: The percentage of jobs in the metro area that require high digital skills, as defined by Muro et al. (2017)
6: The log of quantity of dollars per state resident that the state in which the city resides in received in PPP loans
7: The log of metro area population
8: The log of 2010 population-weighted density from the US Census Bureau
9: The percentage of residents ages 25+ who have obtained a bachelor's degree or equivalent

Table 7B: Low-Preparation Job Vacancies 1 to 60 Days after First COVID-19 Case

Dependent Variable: *Low-Preparation Job Vacancies 1 to 60 Days after First Case (1)*

Independent Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Constant	-0.22***	-0.22***	-0.22***	-0.22***	-0.22***	-0.22***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Share of Trump Votes 2016 (2)	-0.13					0.18
	(0.15)					(0.26)
Accommodation Spending (3)		-0.02				-0.03
		(0.03)				(0.03)
Median Household Income (4)			0.11			0.09
			(0.07)			(0.08)
Share of High Digital Skill Jobs (5)				0.01		0.01
				(0.00)		(0.01)
Density (6)					0.04	0.05
					(0.03)	(0.05)
Obs.	52	50	52	52	52	50
R^2	0.01	0.01	0.05	0.06	0.03	0.14

1: This represents the average change in new low-preparation job postings on online job boards for each city during the specified time period, indexed to January 2020 and not seasonally adjusted
2: The percentage of votes in the metro area for Donald Trump in the 2020 Presidential Election
3: The log of the quantity of money spent on accommodation, the combination of lodging and dining, in a city per resident in 2012 in thousands of dollars, per the US Census.
4: The log of the median household income for a city between 2014-2018, per the US Census Bureau.
5: The percentage of jobs in the metro area that require high digital skills, as defined by Muro et al. (2017)
6: The log of 2010 population-weighted density from the US Census Bureau

Further Analysis of High-Preparation Job Vacancies

Table 10B: High-Preparation Job Vacancies After First COVID-19 Case

Dependent Variable: *High-Preparation Job Vacancies After First Case (1)*

Independent Variables	1 to 30 Days	31 to 90 Days	91 to 150 Days	151 to 210 Days	211 to 270 Days
Constant	-0.05**	-0.29***	-0.22***	-0.27***	-0.17***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Share of Votes for Trump (2)	0.13	0.20	0.30	0.46**	0.06
	(0.19)	(0.19)	(0.17)	(0.16)	(0.24)
Accommodation Spending (3)	0.01	0.01	0.00	-0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)
Median Household Income (4)	0.12	0.14*	0.13*	0.14**	0.18*
	(0.06)	(0.06)	(0.06)	(0.05)	(0.08)
Share of High Digital Skill Jobs (5)	0.00	0.00	-0.01	-0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Density (6)	0.03	0.03	-0.01	0.02	0.05
	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)
Obs.	50	50	50	50	50
R^2	0.21	0.22	0.26	0.31	0.29

1: This represents the average change in new high-preparation job vacancies on online job boards for each city during the time period specified, indexed to January 2020 and not seasonally adjusted

2: The percentage of votes in the metro area for Donald Trump in the 2020 Presidential Election

3: The log of the quantity of money spent on accommodation, the combination of lodging and dining, in a city per resident in 2012 in thousands of dollars, per the US Census.

4: The log of the median household income for a city between 2014-2018, per the US Census Bureau.

5: The percentage of jobs in the metro area that require high digital skills, as defined by Muro et al. (2017)

6: The log of 2010 metro area population-weighted density from the US Census Bureau

