Surging Business Formation in the Pandemic: Causes and Consequences

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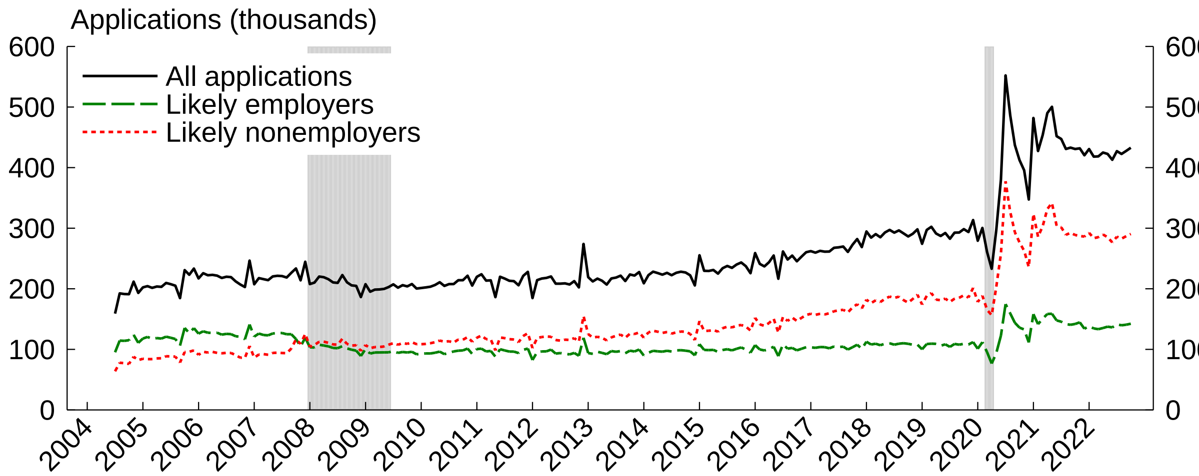
Abstract

Applications for new businesses surged during the COVID-19 pandemic. We find evidence that surging applications is associated with increased creation of employer businesses and related job and worker flows. Applications rose most in industries rooted in pandemic-era changes to work and lifestyles, with significant cross-industry restructuring. Surging applications were quickly followed by increased births of employer establishments with notable associated job creation, and establishment entry is positively correlated with business applications across industry and geography. We also observe a strong increase in job reallocation across firm age groups and a tight spatial correlation between applications and excess job separations (a proxy for quits). Within major cities, applications, net establishment births, and excess job separations exhibit a "donut pattern" with less growth in city centers than in the surrounding areas. Our findings strongly suggest that the pandemic surge in business applications was followed by true employer business creation with significant labor market implications.

1 Introduction

A striking feature of the U.S. economic experience during the COVID-19 pandemic has been a surge in applications for new businesses. After initially dropping in March and April of 2020, applications rose to record levels, reaching an all-time high in July 2020 and remaining historically elevated through the fall of 2022 (figure 1).[1] The surprising growth of business applications received widespread attention amidst elevated unemployment and broader economic volatility, in part because the surge was apparent even among "likely employers," that is, applications with characteristics that are likely to result in the hiring of workers and growth. Historically, there has been a tight relationship between business applications and true business formation, but questions have remained about the degree to which the pandemic's surging applications would translate into actual employer businesses with broader labor market implications.



Note: Seasonally adjusted. All applications = BA series; likely employers = HBA series; likely nonemployers is residual. Shaded areas indicate NBER recession dates.
Source: Census Bureau Business Formation Statistics.

Figure 1: New business applications

The consequences of surging applications are closely related to the likely causes of these applications. In this paper, we provide an initial exploration of the origins and results of surging applications by exploring the sectoral and geographic dimensions of pandemic business formation and documenting relationships between business formation, establishment creation, and job and worker flows. While a more thorough study must wait for the availability of high-quality administrative microdata, we find compelling suggestive evidence—across several data sources—that the surge in business applications has been associated with the creation of employer establishments, significant job reallocation, and elevated worker flows.

[1]This paper builds on Haltiwanger (2022), which documented the surge in applications and the historical relationship between applications and employer startups. The present paper focuses more on the emerging evidence of changing real activity connected to this surge in applications.

The sectoral and spatial pattern of pandemic business applications reveals hints about the origin of the application surge. The rise in applications is concentrated in industries that are friendly to pandemic patterns of work and life (such as online retail and other high-tech industries), and a sharp rise in cross-industry dispersion of applications indicates sectoral shifts consistent with the changing structure of the economy. We also observe elevated dispersion of county-level application growth consistent with geographic restructuring; and within large cities we observe a "donut effect" with applications surging more in the outer rim of metropolitan areas than in central business districts, consistent with earlier work by Fazio et al. (2021) and echoing patterns documented in literature on remote work and related pandemic trends.

With application patterns apparently rooted in pandemic-related economic shifts, it is likely that real economic flows of businesses, jobs, and workers resulted. Indeed, births of new employer establishments rose sharply during the pandemic, accounting for historic job creation during 2021 and early 2022.[2] We observe a strong spatial correlation between business applications and net establishment entry at the county level, and net establishment entry in large cities is characterized by a "donut" pattern similar to that of business applications. Job reallocation across categories of firm age, firm size, industry, and geography also rose during the pandemic, particularly across cells delineated by firm age groups, with a decline in the share of employment accounted for by mature firms. Finally, worker churn rose sharply, illustrated by excess separations (which historically tend to move closely with quits); we document a tight spatial correlation between surging excess separations and business applications, which may shed light on the so-called "Great Resignation" pattern of elevated quits during the pandemic.

While data limitations preclude more rigorous, well-identified study of pandemic business formation, our results strongly suggest that the pandemic sparked a genuine surge in business formation activity with material implications for industries, cities, and employment outcomes. Our work complements Fazio et al. (2021), which documents similar aggregate patterns using data on business registrations in eight states from the Startup Cartography Project; those authors report striking time series relationships between pandemic fiscal stimulus and the application surge and find that the surge was concentrated in zip codes with (a) relatively high African American population and (b) above-median income. Fazio et al. (2021) also find that the surge is apparent outside city centers within large cities; we show that this within-city pattern is apparent in county-level applications data for the U.S. as a whole, and we build on their earlier work by studying outcomes for net establishment entry and excess worker flows as well.[3] We also expand on Decker and Haltiwanger (2022),

[2] In U.S. statistical parlance, an "establishment" is a single operating location of a business, while a "firm" is a collection of one or more establishments under common ownership or operational control (or, in some cases, under a common tax identifier). A new establishment can be opened either by an entirely new firm or by an expanding incumbent firm; data on *establishment* births are currently available through 2022:Q1 from the Bureau of Labor Statistics (BLS) Business Employment Dynamics (BED) product, while data on *firm* births during the main parts of the pandemic will not begin to be released until 2023 in the Census Bureau's Business Dynamics Statistics (BDS).

[3] Relative to Fazio et al. (2021), our contribution is to explore data for a larger set of states, track a longer

which provided a first look at the relationships between business applications and establishment births in official data. We draw on several data sources in our investigation: the BLS BED, Quarterly Census of Employment and Wages (QCEW), and Job Openings and Labor Turnover Survey (JOLTS), and the Census Bureau's BFS and Quarterly Workforce Indicators (QWI).

We review and document patterns of business applications in Section 2. We explore employer establishment entry and its empirical relationship with applications during the pandemic in Section 3. We then turn to job and worker flows in Section 4. We take stock in Section 5 then speculate about potential implications for the future in Section 6. Supplementary material is available in the appendix.

2 Business application patterns

2.1 Applications and employer businesses in history

Data on births of employer businesses in the U.S. are published with substantial lags, but in 2017 the U.S. Census Bureau introduced a timely, high-frequency product reporting applications to the Internal Revenue Service (IRS) to obtain a new Employer Identification Number (EIN).[4] The Business Formation Statistics (BFS), described initially by Bayard et al. (2018), is published monthly and and weekly with scope of all EIN applications, including applications for non-corporate businesses.[5,6] The BFS features several different series including, among others, total applications ("BA" in published tabulations) and applications with high propensity to become employer businesses ("HBA"). In this paper, we use the terms "likely employer applications" and "high-propensity applications" interchangeably. We refer to the difference betwen "BA" and "HBA" as "NHBA" or "likely nonemployers". The data also include actual formations from the applications within four and eight quarters; the latter are

time series (into the fall of 2022), study within-city patterns with (admittedly simple) econometrics, and track outcomes beyond registrations and applications.

[4]Quarterly data on employer establishment births in the BLS BED are published with a lag of roughly three quarters; the published tabulations do not distinguish between births associated with incumbent firms and births associated with newly formed firms. Annual data on both employer establishment and employer firm births in the Census Bureau Business Dynamics Statisics (BDS) are published roughly 2.5 years after the March snapshot they contain; BDS data for March 2020 recently became available, but data for the first year of the pandemic through March 2021 will be published in fall of 2023.

[5]Business owners operating under their social security number will not appear in BFS, and EIN applications associated with trusts, probate, and other non-economic activities are excluded. Importantly, many sole proprietorships obtain EINs. Employer sole proprietors are required to have an EIN to file payroll taxes. For nonemployer sole proprietors, having an EIN facilitates doing business with other businesses and other aspects of running a business (e.g., having a business bank account) and can help prevent identity theft and related fraud. Nonemployer sole proprietors with EINs are on average three times larger in terms of revenue than sole proprietors without EINs (Davis et al., 2009).

[6]The experimental version of the BFS released in 2017 was at a quarterly frequency. At the onset of the pandemic, the demand for high-frequency economic data prompted the release of weekly and monthly statistics on an almost real-time basis. The weekly series is released on Thursday for the prior week. The monthly series is released within two weeks of the end of the reference month.

only available with a delay, so there are also model-based predictions of employer business formations within four and eight quarters available immediately.

At the onset of the pandemic, plummeting weekly business application and registration data received widespread attention (e.g., Fazio et al., 2020; Haltiwanger, 2020; Board of Governors of the Federal Reserve System, 2020).[7] But, as shown on figure 1, applications quickly recovered and surged to historic levels, remaining elevated through Fall 2022. The surge is apparent in all BFS series including total applications and applications with a high propensity to turn into employer businesses (both shown on figure 1) as well as applications with planned wages and applications for corporations.[8] The growth in likely employers has been resilient with average monthly applications in 2022 about 30% higher than in 2019.

Not only is the magnitude of the pandemic application surge striking, but it is also notable that the surge includes a sharp rise in the "likely employers" series, a stark contrast to the previous recession. Dinlersoz et al. (2021) and Haltiwanger (2022) explore this comparison in detail; here we note that the decline in total applications seen in the Great Recession was driven by the "likely employer" series, while the "likely nonemployer" series was roughly flat.[9] Flat or even rising nonemployer entrepreneurship during a recession can easily be rationalized in light of lack of opportunities in formal labor markets, which may push many individuals to resort to "of necessity" self-employment activities; and, indeed, one plausible explanation for the pandemic surge in applications was that unemployment was elevated in the wake of spring 2020 shutdowns. But rising *employer* entrepreneurship is more difficult to understand, as businesses hiring employees are more likely to be taking advantage of genuine entrepreneurial opportunities; hence, the stark difference in "likely employer" behavior between the pandemic recession and the prior recession is all the more striking. And applications have remained elevated—albeit declining gradually—in the wake of the pandemic, even as the unemployment rate has fallen toward historic lows.

As discussed in Haltiwanger (2022), a number of factors help account for the surge in applications for likely employers in the pandemic compared to the drop of likely employer applications and employer startups in the Great Recession. As examples, the pandemic provided new market opportunities given the changing structure of the economy, and financial conditions have been robust compared to the Great Recession (at least through the first half of 2022). The impact of stimulus programs on business formation is an open question. The Payroll Protection Program (PPP), at least in principle, may have dampened new business formation since it provided support for incumbents and thus deterred exit (see Haltiwanger, 2022, for more discussion). There has been some speculation that sole proprietor nonem-

[7]See also Fairlie (2020), which tracks the number of business owners in Current Population Survey (CPS) data. Cognizant of challenges associated with measuring self-employment in CPS data (Abraham et al., 2018), we do not explore CPS data in this paper.

[8]Fazio et al. (2021) similarly find surging business registrations for each of LLCs, partnerships, and corporations; interestingly, however, they find no surge among Delaware corporate forms preferred by venture capitalists.

[9]Data on actual nonemployer activity during the Great Recession broadly confirms the relative resilience of the "likely nonemployer" applications data in that episode. The total number of nonemployer businesses declined just 1.6 percent between 2007 and 2008 but fully rebounded in 2009 then rose further in 2010 and 2011 (Census Bureau Nonemployer Statistics).

ployer applicants for PPP had incentives to acquire an EIN to facilitate processing the paperwork requirements of the PPP; however, a study conducted by Breaux and Gurnani (2022) using a micro-level match of PPP applicants to the BFS finds that only a very small fraction of PPP applicants applied for an EIN in 2020 and 2021.[10]

Even though some factors have been more favorable for business formation in the pandemic than in the Great Recession, an open question is whether genuine employer business creation would result. Historically, high-propensity applications have been strongly predictive of actual employer business entry, with a national correlation of 0.93 and an elasticity above 0.9 within both states and industries.[11] Importantly, there is typically a lag between application and entry (and this lag has increased over time, as shown on figure A5 in the appendix). But appendix figure A4 visually shows a tight relationship between high-propensity applications and employer business formations within eight quarters, and the historical relationship would suggest strongly elevated employer entry during the pandemic as well.[12] Vector autoregression evidence likewise suggests a strong response of total establishment birth rates and net entry rates to high-propensity applications in pre-pandemic data (see figures A6 and A7 in the appendix).[13] But historical relationships may not hold in the unique environment of the pandemic economy, so it has been important to watch for evidence of true employer business entry during the pandemic.

2.2 Sectoral patterns of applications

One clue about the economic substance of surging applications is the pattern across industries. Unfortunately, industry detail beyond broad sectors is not available for the BFS high-propensity application series; however, the series for total applications is available at the 3-digit NAICS industry group level in annually published files.

Nearly one-third of the jump in total applications from 2019 to 2021 was accounted for by nonstore retailers (NAICS 454), which includes online retail. More than half of the overall surge was accounted for by just five 3-digit NAICS industries, shown on figure 2.

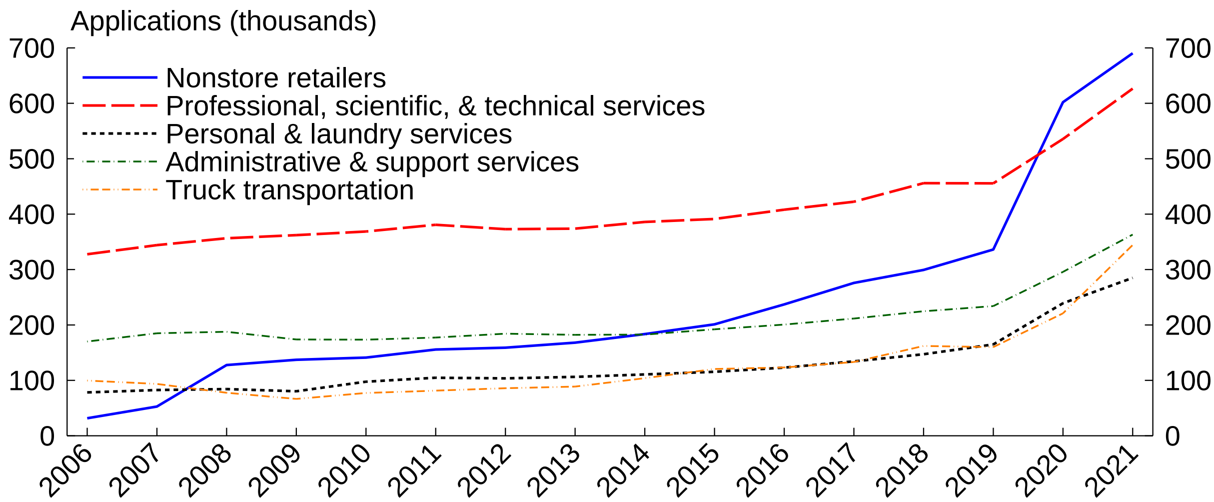
The industries making large contributions to overall application growth can be plausibly related to pandemic patterns of work and life. Nonstore retailers (NAICS 454) include online retail businesses facilitating shopping from home. Professional, scientific, & technical

[10]Only 800 PPP applicants applied for an EIN after they applied for PPP. The average PPP applicant had applied for an EIN about 7 years prior to applying for a PPP. This study also rules out the concern that the surge in the BFS in the pandemic reflects any fraudulent PPP applications wherein individuals applied for an EIN to support fraudulent PPP applications.