Table 10C: High-Preparation Job Vacancies After First COVID-19 Case

Dependent Variable: *High-Preparation Job Vacancies After First Case (1)*

Independent Variables	1 to 30 Days	31 to 90 Days	91 to 150 Days	151 to 210 Days	211 to 270 Days
Constant	-0.05**	-0.29***	-0.22***	-0.27***	-0.17***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Mobility Index After COVID-19 (2)	0.90***	1.43**	0.46	0.74	0.71
	(0.18)	(0.41)	(0.41)	(0.46)	(0.76)
Accommodation Spending (3)	0.01	0.01	-0.02	-0.02	0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Median Household Income (4)	0.05	0.16*	0.15*	0.23*	0.24*
	(0.07)	(0.07)	(0.07)	(0.08)	(0.10)
Share of High Digital Skill Jobs (5)	-0.00	0.01	-0.00	-0.00	0.01
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Paycheck Protection Program Loans (6)	0.00	0.00	0.00	-0.00	0.03
	(0.00)	(0.00)	(0.00)	(0.00)	(0.11)
City Population (7)	-0.04	-0.03	-0.06**	-0.02	0.00
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Density (8)	0.02	0.08*	0.01	-0.01	0.05
	(0.03)	(0.04)	(0.03)	(0.03)	(0.05)
Percentage of Adults with College Degree (9)	0.04	0.01	-0.09	-0.22	-0.09
	(0.17)	(0.20)	(0.18)	(0.18)	(0.27)
Obs.	50	50	50	50	50
R^2	.51	0.43	0.39	0.29	0.32

1: This represents the average change in new high-preparation job vacancies on online job boards for each city during the time period specified, indexed to January 2020 and not seasonally adjusted
2: Google Community Mobility tracks time spent away from home, estimated using cellphone location data, and these values are indexed to January 2020 then averaged over the time period (not seasonally adjusted).
3: The log of the quantity of money spent on accommodation, the combination of lodging and dining, in a city per resident in 2012 in thousands of dollars, per the US Census.
4: The log of the median household income for a city between 2014-2018, per the US Census Bureau.
5: The percentage of jobs in the metro area that require high digital skills, as defined by Muro et al. (2017)
6: The log of quantity of dollars per state resident that the state in which the city resides in received in PPP loans
7: The log of metro area population
8: The log of 2010 metro area population-weighted density from the US Census Bureau
9: The percentage of residents ages 25+ who have obtained a bachelor's degree or equivalent

Table 11B: High-Preparation Job Vacancies 1 to 60 Days after First COVID-19 Case

Dependent Variable: *High-Preparation Job Vacancies 1 to 60 Days after First Case (1)*

Independent Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Constant	-0.25***	-0.25***	-0.25***	-0.25***	-0.25***	-0.25***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Share of Trump Votes 2016 (2)	0.37**					0.26
	(0.13)					(0.23)
Accommodation Spending (3)		-0.03				-0.04
		(0.03)				(0.02)
Median Household Income (4)			-0.01			0.15*
			(0.06)			(0.07)
Share of High Digital Skill Jobs (5)				-0.01*		-0.01*
				(0.00)		(0.00)
Density (6)					-0.05	-0.02
					(0.03)	(0.04)
Obs.	52	50	52	52	52	50
R^2	0.13	0.04	0.00	0.11	0.07	0.26

1: This represents the average change in new high-preparation job postings on online job boards for each city during the specified time period, indexed to January 2020 and not seasonally adjusted

2: The percentage of votes in the metro area for Donald Trump in the 2020 Presidential Election

3: The log of the quantity of money spent on accommodation, the combination of lodging and dining, in a city per resident in 2012 in thousands of dollars, per the US Census.

4: The log of the median household income for a city between 2014-2018, per the US Census Bureau.

5: The percentage of jobs in the metro area that require high digital skills, as defined by Muro et al. (2017)

6: The log of 2010 population-weighted density from the US Census Bureau

Further Analysis of Average Mobility and 2016 Election Results

Table 13B: Average Mobility 1 to 270 Days After First COVID-19 Case

Dependent Variable: *Average Mobility 1 to 270 Days After First COVID-19 Case (1)*

Independent Variables	Model 1	Model 2	Model 3	Model 4
constant	-0.14***	-0.14***	-0.14***	-0.14***
	(0.00)	(0.00)	(0.00)	(0.00)
COVID-19 Case Rate (2)	0.77**			0.23
	(0.25)			(0.19)
State Trump Vote 2016 (3)		0.19***		-0.01
		(0.04)		(0.04)
Metro Trump Vote 2016 (4)			0.25***	0.25***
			(0.03)	(0.04)
Obs.	52	52	52	52
R^2	0.16	0.32	0.66	0.67

1: Google Community Mobility tracks time spent away from home, estimated using cellphone location data, and these values are indexed to January 2020 then averaged over the time period (not seasonally adjusted).
2: The log of the cumulative COVID-19 case rate in the metro area between 1 and 270 days after the first recorded COVID-19 case in the metro area
3: The share of votes in the state for Trump in the 2016 Presidential Election
4: The share of votes in the metro area for Trump in the 2016 Presidential Election

Analysis of Maximum Declines in Dependent Variables

The next analysis focuses on the maximum decline in small business revenue and job vacancies in 2020. The goal of these regressions is to ascertain what static economic variables are associated with the steepest decline in job vacancies and small business revenues. These regressions include five historical variables as well as the number of days between the beginning of 2020 and a city's first COVID-19 case. This variable is included to ascertain if cities that received COVID-19 earliest (New York, Seattle, etc.) were more adversely affected. For Tables 14, 16, and 18 I use cross-sectional OLS regressions to analyze the data unless otherwise specified. The basic regression takes the linear form

$$y_i = \mathrm{X}_i\boldsymbol{\beta} + e_i \; for \; i = 1 \ldots 52$$

where *i* indexes each of the 52 cities in the sample. This regression is run on the maximum decrease of each of the three dependent variables, small business revenues, low-preparation job vacancies, and high-preparation job vacancies, during the first 210 days after the first COVID-19 case in each respective city. Each dependent variable y_i is a 52x1 vector that contains the maximum decrease in the dependent variable between 0 and 210 days after the first COVID-19 case in each respective city in the sample. Here, $\boldsymbol{\beta}$ is a 1x7 vector and $\mathrm{X}_i$is a 7x1 matrix where each respective column represents per-resident accommodation spending, median household income, the share of high digital skill jobs in the metro area, the population-weighted density, the percentage of adults with a college degree, and the numbers of days between January 1st, 2020 and the first COVID-19 case in each respective city.

Finally, regressions of job vacancies and small business revenues after the post-COVID-19 trough are run on static economic variables to explain the variance in recoveries across cities. The data allow for all cities to be analyzed up to 150 days after their maximum decline in small business revenues and vacancies. For Tables 15, 17, and 19 I use cross-sectional OLS regressions to analyze the data unless otherwise specified. The basic regression takes the linear form

$$y_i = \boldsymbol{\beta}\mathrm{X}_i + e_i \; for \; i = 1 \ldots 52$$

where *i* indexes each of the 52 cities in the sample. A regression is run on the average change of the index of each three dependent variables, small business revenues, low-preparation job vacancies, and high-preparation job vacancies, between 1 and 150 days after their maximum decrease following their first respective COVID-19 case. Each dependent variable y_i is a 52x1 vector that contains the maximum decrease in the dependent variable between 0 and 210 days after the first COVID-19 case in each respective city in the sample. Here, $\boldsymbol{\beta}$ is a 52x1 vector and X_i is a 52x7 matrix where each respective column represents average mobility during the 150-day period indexed to January 2020, per-resident accommodation spending, median household income, the share of high digital skill jobs in the metro area, the value of Paycheck Protection Program loans received at the state level, the metro population, and the population-weighted density for each respective city.

Table 14: Maximum Decrease of Small Business Revenues

Dependent Variable: *Maximum Decrease in Small Business Revenue (1)*

Independent Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
constant	-0.55***	-0.55***	-0.55***	-0.55***	-0.55***	-0.55***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Accommodation Spending (2)	-0.04***	-0.03***	-0.03***	-0.03***	-0.03***	-0.03***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Density (3)		-0.06***	-0.07***	-0.04	-0.04	-0.05
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Median Household Income (4)			0.05	0.07	0.08	0.07
			(0.04)	(0.04)	(0.04)	(0.04)
Metro Trump Votes 2016 (5)				0.25*	0.21	0.21
				(0.12)	(0.13)	(0.13)
Share of High Digital Skill Jobs (6)					-0.00	-0.00
					(0.00)	(0.00)
Days to First Case (7)						-0.04
						(0.03)
Obs.	50	50	50	50	50	50
R^2	0.42	0.57	0.54	0.61	0.62	0.63