[11]These statistics are derived from bivariate regressions relating the log of employer startups within eight quarters to the log of high-propensity applications using pooled data at the state and industry levels, respectively. Actual startups within eight quarters of application were available through 2018 at the time of estimation, so these regressions are estimated on monthly data from July 2004 through December 2018.

[12]The most recent release of the BFS includes applications through 2018:4 that transited to employer startups by 2020:4. The tight relationship during this early period of the pandemic suggests that tight relationship will persist into the pandemic and recovery. Haltiwanger (2022) also shows that historically there is a tight relationship between likely nonemployer applications and actual nonemployer businesses.

[13]Related evidence is presented in Asturias et al. (2021) and Haltiwanger (2022).



Note: All applications, selected 3-digit NAICS industries.
Source: Census Bureau Business Formation Statistics.

Figure 2: New business applications, selected industries

services (541) is a tech-intensive sector, with about half of its employment in STEM-intensive industries such as architectural and design services (5413), computer systems design (5415), and scientific research and development services (5417); business formation in these industries is potentially related to facilitating the transition to work-from-home and related changes in the patterns of work and life due to the pandemic. The sector also includes industries such as building inspectors and interior designers potentially associated with the pandemic surge in home sales or rearrangement of home office environments. Personal & laundry services (812) include some industries that were likely harmed by the pandemic (e.g., nail salons) but also industries that enhanced work-from-home environments or facilitated pandemic hobbies, such as pet care. Administrative & support services (561) includes employment services sometimes important during recessions (e.g., temporary help agencies); industries that may facilitate changes in pandemic business models such as document preparation, call centers, and mail carriers; and businesses facilitating work-from-home transitions such as landscaping services and carpet cleaners. Truck transportation includes both general and specialized freight trucking (an example of the latter is "used household and office goods moving"); businesses in this industry likely benefited from changes to use of commercial real estate, the shift toward online shopping, and the rotation of consumer spending away from services and toward goods.

While the data on figure 2 refer to total applications, as noted previously total and high-propensity applications appear to have moved together in the pandemic era. Moreover, we find similar patterns for high-propensity applications at the broad sector level (shown on appendix figure A8); in particular, the retail trade and professional, scientific, and technical services sectors show strong increases in high-propensity applications.

The available data are consistent with real economic shifts associated with the pandemic.

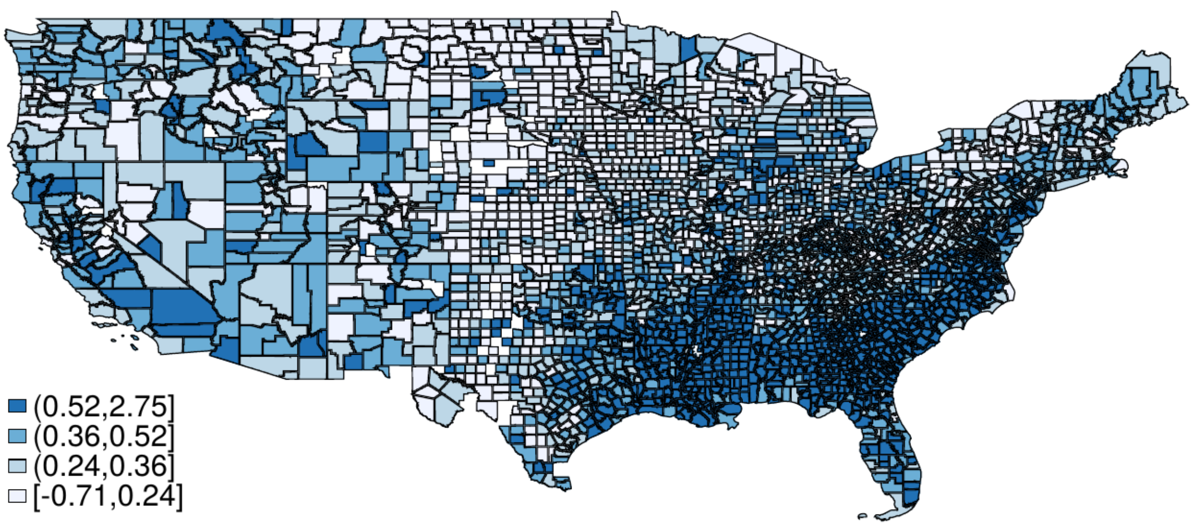
Entrepreneurs likely spotted and sought to exploit new opportunities created by shifts in pandemic patterns of work and spending. Moreover, the data are suggestive of broader economic restructuring during the pandemic, as the cross-industry dispersion of application growth rates rose sharply in 2020 and 2021 (see appendix figure A9).

2.3 Geographic patterns of applications

Annual BFS data on total applications are available at the county level. Growth in business applications has been widespread across U.S. counties; more than 95 percent of counties saw a higher pace of applications during 2020-2021 than during 2010-2019, on average. However, the magnitude of application growth varied widely. We now introduce a measure of the application surge that we will use again later in the paper. Letting g be the growth of applications per capita relative to the pre-pandemic norm, we define g as follows[14]:

$$g = \frac{1}{2}\sum_{t=2020}^{2021} ln(x_t) - \frac{1}{10}\sum_{t=2010}^{2019} ln(x_t), \tag{1}$$

where x_t is applications in year t. That is, we study the difference between the average of (log) applications per capita in 2020-2021 and the average of (log) applications per capita during 2010-2019. Figure 3 shows this log difference g by county, with darker shaded counties having more application growth.



Note: Difference of average (log) all applications per capita, 2020-2021 vs. 2010-2019.
Source: Census Bureau Business Formation Statistics and population estimates.

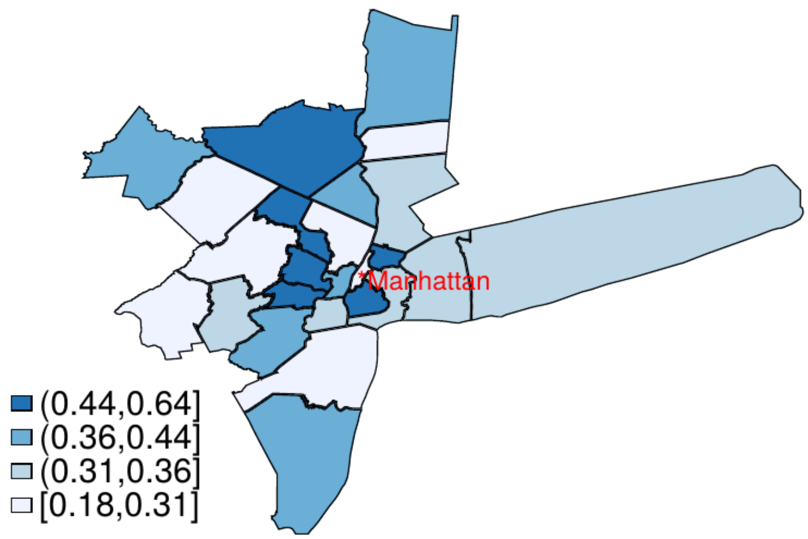
Figure 3: Growth in applications per capita, 2020-2021 vs. 2010-2019

While some counties actually saw declines in applications per capita, the median county saw an increase of 36 log points, and the highest category of counties saw growth of between

[14]We use Census population estimates at the county level by year.

52 and 275 log points. The variation in county-level growth suggests material geographic restructuring, with some counties experiencing dramatically more business applications per capita than in pre-pandemic times. Growth was particularly strong in the south/southeast as well as many counties in the west. While figure 3 refers to total applications per capita (as high-propensity applications are not available at the county level), we observe broadly similar geographic patterns in state-level data on high-propensity applications per capita; this can be seen in appendix figure A10.

Cross-county variation is apparent even within cities, where unique aspects of the pandemic can be seen. Figure 4 zooms in on the counties of the New York City area (which includes counties in New York state, New Jersey, and Pennsylvania), again reporting growth in applications per capita as calculated in equation 1.



Note: Difference of average (log) all applications per capita, 2020-2021 vs. 2010-2019.
Source: Census Bureau Business Formation Statistics and population estimates.

Figure 4: New York City: Growth in applications per capita, 2020-2021 vs. 2010-2019

Growth of application per capita in New York City counties ranges from 18 to 64 log points. We also observe a striking "donut" pattern: growth is stronger outside New York County (i.e., Manhattan)—the central business district of the city—than inside it. These patterns are broadly consistent with zip code-level patterns documented earlier by Fazio et al. (2021) using state business registrations; those authors find that, after the widespread initial registration decline early in the pandemic, Manhattan registrations returned to their 2019 pace while the Bronx, Harlem, and parts of Brooklyn saw historic registration growth.[15]

The donut pattern is apparent in other major cities as well; for example, figure 5 shows the state of Washington, where King County—the central business district for Seattle—shows

[15]Appendix figure A1 shows that prior to the pandemic, Manhattan was one of the top-ranked counties in the NYC CBSA in terms of applications per capita.

less application growth than surrounding counties.[16]

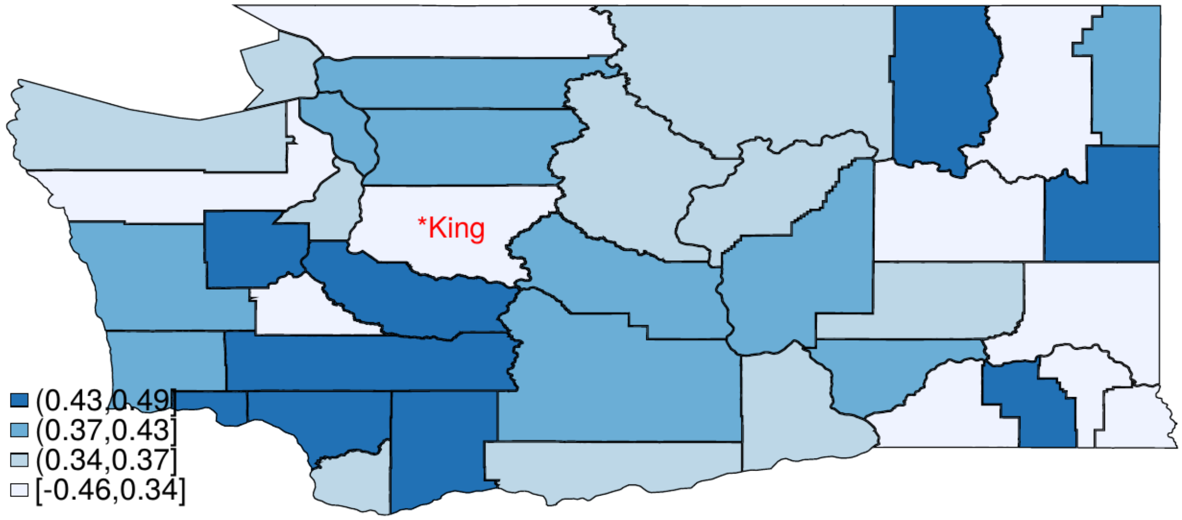


Figure 5: Washington State: Growth in applications per capita, 2020-2021 vs. 2010-2019

In unreported results, we visually observe a similar donut pattern in other cities, including Los Angeles and Atlanta. In more formal results reported in appendix tables B1 and B2 and discussed in appendix section C, we find a highly nonlinear relationship between application growth and county population density (as of 2019) within large CBSAs: we observe strong application growth in counties with very low density and moderately high density, but much lower growth in counties with medium density and high density (e.g., Manhattan).[17] Moreover, we find a similar nonlinear relationship between application growth and *adjacent* county population density (measured in 2019). In addition, we find own-county applications increase substantially with adjacent-county establishments per capita (again measured in 2019, where establishments are measured in the QCEW). This latter finding helps account for the observed donut effects as city centers have higher establishments per capita than do outlying areas.

Like the broader pandemic experience, business application patterns show considerable geographic heterogeneity. And patterns within cities suggest echoes of "donut" patterns of housing and work documented by Ramani and Bloom (2021) and others.

[16]Appendix figure A2 shows that prior to the pandemic, King County was one of the top-ranked counties in the state of Washington in terms of applications per capita.

[17]Fazio et al. (2020) observe a positive, but not statistically significant, linear relationship between density and business registration growth in their eight-state sample, though they do not study nonlinear dimensions.

3 Employer establishment births

With patterns of business applications appearing to be rooted in genuine pandemic economic forces, the next natural question is whether surging applications resulted in surging births of actual employer firms and establishments—and whether the sectoral and spatial patterns described above are evident in employer business data. Importantly, the "gold standard" databases tracking firm, establishment, and job turnover emerge with considerable lags, especially when compared with the extreme timeliness of business application data. It is still too early to measure *firm* births post 2020.[18]

Moreover, without administrative microdata we cannot link establishment or firm births to their respective EIN applications. However, we can now observe high-quality tabulations in official data that bear on several relevant topics. We begin with a study of employer establishment births and openings from the BED, with data through 2022:Q1 currently available.[19]

3.1 Aggregate establishment entry

Figure 6 shows quarterly data on employer establishment births along with high-propensity business applications; the left panel shows the recent period, while the right panel shows a longer time series.

The surge in applications was quickly followed by a surge in establishment births. This is consistent with historical experience, in which applications are strongly predictive of births. However, we emphasize that establishment births include not only establishments associated with newly formed firms but also new establishments opened by incumbent firms, and we cannot distinguish between these in the BED.[20] Like business applications, establishment births have reached record levels during the pandemic.

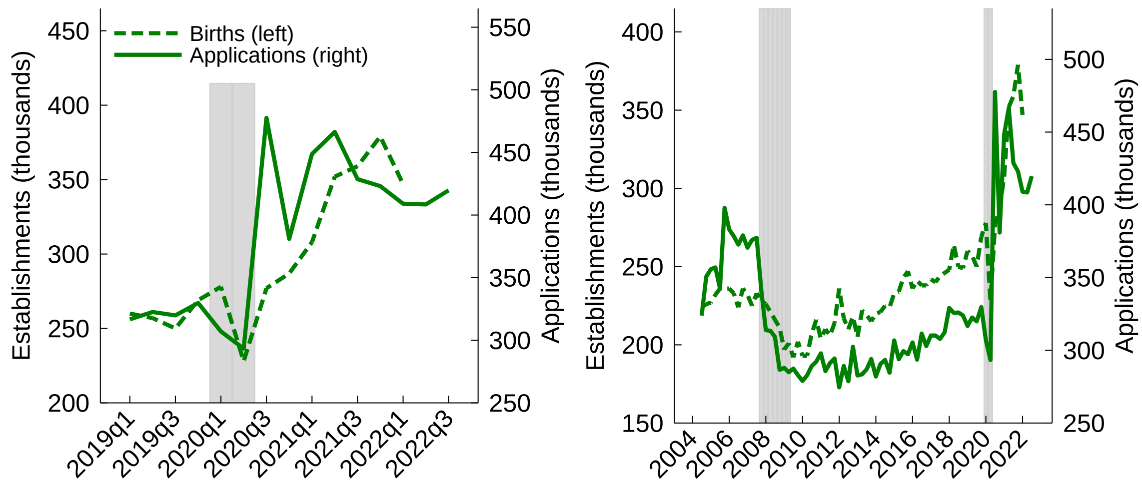
As shown on figure 7, establishment birth has been well in excess of establishment exit (death), on balance, and has accounted for significant job creation. Establishment exits surged at the onset of the pandemic in 2020:Q2 but quickly declined thereafter.[21] Births far

[18]Even here the information is limited. The BDS has released statistics on firm births through March 2020. The BFS includes applications in 2018 that have transitioned to employers through 2020.