1: This represents the maximum decrease in seasonally adjusted small business revenue in a city indexed to January 2020 after the first COVID-19 case in the city.
2: The log of the quantity of money spent on accommodation, the combination of lodging and dining, in a city per resident in 2012 in thousands of dollars, per the US Census.
3: The log of 2010 metro area population-weighted density from the US Census Bureau
4: The log of the median household income for a city between 2014-2018, per the US Census Bureau.
5: The percentage of votes in the metro area for Donald Trump in the 2016 Presidential Election
6: The percentage of jobs in the metro area that require high digital skills, as defined by Muro et al. (2017)
7: The number of days between January 1st, 2020 and the first recorded COVID-19 case in a city

Table 15: Small Business Revenue 1 to 150 Days After Maximum Decrease

Dependent Variable: *Small Business Revenue 1 to 150 Days After Maximum Decrease (1)*

Independent Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
constant	-0.31***	-0.31***	-0.31***	-0.31***	-0.31***	-0.31***	-0.31***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Mobility Index After Maximum Decrease (2)	2.13***	1.88***	1.50***	1.71***	1.62***	1.49***	1.30***
	(0.23)	(0.19)	(0.26)	(0.29)	(0.32)	(0.40)	(0.41)
Accommodation Spending (3)		-0.03***	-0.03***	-0.03***	-0.03***	-0.03***	0.03**
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Density (4)			-0.04*	-0.04*	-0.04*	-0.06*	-0.06*
			(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Median Household Income (5)				0.06	0.08	0.10	0.10*
				(0.04)	(0.05)	(0.05)	(0.05)
Percentage of Adults with College Degree (6)					-0.08	-0.14	-0.07
					(0.12)	(0.13)	(0.13)
Metro Trump Vote 2016 (7)						-0.10	-0.11
						(0.15)	(0.15)
Share of High Digital Skill Jobs (8)							-0.00
							(0.00)
Obs.	52	50	50	50	50	50	50
R^2	0.63	0.78	0.80	0.81	0.81	0.82	0.82

1: This represents the seasonally adjusted average change in small business revenue in a city indexed to January 2020 1 to 150 days after the maximum decrease in small business revenue was recorded.
2: Google Community Mobility tracks time spent away from home, estimated using cellphone location data, and these values are indexed to January 2020 then averaged over the time period (not seasonally adjusted).
3: The log of the quantity of money spent on accommodation, the combination of lodging and dining, in a city per resident in 2012 in thousands of dollars, per the US Census.
4: The log of 2010 metro area population-weighted density from the US Census Bureau
5: The log of the median household income for a city between 2014-2018, per the US Census Bureau.
6: The percentage of residents ages 25+ who have obtained a bachelor's degree or equivalent
7: The percentage of votes in the metro area for Donald Trump in the 2016 Presidential Election
8: The percentage of jobs in the metro area that require high digital skills, as defined by Muro et al. (2017)

Table 16: Maximum Decline of Low-Preparation Job Vacancies

Dependent Variable: *Maximum Decrease in Low-Preparation Job Vacancies (1)*

Independent Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
constant	-0.53***	-0.53***	-0.53***	-0.53***	-0.53***	-0.53***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Accommodation Spending (2)	-0.02**	-0.01**	-0.01*	-0.01*	-0.01*	-0.01*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Density (3)		-0.05***	-0.05**	-0.03	-0.03	-0.02
		(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Median Household Income (4)			-0.02	-0.01	-0.02	-0.01
			(0.04)	(0.04)	(0.04)	(0.05)
Metro Trump Vote Share 2016 (5)				0.10	(0.14)	0.13
				(0.13)	(0.14)	(0.14)
Share of High Digital Skill Jobs (6)					0.00	0.00
					(0.00)	(0.00)
Days to First Case (7)						0.04
						(0.04)
Obs.	50	50	50	50	50	50
R^2	0.18	0.32	0.32	0.33	0.33	0.35

1: This represents the maximum decrease in low-preparation job vacancy postings relative to January 2020 in a city after the first COVID-19 case in the city.

2: The log of the quantity of money spent on accommodation, the combination of lodging and dining, in a city per resident in 2012 in thousands of dollars, per the US Census.

3: The log of 2010 metro area population-weighted density from the US Census Bureau

4: The log of the median household income for a city between 2014-2018, per the US Census Bureau.

5: The percentage of votes in the metro area for Donald Trump in the 2020 Presidential Election

6: The percentage of jobs in the metro area that require high digital skills, as defined by Muro et al. (2017)

7: The number of days between January 1st, 2020 and the first recorded COVID-19 case in a city

Table 17: Low-Preparation Job Vacancies 1 to 150 Days After Maximum Decrease

Dependent Variable: *Low-Preparation Job Vacancies 1 to 150 Days After Maximum Decrease*

Independent Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
constant	-0.18***	-0.18***	-0.18***	-0.18***	-0.18***	-0.18***	-0.18***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Mobility Index After Maximum Decrease (2)	1.95***	1.79***	1.81***	2.06***	2.02***	1.82***	1.87***
	(0.28)	(0.28)	(0.36)	(0.42)	(0.47)	(0.48)	(0.50)
Accommodation Spending (3)		-0.07***	-0.07***	-0.07***	-0.07***	-0.08***	-0.07**
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Density (4)			0.00	0.00	0.00	-0.02	-0.02
			(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Median Household Income (5)				0.07	0.08	0.07	0.07
				(0.06)	(0.08)	(0.07)	(0.08)
Percentage of Adults with College Degree (6)					-0.04	-0.10	-0.14
					(0.18)	(0.19)	(0.20)
Share of Trump Vote 2016 (7)						0.00	0.00
						(0.00)	(0.00)
Share of High Digital Skill Jobs (8)							0.00
							(0.00)
Obs.	51	49	49	49	49	49	49
R^2	0.49	0.60	0.60	0.61	0.62	0.63	0.63

1: This represents the average change in new low-preparation job postings on online job boards for each city 1 to 150 days after the maximum decrease in job vacancies, indexed to January 2020 and not seasonally adjusted.
2: Google Community Mobility tracks time spent away from home, estimated using cellphone location data, and these values are indexed to January 2020 then averaged over the time period (not seasonally adjusted).
3: The log of the quantity of money spent on accommodation, the combination of lodging and dining, in a city per resident in 2012 in thousands of dollars, per the US Census.
4: The log of 2010 metro area population-weighted density from the US Census Bureau
5: The log of the median household income for a city between 2014-2018, per the US Census Bureau.
6: The percentage of residents ages 25+ who have obtained a bachelor's degree or equivalent
7: The percentage of votes in the metro area for Donald Trump in the 2020 Presidential Election
8: The percentage of jobs in the metro area that require high digital skills, as defined by Muro et al. (2017)

Table 17B: Low-Preparation Job Vacancies 1 to 150 Days After Maximum Decrease

Dependent Variable: *Low-Preparation Job Vacancies 1 to 150 Days After Maximum Decrease (1)*

Independent Variables	Model 1	Model 2	Model 3	Model 4	Model 5
constant	-0.18***	-0.18***	-0.18***	-0.18***	-0.18***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Accommodation Spending (2)	-0.04***	-0.04***	-0.04***	-0.03***	-0.03***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Density (3)		-0.06**	-0.06*	-0.01	-0.01
		(0.02)	(0.02)	(0.03)	(0.03)
Median Household Income (4)			-0.08	0.05	-0.04
			(0.06)	(0.06)	(0.07)
Share of Trump Vote 2016 (5)				0.32	0.30
				(0.19)	(0.20)
Share of High Digital Skill Jobs (6)					-0.00
					(0.04)
Obs.	51	51	51	51	51
R^2	0.35	0.43	0.48	0.48	0.48