[19]BED data are quarterly and are released roughly seven months after the end of the reference quarter. The data cover the near universe of private nonfarm employer establishments and are based on the Quarterly Census of Employment and Wages (QCEW) microdata (see Decker et al., 2021, for discussion of the QCEW universe and how it compares with the universe underlying Census Bureau products). The scope of the BED is a bit narrower than the QCEW scope; the main difference is that the BED strictly excludes establishments with zero employment, while such establishments can remain in the QCEW depending on unemployment insurance status.

[20]In the BED, a "birth" is an establishment with positive employment in a given quarter but no reported employment in the previous four quarters. Births are a subset of establishment "openings", where an opening is an establishment with positive employment in a given quarter and no reported employment in the prior quarter.

[21]In the BED, exit is referred to as "death" and is defined as an establishment with positive reported employment in the prior quarter but none in the four subsequent quarters. As such, establishment exits are currently only available through 2021:Q1. See Sadeghi (2008) for analysis of death measurement in the



Note: High-propensity business applications. Seasonally adjusted. Y axes may not start at zero. Shaded areas indicate NBER recession dates.
Source: Business Employment Dynamics (BED) and Business Formation Statistics (BFS).

Figure 6: Business applications and establishment births

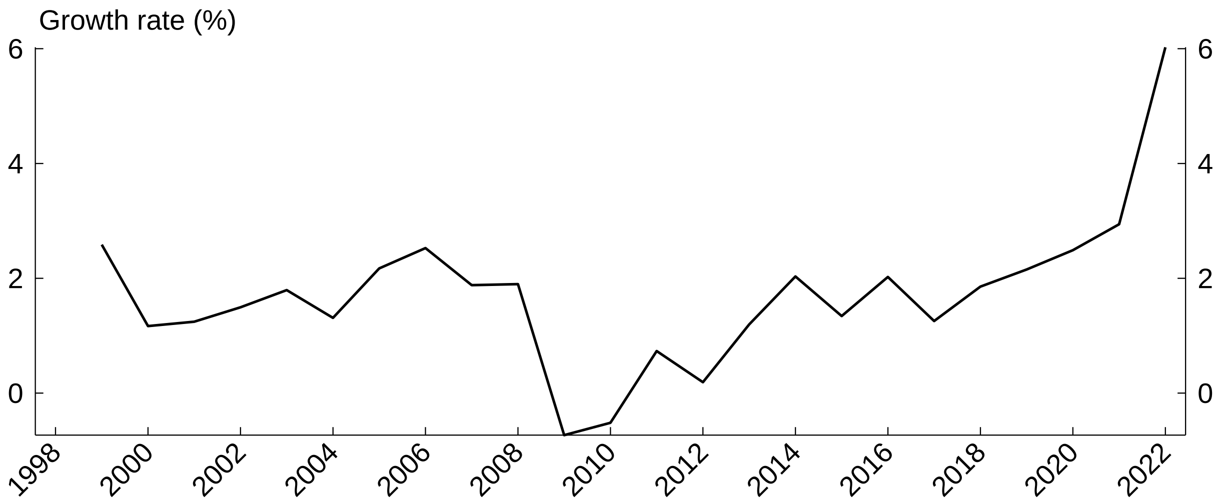
Note: Seasonally adjusted. Y axes may not start at zero. Shaded areas indicate NBER recession dates.
Source: Business Employment Dynamics (BED).

Figure 7: Establishment births and exits

exceeded exits after 2020:Q2; and as the right panel shows, births accounted for roughly 1 million jobs per quarter, on average, during 2021:Q2-2022:Q1. This is a significant contribution to aggregate job creation that is difficult to detect in real-time monthly employment data published by the BLS, which rely on a forecast model to estimate births, and may help

BED.

explain the notable labor market tightness since that time.[22] Figure 8 shows the net result of pandemic birth/exit patterns; on net, the number of establishments grew roughly 3 percent between March of 2020 and March of 2021 then jumped 6 percent in the following year, a historically strong pace.[23]



Note: DHS growth rate of total establishments, March versus year earlier.
Source: BLS QCEW.

Figure 8: Net increase of establishments

Of course, here we have focused on true birth and exit; *temporary* closures and reopenings of establishments also played a large role in early pandemic labor market dynamics as explored in Decker and Haltiwanger (2022).

3.2 Sectoral patterns of establishment formation

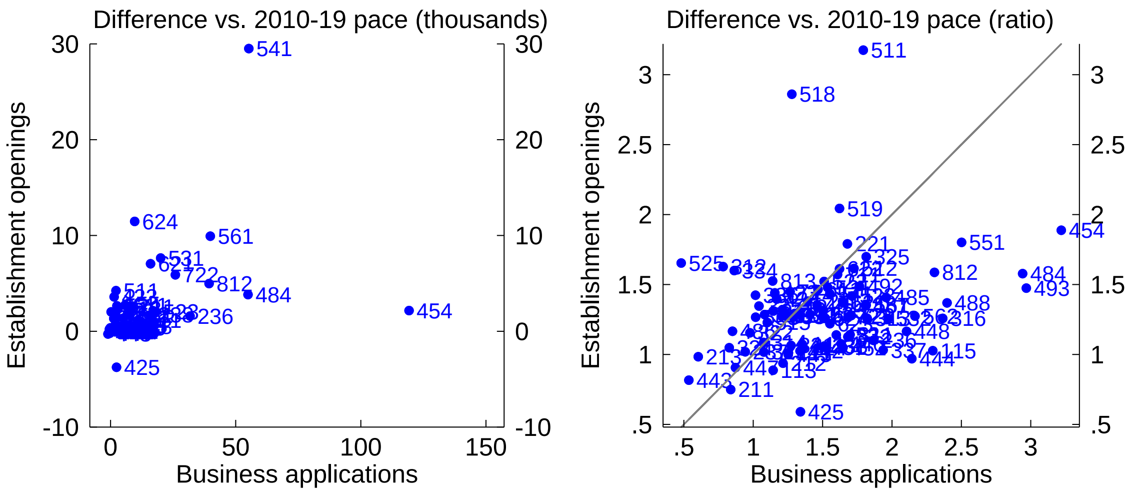
As noted above, the sectoral pattern of business applications is consistent with broader economic restructuring in the pandemic. We next ask whether these industry patterns are reflected in data on establishment formation. Establishment births are available at the broad sector level, while establishment openings (which include reopenings) are available at the 3-digit industry level. Figure A11 in the appendix shows comparisons at the sector level using BED births, but here we focus on 3-digit industry detail using openings. To avoid the spike of reopenings in 2020:Q3, we start in 2020:Q4 and compare the growth of establishment openings to the growth of (total) business applications for the pandemic (2020:Q4-2021:Q4) versus the pre-pandemic period (2010-2019).[24] This is shown on figure 9, where the left

[22]See https://www.bls.gov/web/empsit/cesbd.htm for details on how the BLS estimates net job creation from establishment birth and exit in the monthly Current Employment Statistics.

[23]O'Brien (2022) highlights the net growth of establishments and explores cross-city variation.

[24]At the time of writing, BED data are available through 2022:Q1, as is reflected in figures 6, 7, and other figures in the appendix. However, figure 9 only uses data through 2021:Q4. In the most recent BED data

panel shows the change in levels (thousands) while the right panel shows the ratio of the pandemic pace to the pre-pandemic pace.



Note: 2020:Q4-2021:Q4. Left panel expressed in average seasonally adjusted quarterly pace. Solid line is 45-degree line.
Source: Business Employment Dynamics (BED), Business Formation Statistics (BFS).

Figure 9: Establishment openings and business applications, industry detail

The left panel of figure 9 gives insight into the contribution of different industries to the aggregate surge in establishment openings and business applications. Professional, scientific, & technical services (NAICS 541) leads the surge in establishment openings, while—as noted above—nonstore retailers (NAICS 454) accounts for a large share of surging applications. The right panel of figure 9 reports the ratio of pandemic to pre-pandemic openings and applications, providing further insight into specific industry stories. NAICS 511—publishing, which includes software publishing—leads the surge in the growth of establishment openings (and also shows significant growth in applications), while the tech-intensive sector NAICS 454 (nonstore retail) leads the surge in the growth of new business applications (while also showing strong growth of establishment openings).

The growth of establishment openings and business applications are positively correlated (0.3 and statistically significant); industries with surging applications also tended to have surging establishment openings. Some differences are apparent from the figure, however; these could reflect a number of factors including the role of establishment births within incumbent firms and differing propensity of applications to convert to employer businesses. Decker and Haltiwanger (2022) discuss the potential role of incumbent firms and their responses to pandemic conditions; for example, incumbent firms may have opened data process-

release in late-October 2022, the BLS updated the industry code scheme from NAICS 2017 to NAICS 2022, which resulted in changes at the 3-digit industry level and rendered the series incompatible with the BFS, which is still based on NAICS 2017. We are in the process of addressing this issue with a concordance; in the meantime; 3-digit tabulations from the BED are from a data vintage that is one quarter behind other BED data in this paper.

ing establishments (NAICS 518) to facilitate online retail or remote work at their existing establishments. Overall, however, the industry-level data on establishment openings and business applications are broadly consistent.

3.3 Geographic patterns of establishment formation

Given the striking geographic pattern of business applications described in section 2.3, we next explore county-level correlations. Unfortunately establishment birth (or opening) data are not available at the county level in the BED, so we focus on *net* establishment growth in QCEW data. Figure 10 shows a binscatter plot relating county-level growth in total establishments per capita (2010-2019 versus 2020-2021) to growth in applications per capita (following equation 1).

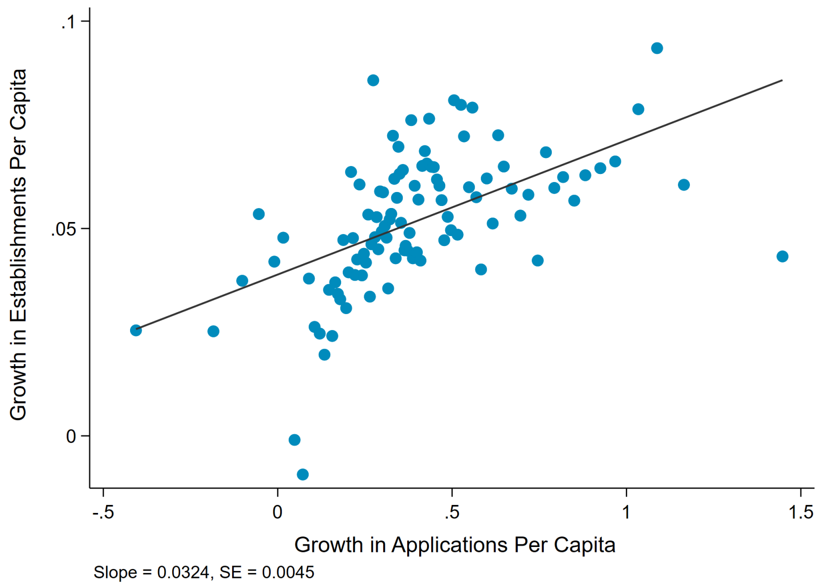


Figure 10: Net establishment growth versus applications per capita growth (binscatter)
Note: County level. Total applications. Source: QCEW and BFS.

We observe a tight, statistically significant relationship between establishment growth and applications. We caution, however, that total establishment growth conflates establishment birth and exit, and the latter has likely been an important margin of local economic adjustment during the pandemic period; see Decker and Haltiwanger, 2022 and Crane et al., 2022 for discussion and estimates of business exit (though note that figure 7 shows that death was not materially elevated after its initial spike in 2020:Q2). Moreover, as in our industry scatterplots above, we have total business applications at the county level, not the narrower category of high-propensity applications. Recall, though, that total applications and high-propensity applications have moved together in the pandemic. The strong spatial relationship between net establishment entry and total applications is suggestive that surging establishment entry has been related to business applications.[25]

As a specific example, figure 11 shows net establishment growth for counties of New York City in the same manner as figure 4. While not identical to the pattern of application growth, we still observe a donut pattern of strong growth in the outer rim of the city with less growth in the city center of Manhattan. Moreover, figure 12 shows *predicted* establishment growth using a simple spatial model predicting establishment growth as a function of application growth in the same and adjacent counties. Again, while not a perfect match, the predictive model suggests a strong relationship between applications and establishment growth, even with relation to the donut dynamics found for applications alone.

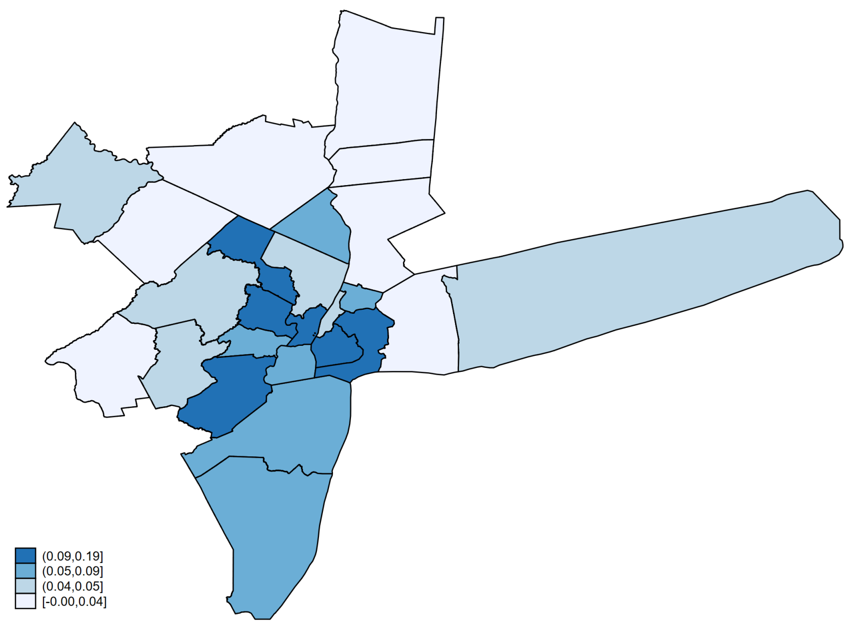


Figure 11: Net establishment growth, New York City

Summing up this section, while we lack the necessary microdata to link applications with establishment births, spatial patterns of net establishment growth during the pandemic are similar to spatial patterns of business applications; and better data on industry-level establishment openings likewise relate closely to surging applications. More broadly, the pandemic's geographic and economic stories—with thriving business creation in industries that complement pandemic changes in work and lifestyles and movement of some forms of economic activity from city centers to outer areas—are evident in both the applications data and the establishment data.

[25]The small slope coefficient reflects the much greater variation in the growth of applications per capita relative to growth of estabslishments per capita.