1: The average change in new low-preparation job postings on online job boards for each city 1 to 150 days after the maximum decrease in job vacancies, indexed to January 2020 and not seasonally adjusted.
2: The log of the quantity of money spent on accommodation, the combination of lodging and dining, in a city per resident in 2012 in thousands of dollars, per the US Census.
3: The log of 2010 metro area population-weighted density from the US Census Bureau
4: The log of median household income in the metro area
5: The percentage of votes in the metro area for Donald Trump in the 2020 Presidential Election
6: The percentage of jobs in the metro area that require high digital skills, as defined by Muro et al. (2017)

Table 18: Maximum Decrease of High-Preparation Job Vacancies

Dependent Variable: *Maximum Decrease in High-Preparation Job Vacancies (1)*

Independent Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
constant	-0.46***	-0.46***	-0.46***	-0.46***	-0.46***	-0.46***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Accommodation Spending (2)	-0.00	-0.00	-0.01	-0.01	-0.01	-0.01
	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)
Density (3)		-0.00	-0.02	-0.02	-0.02	-0.02
		(0.01)	(0.02)	(0.01)	(0.02)	(0.02)
Median Household Income (4)			0.10**	0.11*	0.09*	0.12*
			(0.04)	(0.05)	(0.06)	(0.06)
Percentage of Adults with College Degree (5)				-0.01	-0.12	-0.06
				(0.12)	(0.15)	(0.14)
Share of High Digital Skill Jobs (6)					-0.00	0.00
					(0.00)	(0.00)
Days to First Case (7)						0.00
						(0.00)
Obs.	50	50	50	50	50	50
R^2	0.00	0.00	0.14	0.16	0.17	0.17

1: This represents the maximum decrease in high-preparation job vacancy postings on online job boards relative to January 2020 in a city after the first COVID-19 case in the city.

2: The log of the quantity of money spent on accommodation, the combination of lodging and dining, in a city per resident in 2012 in thousands of dollars, per the US Census.

3: The log of 2010 metro area population-weighted density from the US Census Bureau

4: The log of the median household income for a city between 2014-2018, per the US Census Bureau.

5: The percentage of residents ages 25+ who have obtained a bachelor's degree or equivalent

6: The percentage of jobs in the metro area that require high digital skills, as defined by Muro et al. (2017)

7: The number of days between January 1st, 2020 and the first recorded COVID-19 case in a city

Table 18B: Maximum Decrease of High-Preparation Job Vacancies

Dependent Variable: *Maximum Decrease in High-Preparation Job Vacancies (1)*

Independent Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
constant	-0.46***	-0.46***	-0.46***	-0.46***	-0.46***	-0.46***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Accommodation Spending (2)	0.00	0.00	-0.00	-0.00	-0.00	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Density (3)		0.00	-0.01	-0.00	-0.00	-0.00
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Median Household Income (4)			0.13**	0.13**	0.13**	0.13**
			(0.04)	(0.04)	(0.04)	(0.04)
Trump Metro Vote 2016 (5)				0.09	0.09	0.09
				(0.12)	(0.12)	(0.12)
Share of High Digital Skill Jobs (6)					0.00	0.00
					(0.00)	(0.00)
Days to First Case (7)						0.02
						(0.03)
Obs.	50	50	50	50	50	50
R^2	0.00	0.00	0.18	0.19	0.19	0.20

1: This represents the maximum decrease in high-preparation job vacancy postings on online job boards relative to January 2020 in a city after the first COVID-19 case in the city.

2: The log of the quantity of money spent on accommodation, the combination of lodging and dining, in a city per resident in 2012 in thousands of dollars, per the US Census.

3: The log of 2010 metro area population-weighted density from the US Census Bureau

4: The log of the median household income for a city between 2014-2018, per the US Census Bureau.

5: The percentage of votes in the metro area for Donald Trump in the 2020 Presidential Election

6: The percentage of jobs in the metro area that require high digital skills, as defined by Muro et al. (2017)

7: The number of days between January 1st, 2020 and the first recorded COVID-19 case in a city

Table 19: High-Preparation Job Vacancies 1 to 150 Days After the Maximum Decrease

Dependent Variable: *High-Preparation Job Vacancies 1 to 150 Days After Maximum Decrease*

Independent Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
constant	-0.26***	-0.26***	-0.26***	-0.26***	-0.26***	-0.26***	-0.26***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Mobility Index After Maximum Decrease (2)	0.81**	0.84*	0.66	1.18*	0.91	1.07*	1.00
	(0.30)	(0.31)	(0.39)	(0.46)	(0.48)	(0.51)	(0.51)
Accommodation Spending (3)		-0.01	-0.01	-0.02	-0.00	-0.00	-0.01
		(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)
Density (4)			-0.02	-0.02	-0.03	-0.01	-0.01
			(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Median Household Income (5)				0.13	0.19*	0.19*	0.20**
				(0.06)	(0.07)	(0.07)	(0.07)
Percentage of Adults with College Degree (6)					-0.28	-0.24	-0.13
					(0.17)	(0.18)	(0.19)
Paycheck Protection Program Loans (7)						-0.00	-0.00
						(0.00)	(0.00)
Share of High Digital Skill Jobs (8)							0.01
							(0.00)
Obs.	52	50	50	50	50	50	50
R^2	0.13	0.14	0.16	0.16	0.27	0.28	0.32

1: This represents the average change in new high-preparation job vacancies on online job boards for each city 1 to 150 days after the maximum decrease in job vacancies, indexed to January 2020 and not seasonally adjusted.

2: Google Community Mobility tracks time spent away from home, estimated using cellphone location data, and these values are indexed to January 2020 then averaged over the time period (not seasonally adjusted).

3: The log of the quantity of money spent on accommodation, the combination of lodging and dining, in a city per resident in 2012 in thousands of dollars, per the US Census.

4: The log of 2010 metro area population-weighted density from the US Census Bureau

5: The log of the median household income for a city between 2014-2018, per the US Census Bureau.

6: The percentage of residents ages 25+ who have obtained a bachelor's degree or equivalent

7: The log of the quantity of dollars per state resident that the state in which the city resides in received in PPP loans

8: The percentage of jobs in the metro area that require high digital skills, as defined by Muro et al. (2017)

Table 19B: High-Preparation Job Vacancies 1 to 150 Days After the Maximum Decrease

Dependent Variable: *High-Preparation Job Vacancies 1 to 150 Days After Maximum Decrease*

Independent Variables	Model 1	Model 2	Model 3	Model 4	Model 5
constant	-0.26***	-0.26***	-0.26***	-0.26***	-0.26***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Accommodation Spending (2)	-0.01	-0.00	-0.00	-0.00	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Density (3)		-0.04*	-0.05*	0.01	0.00
		(0.02)	(0.02)	(0.03)	(0.03)
Median Household Income (4)			0.04	0.07	0.11*
			(0.05)	(0.05)	(0.05)
Metro Trump Vote 2016 (5)				0.50**	0.36*
				(0.16)	(0.16)
Share of High Digital Skill Jobs (6)					-0.01
					(0.00)
Obs.	50	50	50	50	50
R^2	0.02	0.10	0.11	0.25	0.29

1: This represents the average change in new high-preparation job vacancies on online job boards for each city 1 to 150 days after the maximum decrease in job vacancies, indexed to January 2020 and not seasonally adjusted.
2: Google Community Mobility tracks time spent away from home, estimated using cellphone location data, and these values are indexed to January 2020 then averaged over the time period (not seasonally adjusted).
3: The log of the quantity of money spent on accommodation, the combination of lodging and dining, in a city per resident in 2012 in thousands of dollars, per the US Census.
4: The log of 2010 metro area population-weighted density from the US Census Bureau
5: The log of the median household income for a city between 2014-2018, per the US Census Bureau.
6: The percentage of jobs in the metro area that require high digital skills, as defined by Muro et al. (2017)