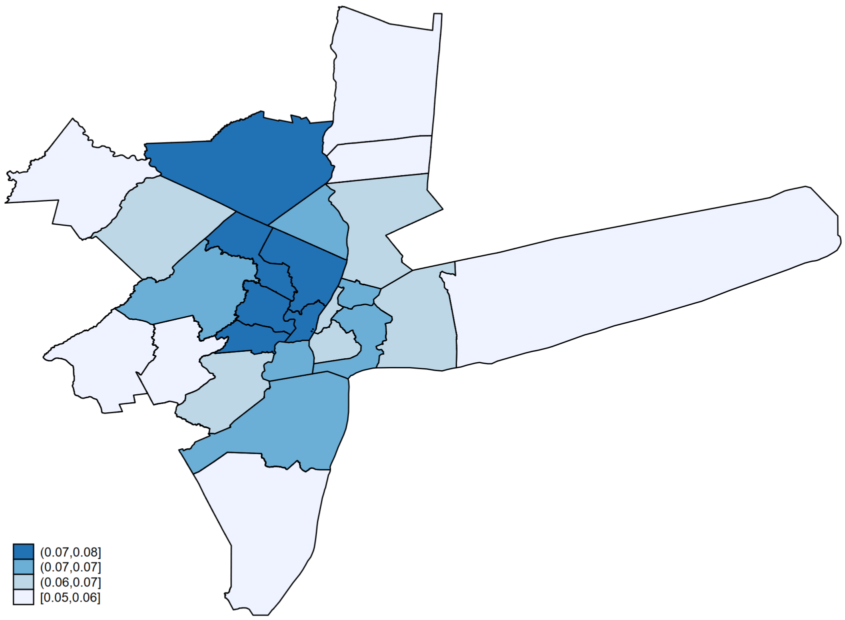


Figure 12: Predicted net establishment growth, New York City

4 Gross job and worker flows

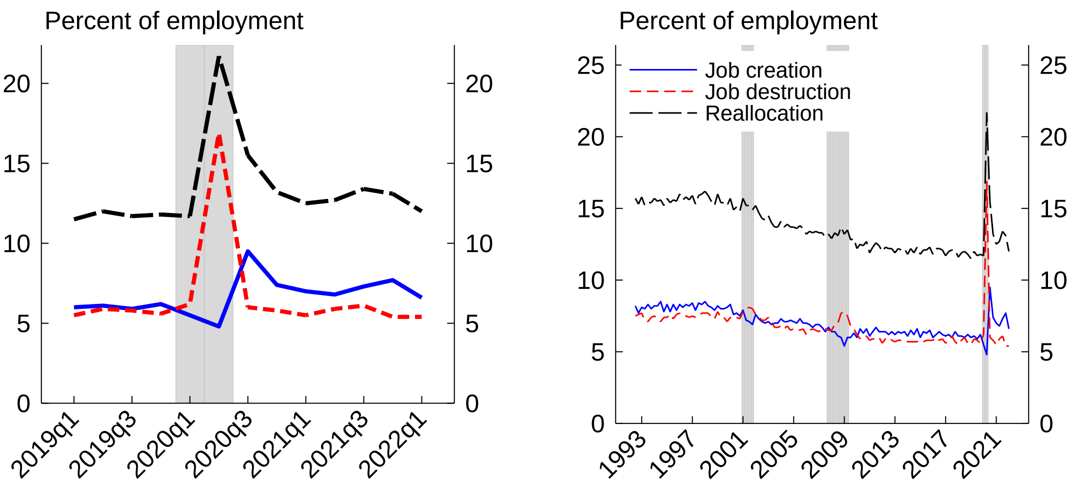
A natural question is whether surging business applications—and establishment births—have had material implications for labor markets. As noted above (and shown on figure 7), establishment entry accounted for more than one million jobs per quarter, on average, for the second quarter of 2021 through the first quarter of 2022. This record pace of job creation from establishment births already shows that births must have played a large role in overall job flows during the pandemic. Forward-looking evidence from early in the pandemic suggested that the pandemic event would spark a surge of job reallocation (Barrero et al., 2020), and elevated job creation from new entrants would likely contribute to such reallocation. Perhaps relatedly, historically elevated worker *quits* have received widespread attention (some have labeled this phenomenon "the Great Resignation"), which could also potentially relate to abundant job opportunities at newly created establishments. In this section, we briefly explore evidence—largely suggestive, as elsewhere in the paper—relating job and worker reallocation to business entry in the pandemic.

4.1 Gross job flows

Following a long literature (e.g., Davis and Haltiwanger, 1992), we define the job reallocation rate as:

$$jr_t = \frac{jc_t + jd_t}{\frac{1}{2}(e_{t-1} + e_t)} \tag{2}$$

where jc_t is gross job creation (total jobs created by entering and expanding establishments), jd_t is gross job destruction (total jobs destroyed by downsizing and exiting establishments), e_t is employment, and t indexes time (quarters, for our purposes). Job reallocation is a summary measure of the reallocation of jobs across expanding, opening, contracting and closing establishments. The denominator in equation 2 is the "DHS" denominator after Davis et al. (1996). Figure 13 shows gross job creation, gross job destruction, and job reallocation; the left panel zooms in on the pandemic period, while the right panel shows a longer view.



Note: Seasonally adjusted. Reallocation is JC+JD. Shaded areas indicate NBER recession dates.
Source: Business Employment Dynamics (BED).

Figure 13: Gross job flows

Job reallocation spiked early in the pandemic; as shown on the right panel, the pandemic spike was historic. In 2020:Q2, the spike in reallocation was driven by the surge of job destruction; in the following quarter, reallocation moved down some but remained elevated due to the surge of job creation as temporarily destroyed jobs returned.

There are two critical points to make about the spike in reallocation. First, as just noted, the 2020:Q2 spike was driven entirely by surging job destruction and therefore simply reflects net job growth in that quarter rather than a phenomenon of simultaneous job creation and destruction across establishments; the 2022:Q3 elevation is similar but driven by job creation. Second, the pandemic was peculiar in that many of the jobs created in 2020:Q3 (and the immediately following quarters) were the same jobs—in the same establishments—that were destroyed in 2020:Q2, as pandemic business restrictions or voluntary social distancing causing initial business closures and temporary layoffs were followed by quick resumption of business activities and recalls (Cajner et al., 2020). As a result, quarterly *excess* job reallocation (job reallocation in excess of absolute net employment growth, or $jr_t - |jc_t - jd_t|$) actually moved *down* in 2020:Q2 and has not generally been significantly elevated during the pandemic. But readers should carefully note that excess reallocation measures can be misleading in quarterly data (as noted in Davis and Haltiwanger, 1992, and related work), especially in events where creation and destruction are decoupled in terms of timing. Further perspective emerges from measuring excess job reallocation using multi-quarter averages of job creation and destruction. Excess reallocation measured at 2-, 4-, or 6-quarter horizons did indeed surge to a high pace not seen in more than a decade, as can be seen in appendix figure A12 (which also shows the dip in 1-quarter reallocation).[26]

Without access to the microdata, though, we still cannot be certain that this multi-quarter horizon increase in excess job reallocation does not simply reflect job destruction in one quarter followed by job creation in the same establishment in subsequent quarters. To overcome this limitation, we focus on between-cell excess job reallocation, where cells are categories that can be defined in terms of firm age groups, firm size groups, geographic divisions, or industries. Following Davis and Haltiwanger (1992), for a set of cells indexed by s, between-cell excess reallocation is given by:

$$br_t = \sum_{s=1}^{S} |jc_t^s - jd_t^s| - |jc_t - jd_t| = \sum_{s=1}^{S} |net_t^s| - |net_t| \tag{3}$$

That is, between-cell excess reallocation br_t is obtained by calculating cell-level absolute employment changes, summing across cells, and subtracting the aggregate absolute employment change.[27] Between-cell excess job reallocation for a given set of cell definitions over a multi-quarter horizon has the property that if all cells exhibit net employment contraction early in the horizon followed by matching net employment expansion later in the horizon, then between-cell excess job reallocation will be zero. Moreover, even if the recovery is not complete but is even across cells then between-cell excess job reallocation will be zero. Using a sufficiently long horizon permits offsetting net contractions and expansions within cells to cancel out. In contrast, net contraction in one cell followed by net expansion in a different cell—that is, actual net movement of jobs across cells—contributes positively to between-cell excess job reallocation.

Between-cell excess reallocation can be constructed as a rate when divided by the DHS denominator, $\frac{1}{2}(e_{t-1} + e_t)$. Data from the Census Bureau's QWI allow us to construct between-cell reallocation across several different cell schemes of interest, with data currently extending through 2021:Q3.[28]

[26]Excess reallocation measured at an h-quarter horizon is given by:

$$er_t^h = \bar{jc}_t^h + \bar{jd}_t^h - |\bar{jc}_t^h - \bar{jd}_t^h|,$$

where $\bar{jc}_t^h$ is average quarterly job creation over the h quarters leading up to (and including) t, and $\bar{jd}_t^h$ is the corresponding average of job destruction.

[27] *Within*-cell excess reallocation is given by $wr_t = \sum_{s=1}^{S}(jr_t^s - |jc_t^s - jd_t^s|)$. Aggregate excess reallocation is $br_t + wr_t$.

[28]The QWI is based on the Census Bureau's Longitudinal Employer-Household Dynamics (LEHD), which uses the microdata from the same ultimate Unemployment Insurance sources as the QCEW. An advantage of the QWI is its linkages to high-quality Census Bureau firm identifiers (the same used for Business Dynamics Statistics data and related products). Importantly, the Census Bureau receives QWI source data on a state-

The magnitude of the between-cell excess reallocation rate depends, of course, on the way cells are defined. We focus on the following cell schemes permitted by the QWI:

- Firm age categories: 0-1 years old, 2-3 years old, 4-5 years old, 6-10 years old, and greater than 10 years old, where a firm is age 0 in the first year in which one of its establishments has positive employment
- Firm size categories: 0-19 employees, 20-49 employees, 50-249 employees, 250-499 employees, and 500 or more employees
- States
- Broad NAICS sectors
- 3- or 4-digit NAICS industries
- Interactions of some of the above as permitted by the public-use data

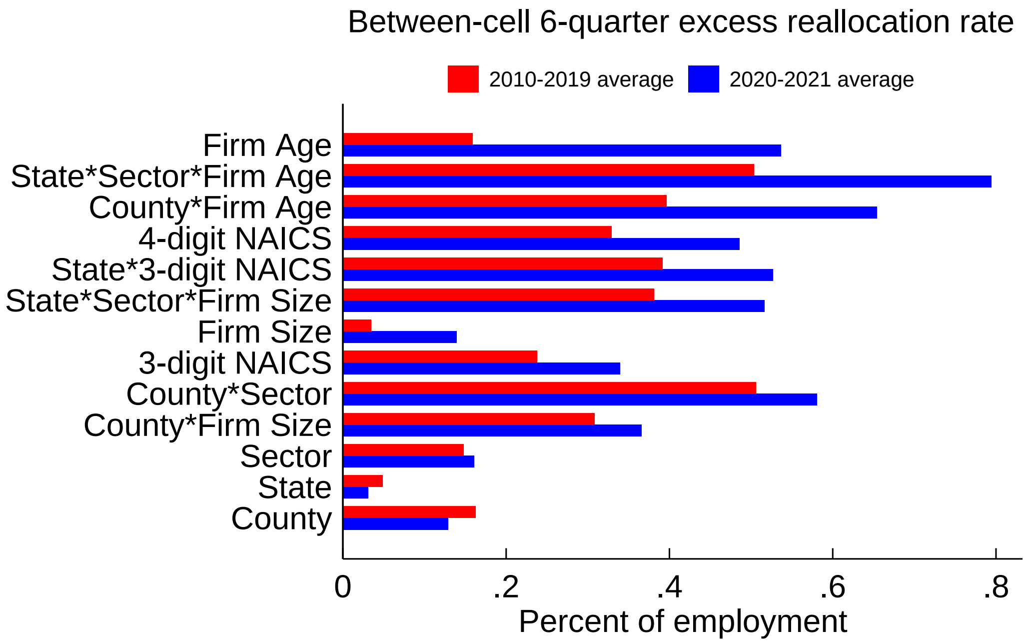
Figure 14 shows the between-cell excess reallocation rate for the pre-pandemic period (2010-2019) and the pandemic period (2020:Q1-2021:Q3) for several different cell schemes, where reallocation is defined on a 6-quarter horizon (that is, net changes are averaged over the trailing six quarters before constructing equation 3).[29] We use a 6-quarter horizon to permit offsetting net changes within cells to cancel out.

The chart is sorted in descending order of the change from 2010-2019 to 2020-2021 (i.e., the difference between the blue and red bar) such that the largest increases are shown at the top. In general, between-cell reallocation rose markedly in the pandemic, as evidenced by larger blue bars. Focusing on the first row of the figure, the rate of excess reallocation between firm age categories jumped from about 0.2 percent per quarter (for 2010-2019 on average) to over 0.5 percent per quarter during the pandemic. We also observe large jumps in between-cell excess reallocation across state × sector × firm age and across county × firm age categories.[30]

by-state basis. Some states currently report data through 2021:Q4. We focus on a balanced panel of 44 states with coverage for 2004:Q1-2021:Q3; these states account for roughly 90 percent of U.S. private employment. Results are very similar in a panel with a longer time series starting in 1998 and covering roughly two-thirds of employment.

[29] In the QWI, the DHS denominator is the average of Emp and EmpEnd, which are the beginning- and end-of-quarter employment, respectively. We measure job destruction with the FrmJbLs variable and job creation with the FrmJbGn variable; FrmJbLs is end-of-quarter employment minus beginning-of-quarter employment among firms that shrank in a given quarter, and FrmJbGn is the job gain counterpart. Job flow rate fluctuations in the QWI are broadly similar to those found in the BED but tend to be at a somewhat lower level due to subtle conceptual differences in their construction. In particular, QWI job flows measure flows across firms (and do not capture flows across units within firms), while BED job flows measure all flows across establishments. Seasonality may also be more pronounced in BED data. We thank Erika McEntarfer for a helpful discussion of these differences.

[30] Figure A13 in the appendix follows the same concept as figure 14 using a 4-quarter reallocation horizon instead of a 6-quarter horizon. The horizon does matter; we prefer the 6-quarter horizon to capture more of the early and later pandemic dynamics and allow the surge in business entry to more fully play out. That



Note: Averages of quarterly seasonally adjusted data through 2021q3.
Sorted (descending) by change 2010-2019 to 2020-2021.
Source: Census Bureau Quarterly Workforce Indicators (QWI)
and author calculations.

Figure 14: Between-cell reallocation rate (6-quarter horizon)

The large jumps in categorizations including firm age are striking and suggest that pandemic reallocation was closely tied to firm lifecycle dynamics. What does this say about firm birth specifically? Like the BED, the QWI is limited in its ability to directly study firm birth; in particular, the QWI provides only tabulations of total employment by firm age group—without separate reporting for birth and exit—and the QWI's youngest age category ranges from 0 to 1 such that, even in 2021:Q3, the category includes firms born just prior to the onset of the pandemic, some of which may have exited during the pandemic. Moreover, the source data used to identify firms in the QWI are not fully up to date through 2021, so firm age for young firms is measured with error in the most recent years.[31] However, identification of mature firms is more accurate, and we can observe that the share of employment accounted for by mature firms—in this case, firms older than 10 years—declined materially during the pandemic; this is shown on appendix figure A14. In other words, young firms—as a group—have been more resilient than more mature firms during the pandemic, and this is reflected in reallocation of employment from older to younger firms. The specific role of firm *birth* in this reallocation is, as of yet, unclear.

We also note that simple reallocation across simple firm age categories is not the only

said, the firm age-related schemes feature prominently in the 4-quarter horizon as well, still ranking high in terms of the rise in between-cell reallocation.

[31]See Haltiwanger et al. (2014).

story told by figure 14: reallocation across firm age categories appears to have important geographic and industry dimensions as well.

4.2 Worker flows

Having found striking—if suggestive—evidence relating the growth of business applications with establishment entry and job flows, we now turn to worker flows. Flows of workers across firms have received widespread attention during the pandemic, with the most notable example being stories about the "Great Resignation" associated with record numbers of workers quitting their jobs.

While data on quits—provided as part of the BLS JOLTS product—are available only with very limited granularity, data on other worker flows are available in the QWI at the county level. We focus on excess separations (es_t), which are constructed as:

$$es_t = s_t - jd_t, \tag{4}$$

where s_t is total separations of workers from jobs and jd_t is job destruction. We measure excess separations as a rate by dividing through by employment.

It is important to grasp the intuition of excess separations. Separations include quits and layoffs. Workers may be separated from jobs because those jobs are being destroyed as a firm contracts; for example, a firm may be eliminating a position entirely as part of a downsizing or restructuring plan. In these cases, there is no excess separation, and worker and job flows are equal. But many workers are separated from jobs while those jobs continue to exist and will be filled by another worker. A likely reason for such a separation is that the worker is quitting the job to start a new job elsewhere; in practice, excess separations are therefore closely related to quits, and layoffs are closely related to job destruction (Davis et al., 2012).[32] We might expect surging business births, with associated labor demand, to be closely related to surging quits, as many newly hired employees of newly formed businesses may have voluntarily flowed from prior jobs—particularly as the labor market tightened as the pandemic progressed. We find suggestive evidence of this in both the time series and the cross section. Figure 15 shows aggregate excess separations (from QWI), quits (JOLTS), establishment births (BED), and high-propensity business applications (BFS) since 2005 (all series indexed to one in 2019).[33]

The dashed green line shows the widely remarked-upon surge in quits after an initial decline early in the pandemic. Prior to the pandemic, quits and excess separations moved in

[32] During 2010-2019, quits accounted for about 55 percent of total separations, on average, with an upward trend throughout that period (per JOLTS data). The share was above 60 percent in every month from February 2018 through February 2020. The share has been even higher recently; after plunging at the onset of the pandemic, quits as a share of total separations has been above 70 percent since April 2021.

[33] In the QWI data we measure separations using the SepBeg variable rather than the simple Sep variable. The latter measures all separations occurring in a quarter, which includes an often large number of short-duration within-quarter jobs. SepBeg measures separations of workers who held the job in the prior quarter and were separated in the current quarter; this measure tends to be more quantitatively comparable to JOLTS worker flow estimates.

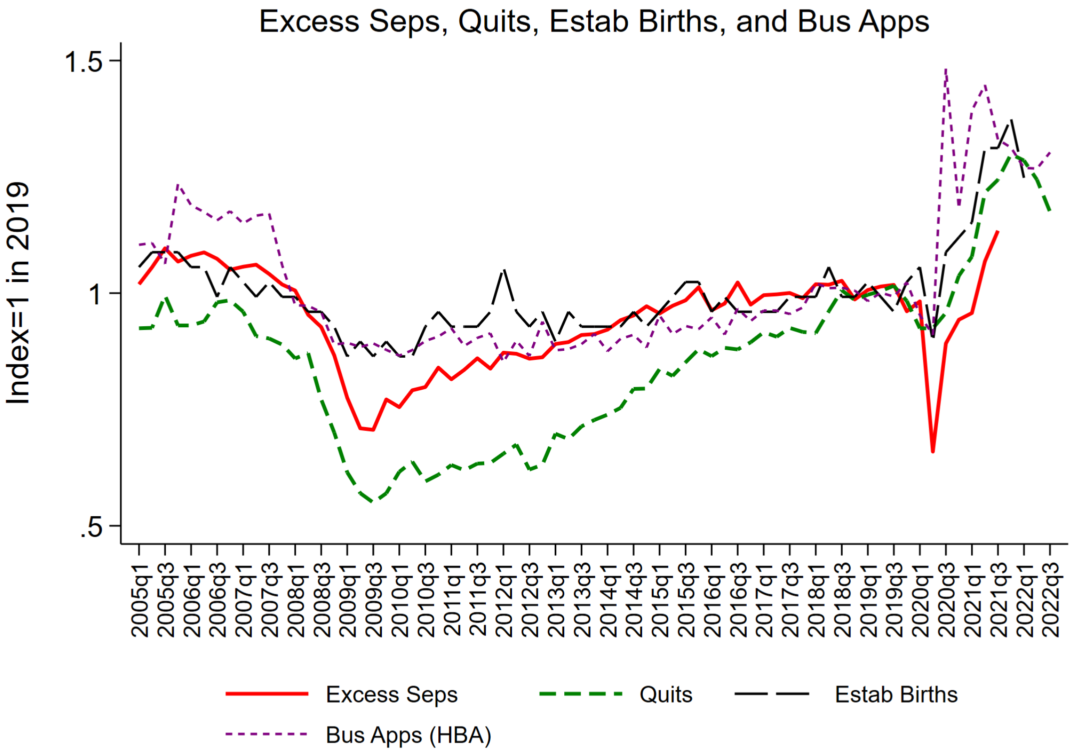


Figure 15: Excess separations, quits, births, and applications
Source: QWI, JOLTS, BED, and BFS.

similar patterns (albeit with some level shift), consistent with their close conceptual relationship. Figure 16 zooms in on the period since 2019, revealing reasonably close comovement during the pandemic as well—though excess separations dipped more than quits during 2020:Q2, likely due to the jump in job destruction in that quarter.

Like many other aggregate series, those shown on figure 16 follow a broadly similar pattern during the pandemic, with an initial drop in the spring of 2020 followed by sharp increases during the later pandemic period. The aggregate time series are suggestive of a relationship between applications, births, and worker flows as measured by quits and its close proxy, excess separations, but we also observe a tight relationship between changes in worker flows and business formation at the local level: figure 17 shows a binscatter plot of county-level growth in the excess separations rate and county-level growth in (total) business applications per capita, where growth is constructed as in equation 1.

We observe a tight, statistically significant spatial relationship between growth in excess separations and growth in business applications, a striking and potentially important finding. While we might imagine multiple theories for this tight relationship, a natural explanation is that surging business creation and resulting labor demand is an important component of the overall story of worker flows in the pandemic, including quits. New businesses are

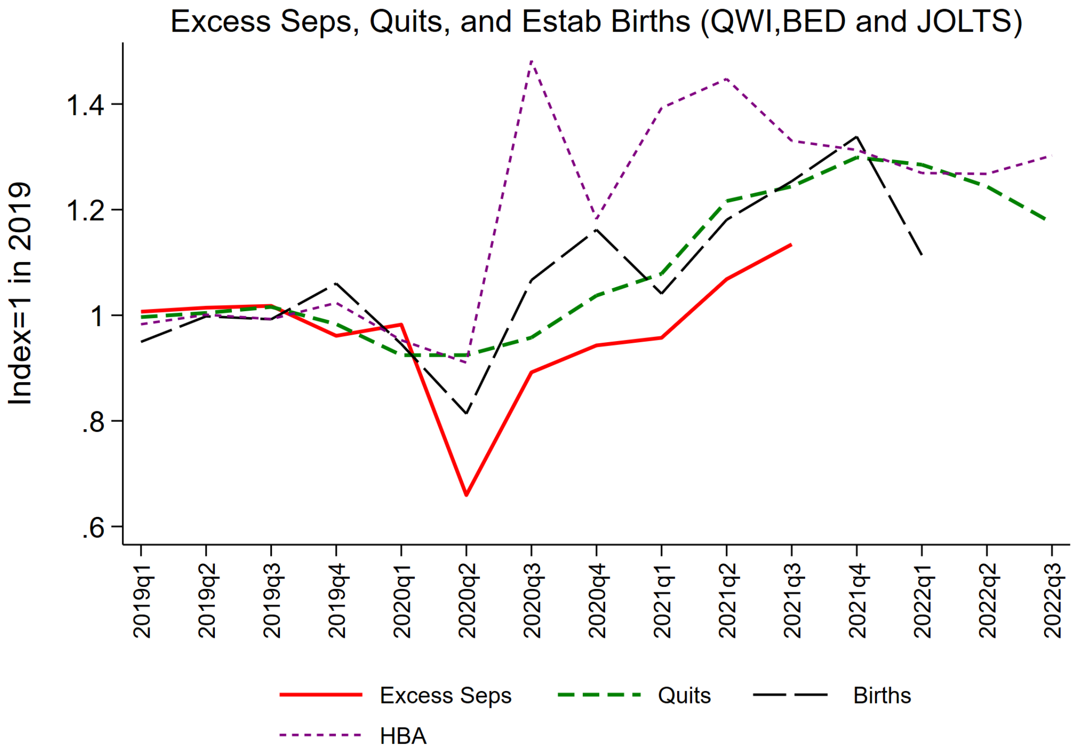


Figure 16: Excess separations, quits, births, and applications, 2019-2022
Source: QWI, JOLTS, BED, and BFS.

known for aggressively poaching workers from other firms (Haltiwanger et al., 2018) and, therefore, likely contributed to the pandemic reallocation of workers by providing new opportunities in pandemic-friendly industries. We know from figure 7 that job creation by establishment births during 2021 was massive; with new establishments creating close to one million jobs per quarter some job-to-job flows—arising from excess separations—would likely result. Interestingly, within cities we find a donut pattern of excess separation growth somewhat similar to the pattern for applications (and net establishment births); in the appendix, figure A15 shows county-level growth in excess separations for the New York City area, and figure A16 shows *predicted* growth in excess separations as a function of county and adjacent-county business applications; the two figures show broadly similar patterns consistent with a close spatial relationship between applications and worker flows.

Again, we view this evidence as strongly suggestive, though a clear understanding of the role of new businesses in the elevated quit rate must await high-quality microdata on job-to-job flows.

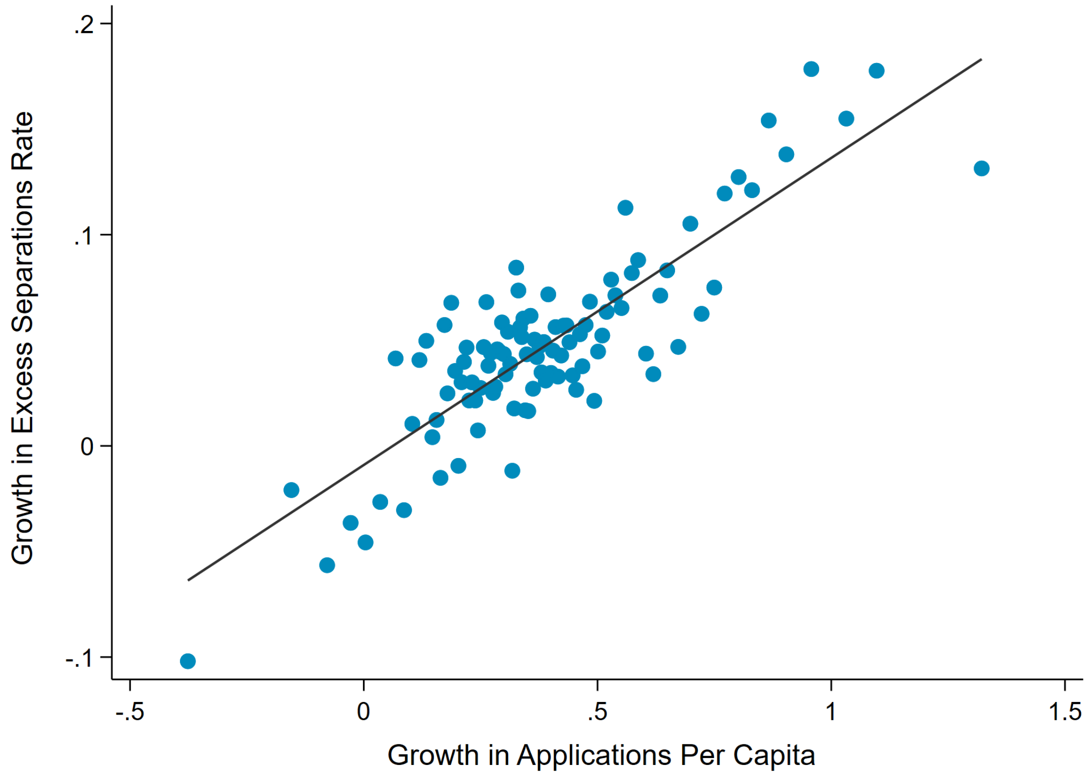


Figure 17: Growth of excess separations rate and applications per capita, 2020-2021 vs. 2010-2019 (binscatter)

Note: County level. Total applications. Source: QWI and BFS.

5 Taking stock

Using several official data sources, we document close relationships between business applications, establishment entry, and job and worker flows during the pandemic. Our findings suggest that the surprising surge in business applications and registrations seen during the pandemic represented genuine entrepreneurial activity and likely resulted in considerable job creation and reallocation of jobs and workers. This apparent surge in employer entrepreneurship is remarkable given the weakness in broader economic conditions from which it emerged, and it stands in sharp contrast with the plunge in employer entrepreneurship seen during the Great Recession.

Our findings are strongly suggestive that many new business applicants did make the transition from potential to actual employer businesses. However, it is still too early to study these transitions directly, a task that will require microdata not currently available: the microdata will permit studying applications that transitioned into employer startups with a focus on characteristics like industry, location, and entrepreneur demographics, along with post-entry lifecycle dynamics. Investigating the demographic patterns of pandemic entrepreneurship looks to be of considerable interest; for example, Fazio et al. (2021) find that zip code-level African American population is strongly predictive of business registrations. Did the pandemic shifts in economic patterns provide durable entrepreneurial opportunities to minority groups that have historically faced challenges to business entry? We must leave this and related questions for future research. In the meantime, our existing results suggest that entrepreneurship has played a key role in pandemic-era labor market dynamics.

Our findings on business formation raise separate questions about measurement of economic activity in the pandemic. In general, employer entry is not well captured in key headline economic statistics. The monthly payrolls report—the BLS Current Employment Statistics—measures the growth of continuing establishments supplemented with a *forecast* of job creation from net birth and exit that relies on actual birth and exit data that lag by at least 9 months; while these data are eventually revised with high-quality administrative sources (primarily QCEW), the benchmark revision covering the last three quarters of 2021 will not be published until early 2023.[34] The key Census Bureau spending surveys that underlie quarterly GDP data releases—such as the Monthly Retail Trade Survey, the Manufacturers' Shipments, Inventories, & Orders survey (the "M3"), and the Quarterly Services Survey—likewise rely on growth of continuing firms or establishments with an adjustment based on past benchmark revisions to account for the role of net business birth and exit and other sources of error; GDP data were recently revised through 2021:Q4, though benchmark revisions for the surveys just mentioned still rely on (annual) survey data.[35] As such, it is still unclear how well economic statistics captured the pandemic surge of business entry and any associated boost to employment and output.

6 Implications for the Future?

Given that we are only beginning to observe the real activity effects connected to the surge in new business applications, discussion of the implications of this surge for the future of U.S. economic activity can only be highly speculative. Nevertheless, here we provide some discussion about what potential patterns are worth contemplating in the coming months and years.

First, we emphasize that the full implications of the pandemic startup surge will take

[34] The BLS did publish a preliminary estimate of the benchmark revision for the period of March 2021-March 2022; it suggested a sizeable upward revision to the level of employment at the end of this period, which could be related to the large numbers of jobs created by establishment births during 2021:Q2-2022:Q1 (see https://www.bls.gov/web/empsit/cesprelbmk.htm). The final benchmark revision, which could differ from the preliminary estimate, will be published in early February 2023 and will include a tabulation of net birth and exit forecast errors.

[35] For example, see the Monthly Retail Trade Survey documentation at https://www.census.gov/retail/index.html. While the survey—in which the unit of analysis is the firm—does attempt to identify and include firm births, the earliest they can appear in the production sample is nine months after they start operations. The Census Bureau also attempts to sample births in the annual surveys, but fully capturing business entry and exit cannot be assured until the Economic Census-based benchmark revisions that occur every five years.

several years to unfold. This reflects the highly volatile nature of startups, especially over their first five-to-ten years. Most startups fail or, at least, do not grow (Decker et al., 2014). A small fraction grow rapidly, and this small subset of entrants is disproportionately important for the contribution of startups to job creation, innovation, and productivity growth (Decker et al., 2014; Guzman and Stern, 2020). Theory and evidence suggest that startups are a core part of the experimentation that accompanies the development and adoption of new technologies and production processes, though this experimentation necessarily involves many business failures (see, e.g., Foster et al., 2019).

Second, this surge in startups has occurred in spite of factors that were dampening the pace of business entry—and business dynamism more generally—in the decades leading up to the pandemic (Decker et al., 2020). It is unlikely that those factors, while still not completely understood, have disappeared entirely. Whether the countervailing forces driving the pandemic surge are sufficient to change the pre-pandemic trend decline is unclear.

Third, it may be important to consider the dynamics of aggregate productivity prior to the pandemic. In appendix figures A17 and A18, the well-known productivity slowdown in the post-2005 period, and especially since 2014, is evident even in the innovative high-tech sectors of the economy. Many factors have been proposed as underlying this slowdown including the decline in dynamism and entrepreneurship (e.g., Decker et al., 2020), so the pandemic-era pattern of business formation may have implications for how productivity evolves going forward.

This discussion suggests some possible implications of the pandemic business entry surge. One possibility is that this surge is associated with a burst of innovation, with startups being an important component of the experimentation leading to that innovation. Hints of this possibility may be seen in the industry composition of surging applications and establishment openings (figure 9), with high-productivity industries like nonstore retail, software publishing, computer systems design, and data processing apparently seeing especially elevated entry. Tracking the potential for surging entrepreneurship to spark economic growth and technological progress should be a high priority; eventually we would hope to see such progress reflected in productivity statistics, and a productivity boost from surging startups could mean stronger growth of potential output for the economy overall. Again, it will take some time for these dynamics to unfold, but early signals of the nature and composition of this surge might be detected, for example, using the nowcasting methodology of Guzman and Stern (2017).

Alternatively, this surge may reflect the type of spatial and sectoral restructuring that we have detected but only insofar as such restructuring is necessary for providing basic support activities for the changing nature of work and lifestyle, with no broader spillovers in terms of innovation, productivity, and growth. In other words, the surge in startups suggested by the data we have reviewed could reflect a reshuffling of economic activity without leading to additional technological progress or growth. The surge of entrants in the personal and laundry services industry could be consistent with this outcome. And the donut effects we observe in the spatial patterns of applications and actual increases in net establishment growth may reflect business formation to support the increased fraction of working hours spent at home, and little else. Such support activity is likely very important to enable the changing nature of work, but it is unclear that such reallocation would herald a burst of innovation and productivity growth.

Finally, we acknowledge the widely discussed prospect of an economic slowdown in the coming quarters. During 2022, U.S. monetary policy has tightened materially in response to elevated inflation, and policymakers have signaled an expectation that further policy tightening is still ahead.[36] While some indicators of growth, such as payroll gains, have remained strong during 2022, monetary policy is typically thought to operate with "long and variable lags;" and some private forecasters now expect the U.S. economy to fall into recession during the next year (e.g., Goel et al., 2022). While these forecasts are highly uncertain, existing literature (e.g., Davis and Haltiwanger, 2021) finds that startups and young businesses are particularly sensitive to business cycle fluctuations, particularly those associated with tight financial conditions (e.g., falling house prices, rising interest rates, or declining business lending activity). The young businesses started during the pandemic, and the continued elevated trend of business applications, may be at risk in the event of a broad economic slowdown.

[36]For example, see the September, 2022 Federal Open Market Committee Summary of Economic Projections at https://www.federalreserve.gov/monetarypolicy/files/fomcprojtabl20220921.pdf.

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A Supplemental figures

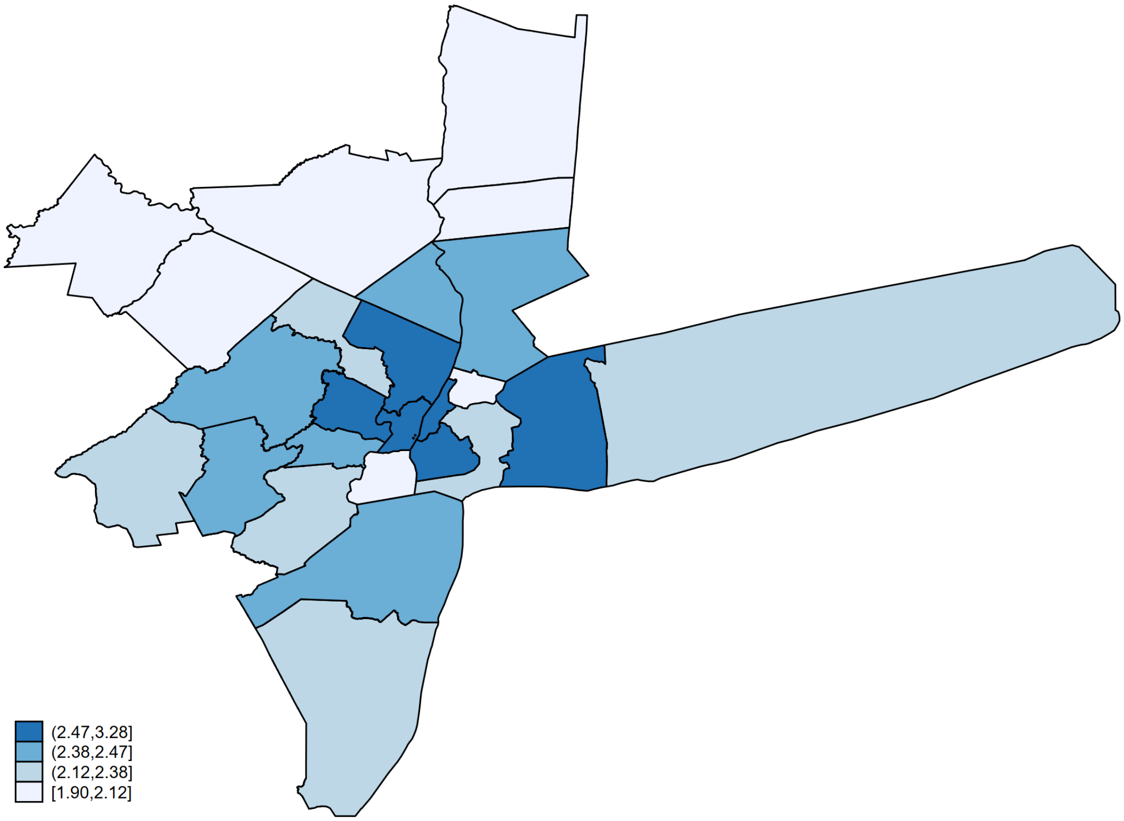


Figure A1: Average Applications Per Capita, NYC, 2010-19

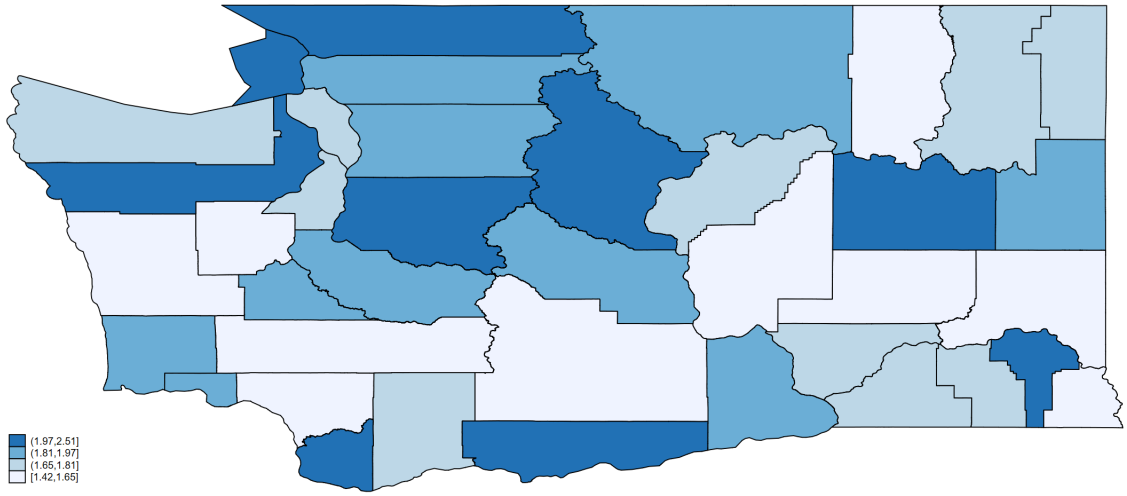


Figure A2: Average Applications Per Capita, Washington State, 2010-19

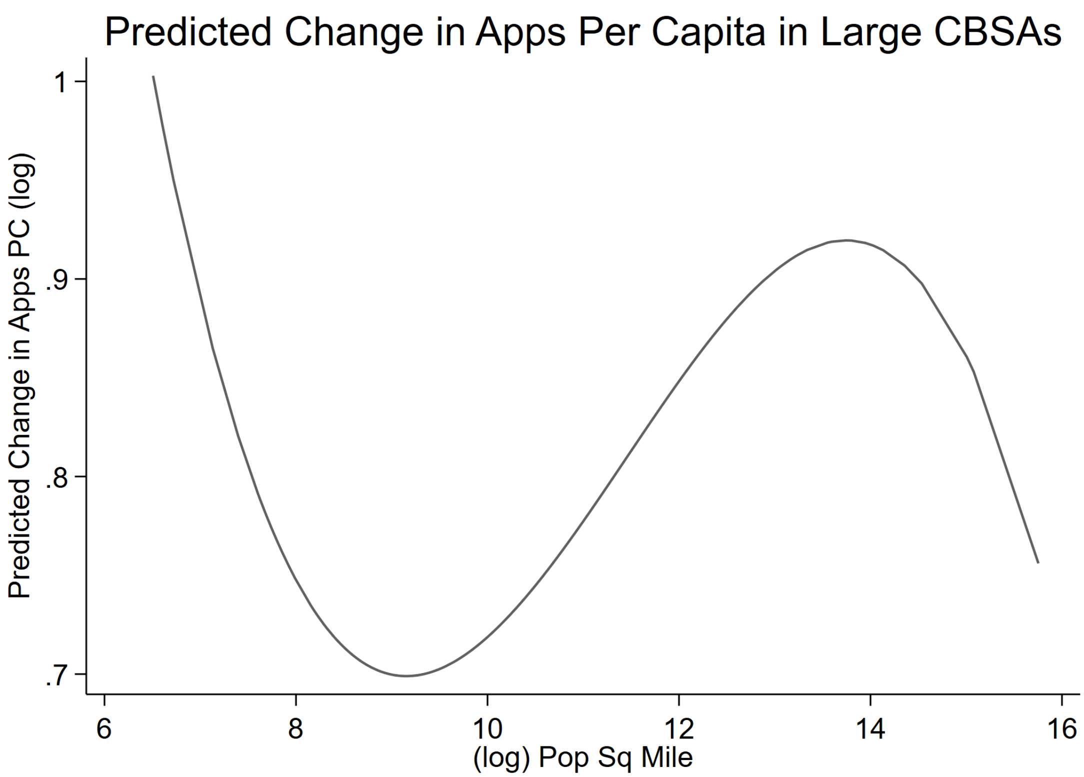
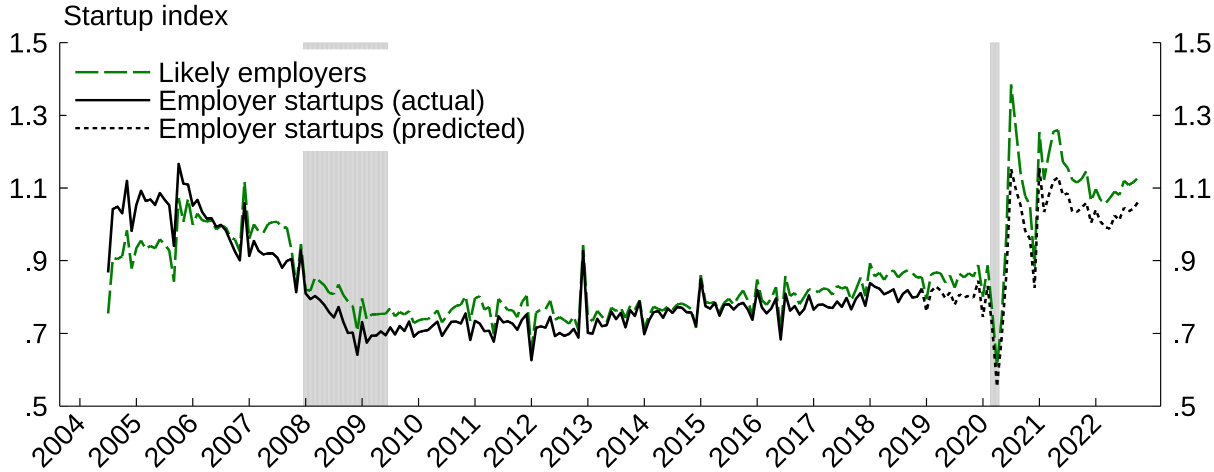
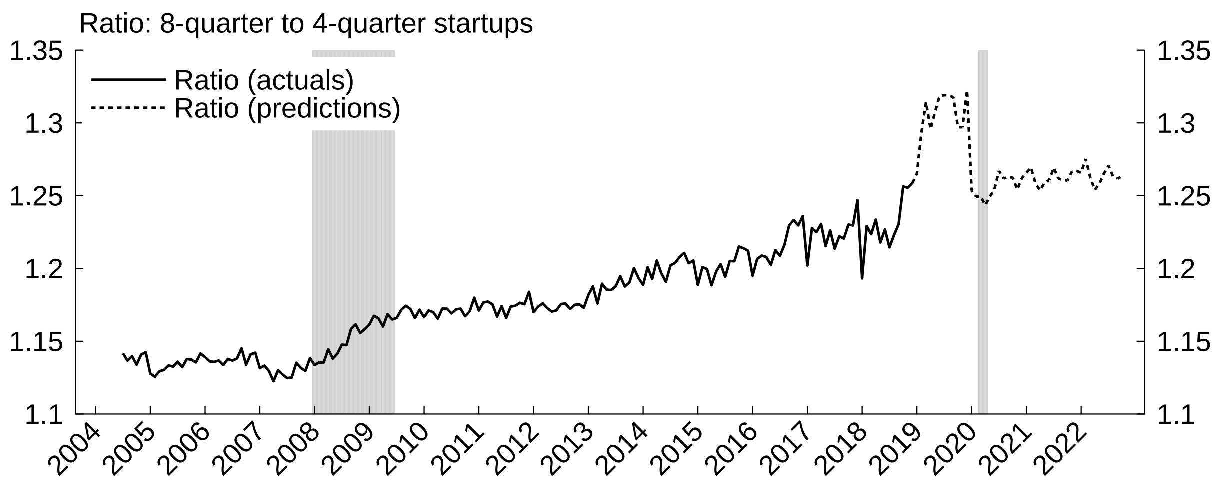


Figure A3: Relationship Between Growth of Applications Per Capita and Population Density, Counties in Large CBSAs



Note: Startups within 8 quarters. Seasonally adjusted. Normalized by average 2006 levels.
Shaded areas indicate NBER recession dates.
Source: Census Bureau Business Formation Statistics.

Figure A4: High-propensity business applications and startups 8 quarters ahead



Note: Ratio of startups within 8 quarters of application to startups within 4 quarters of application.
Seasonally adjusted before calculation. Shaded areas indicate NBER recession dates.
Source: Census Bureau Business Formation Statistics.

Figure A5: Ratio of startups 8 quarters after application to startups 4 quarters after application

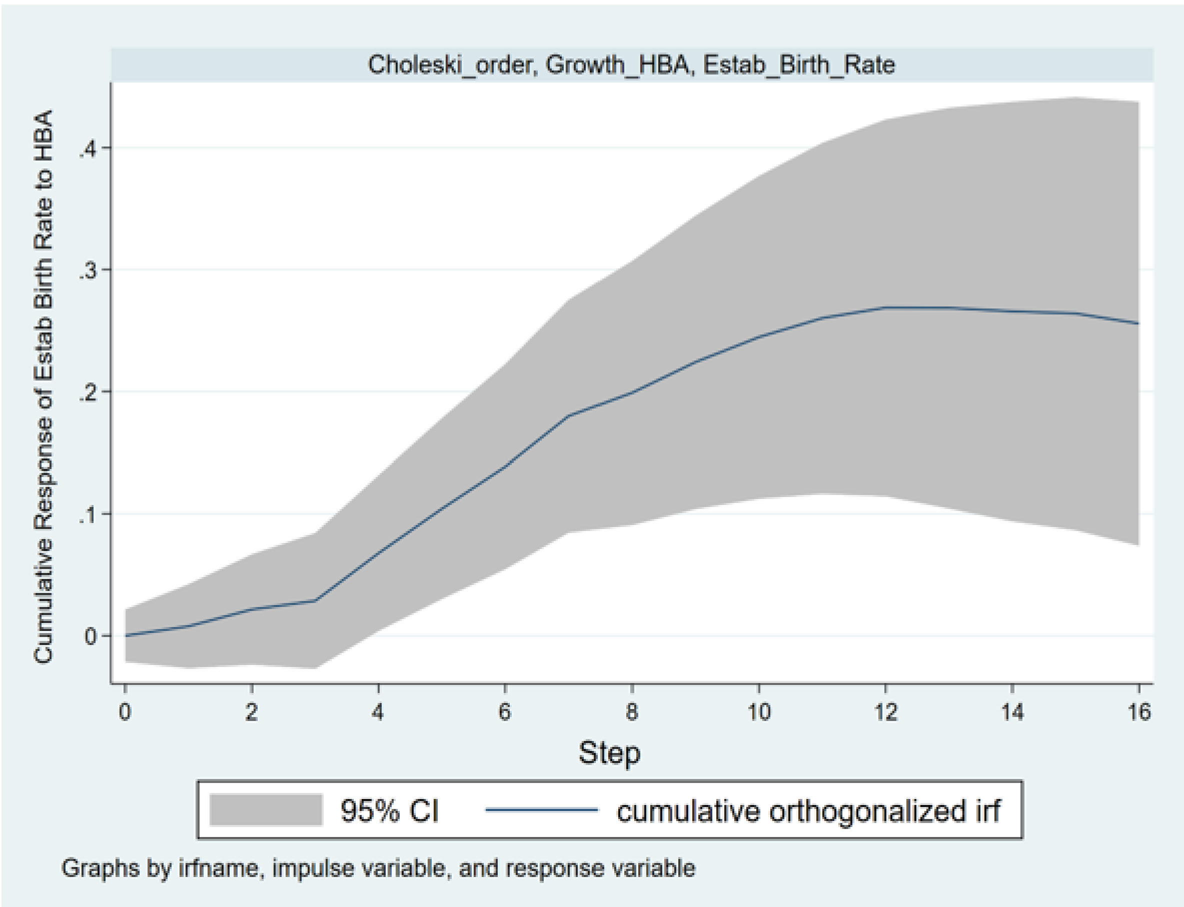


Figure A6: Impulse response function: Establishment birth response to high-propensity applications

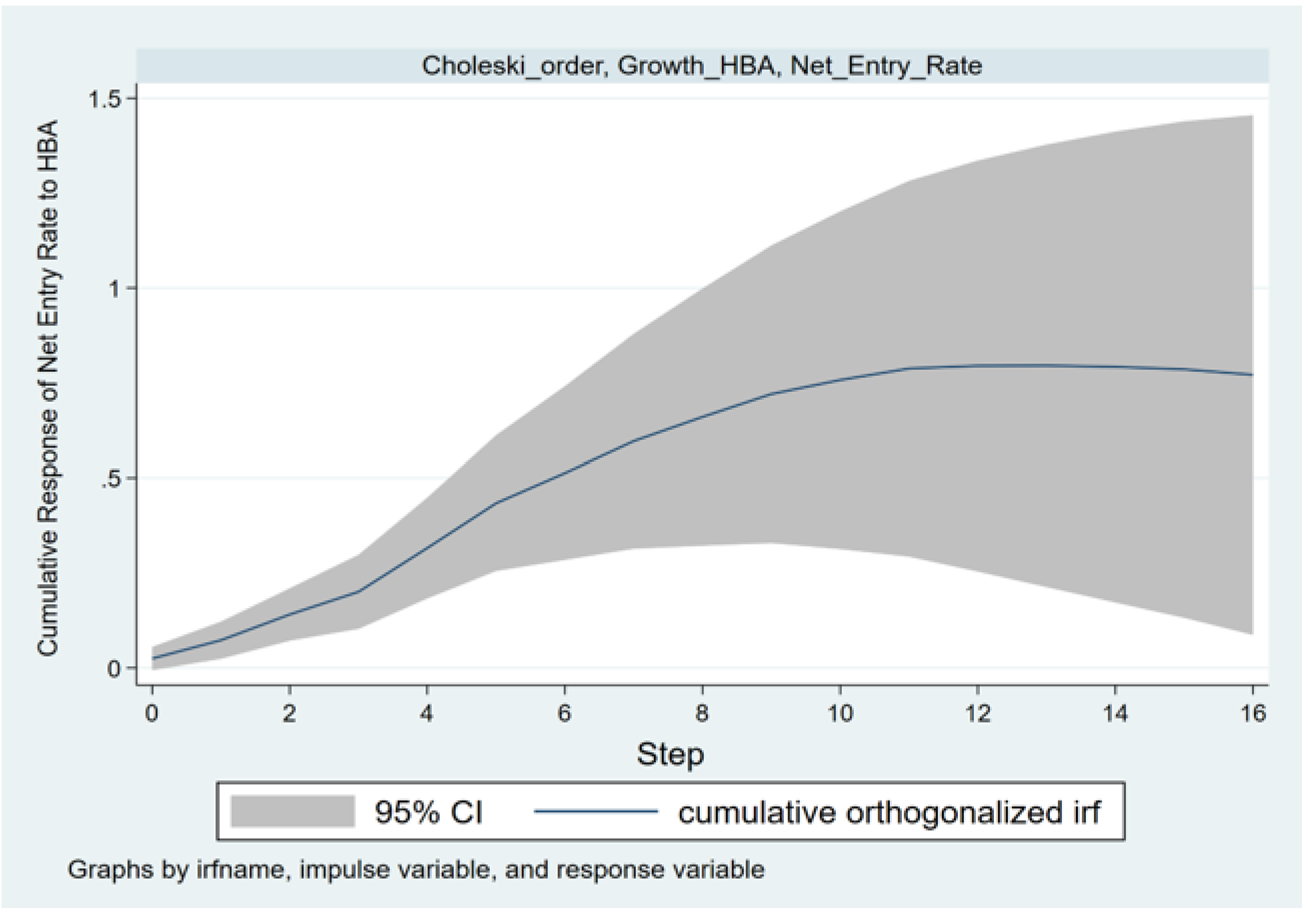


Figure A7: Impulse response function: Net establishment entry response to high-propensity applications

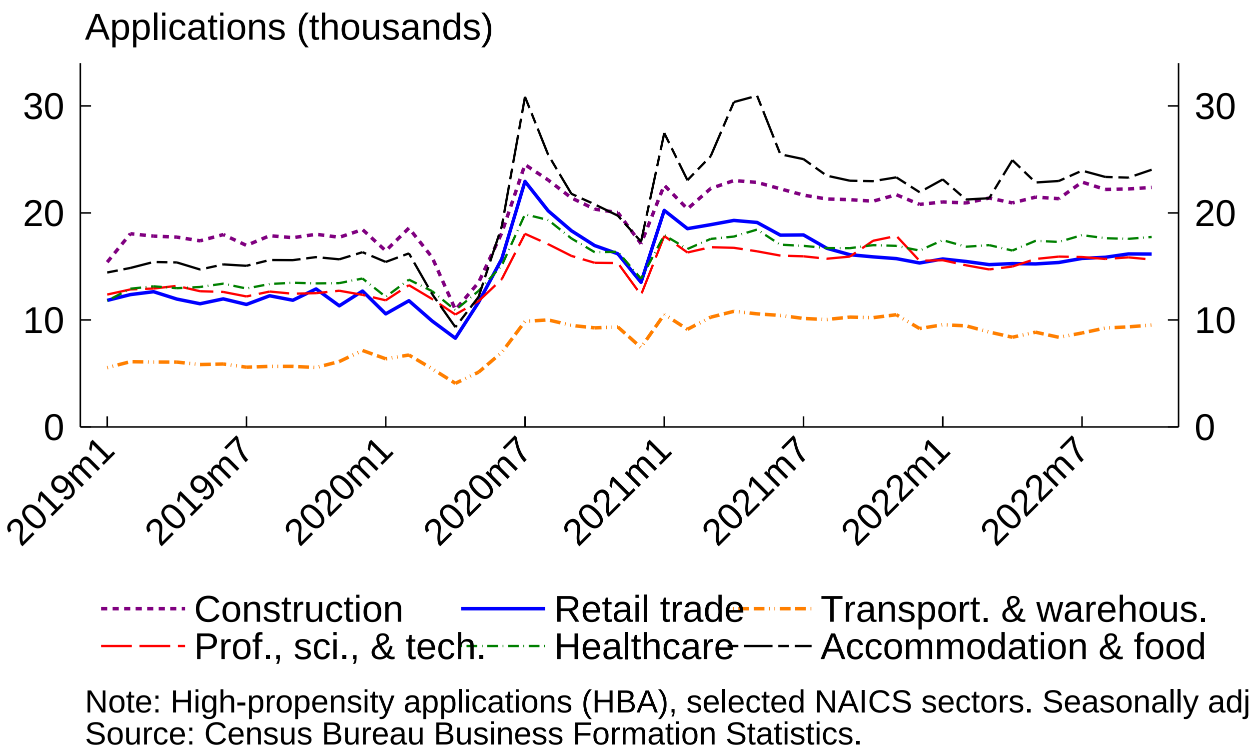


Figure A8: New business applications, selected industries

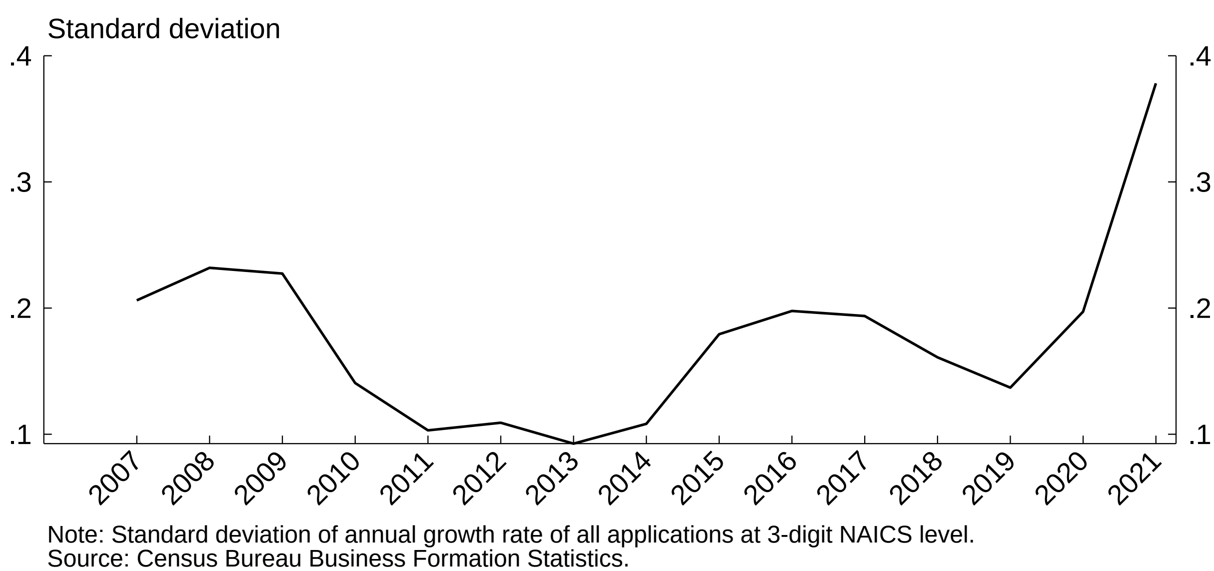


Figure A9: Dispersion of industry-level application growth

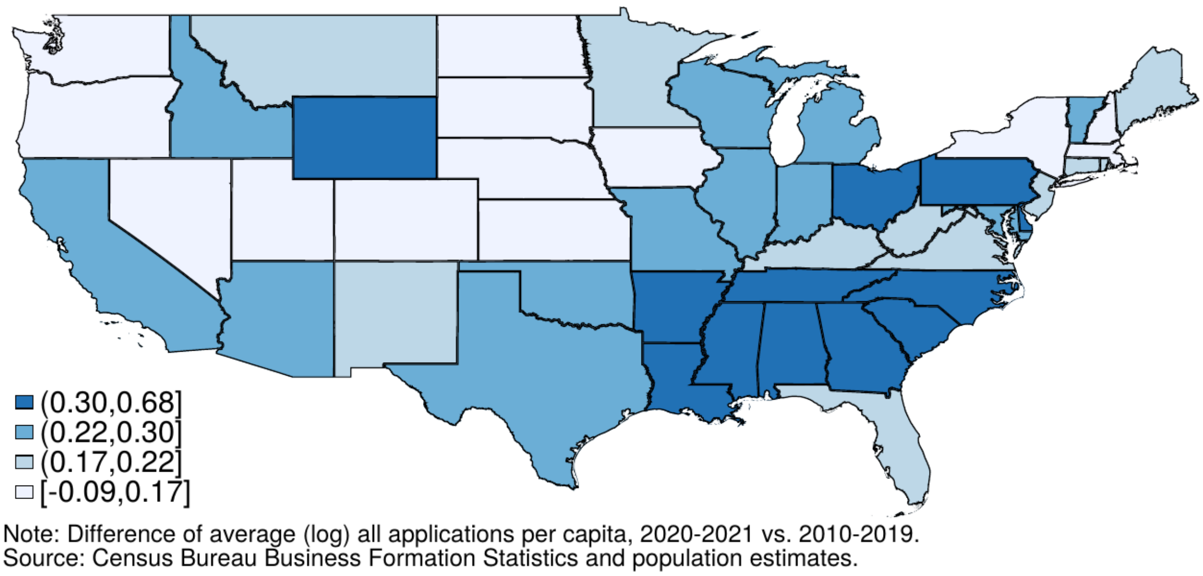


Figure A10: Growth in high-propensity applications, 2020-2021 vs. 2010-2019

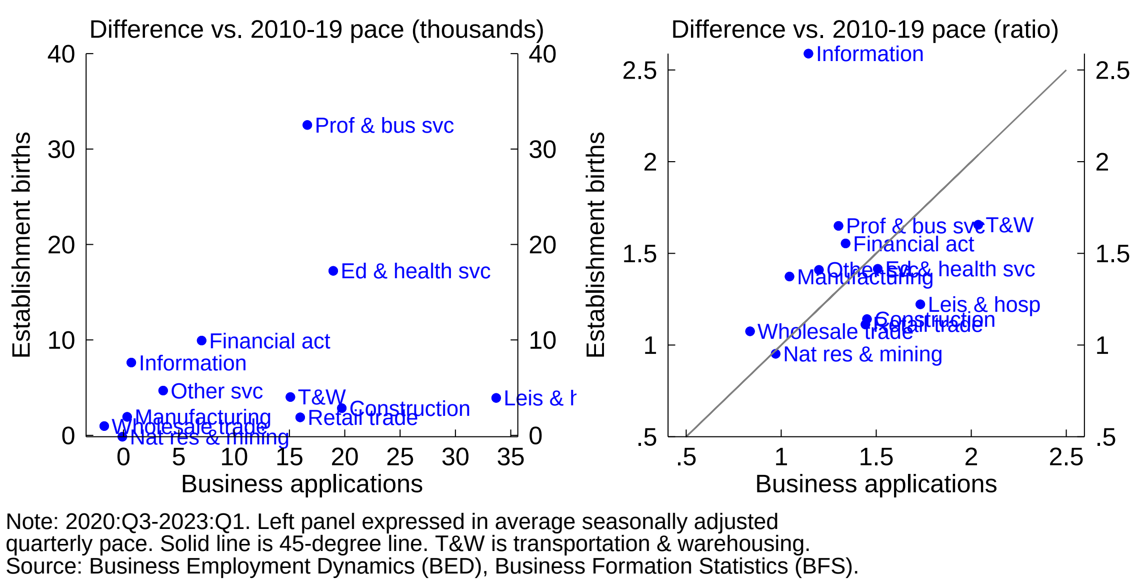
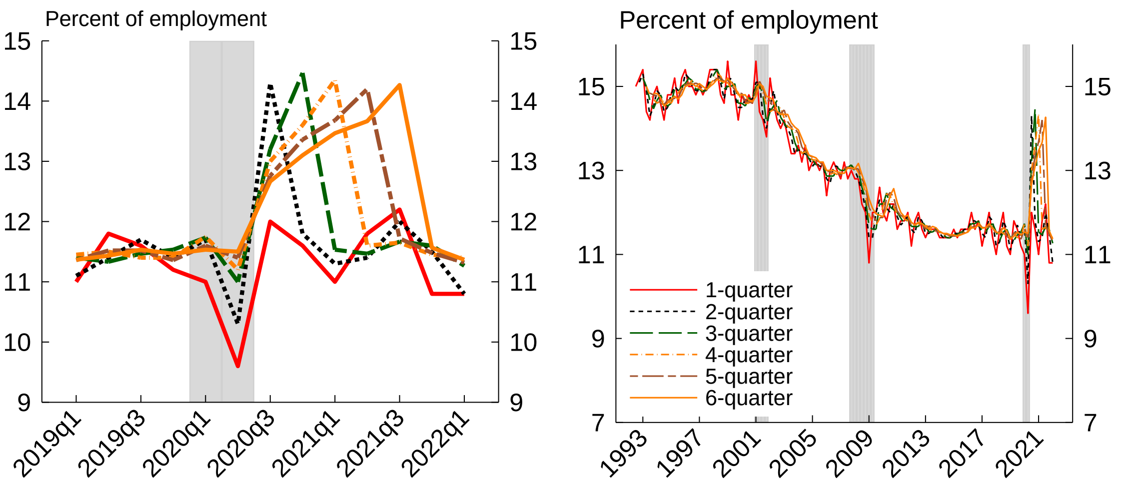
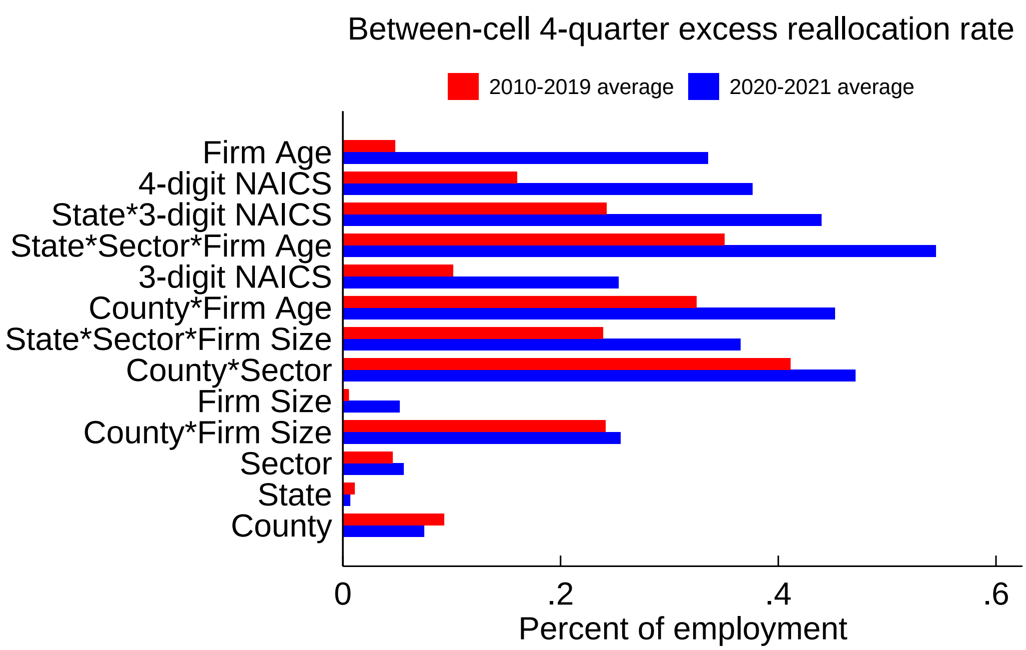


Figure A11: Establishment births and business applications, sectors



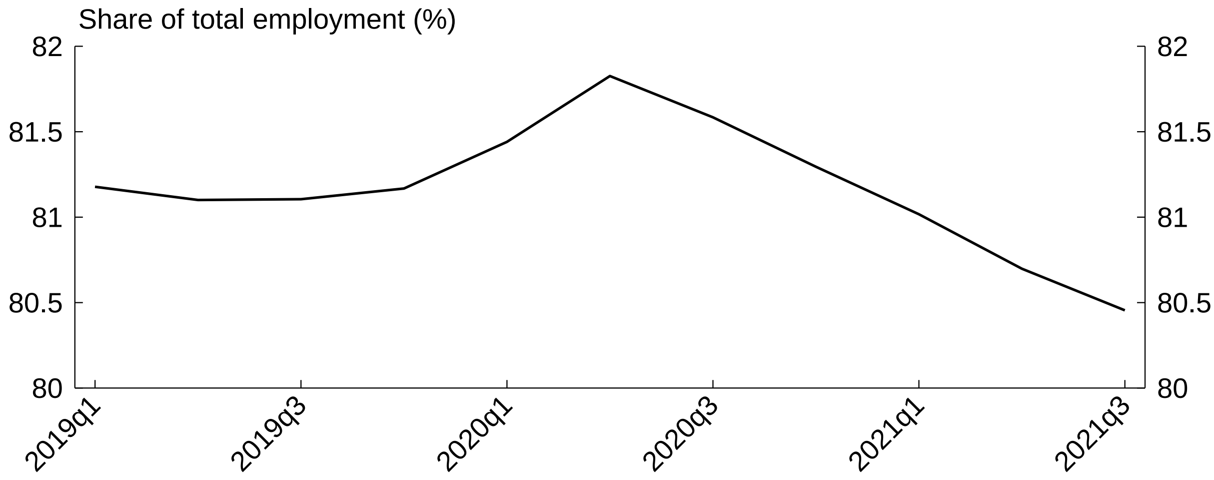
Note: Excess reallocation is JC+JD-|JC-JD|, with JC and JD averaged over indicated horizon. JC and JD are seasonally adjusted. Shaded areas indicate NBER recession dates.
Source: Business Employment Dynamics (BED) and author calculations.

Figure A12: Excess job reallocation, various horizons



Note: Averages of quarterly seasonally adjusted data through 2021q3.
Sorted (descending) by change 2010-2019 to 2020-2021.
Source: Census Bureau Quarterly Workforce Indicators (QWI)
and author calculations.

Figure A13: Between-cell reallocation rate (4-quarter horizon)



Note: Y axis does not begin at zero. Seasonally adjusted average of beginning- and end-of-quarter employment, mature firms as share of total. Seasonally adjusted.
Source: Quarterly Workforce Indicators.

Figure A14: Mature firms' share of employment

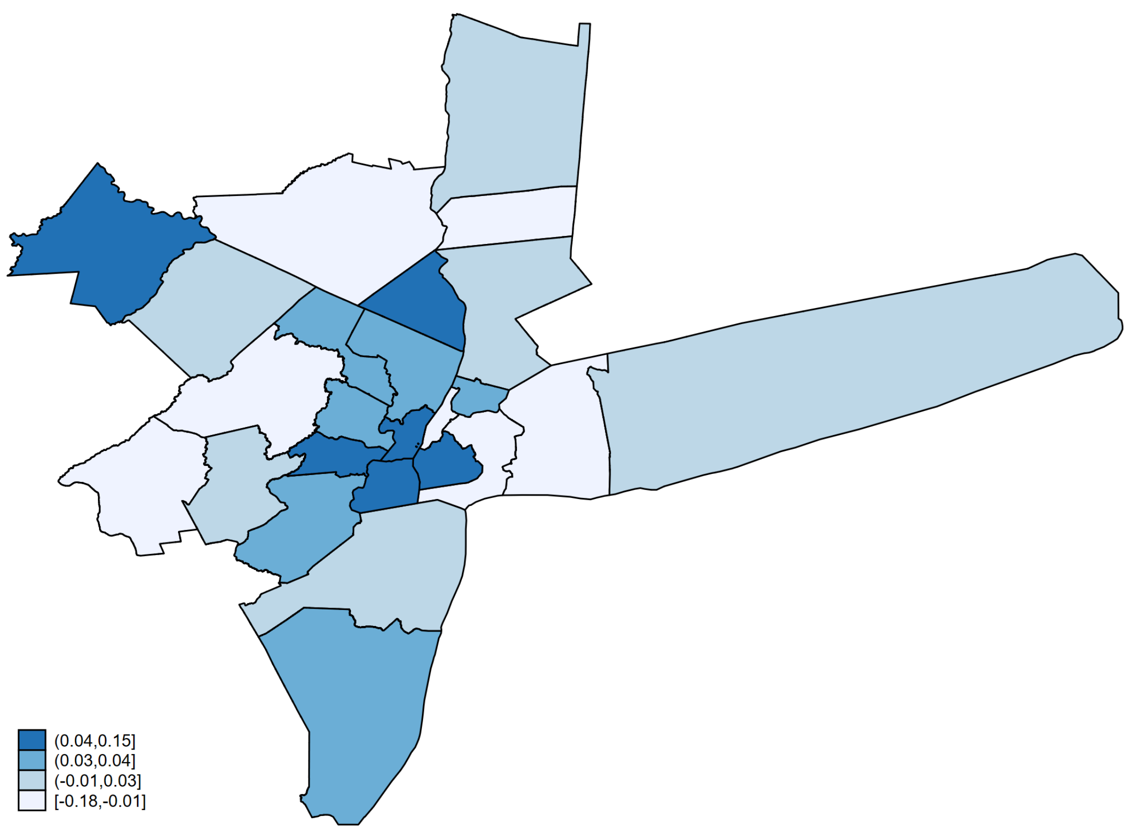


Figure A15: New York City: Growth in excess separations, 2020-2021 vs. 2010-2019
Source: QWI.

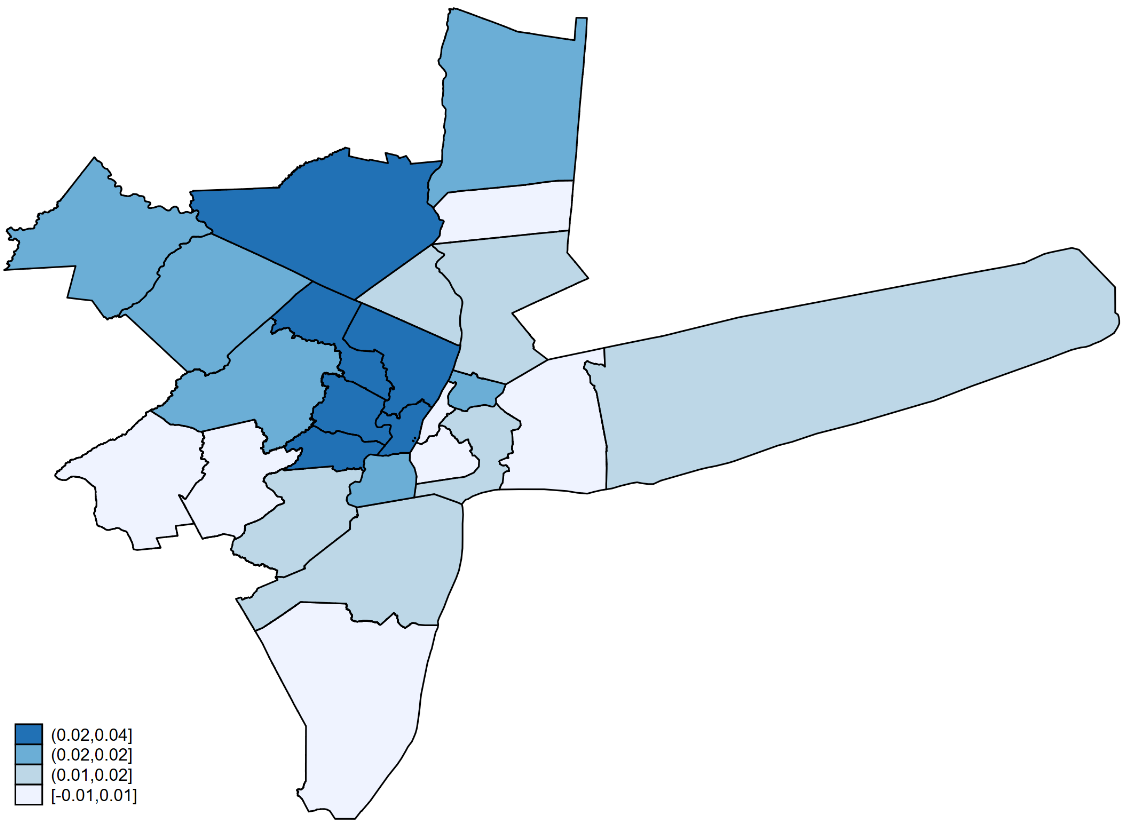


Figure A16: New York City: Predicted growth in excess separations, 2020-2021 vs. 2010-2019

Source: QWI.

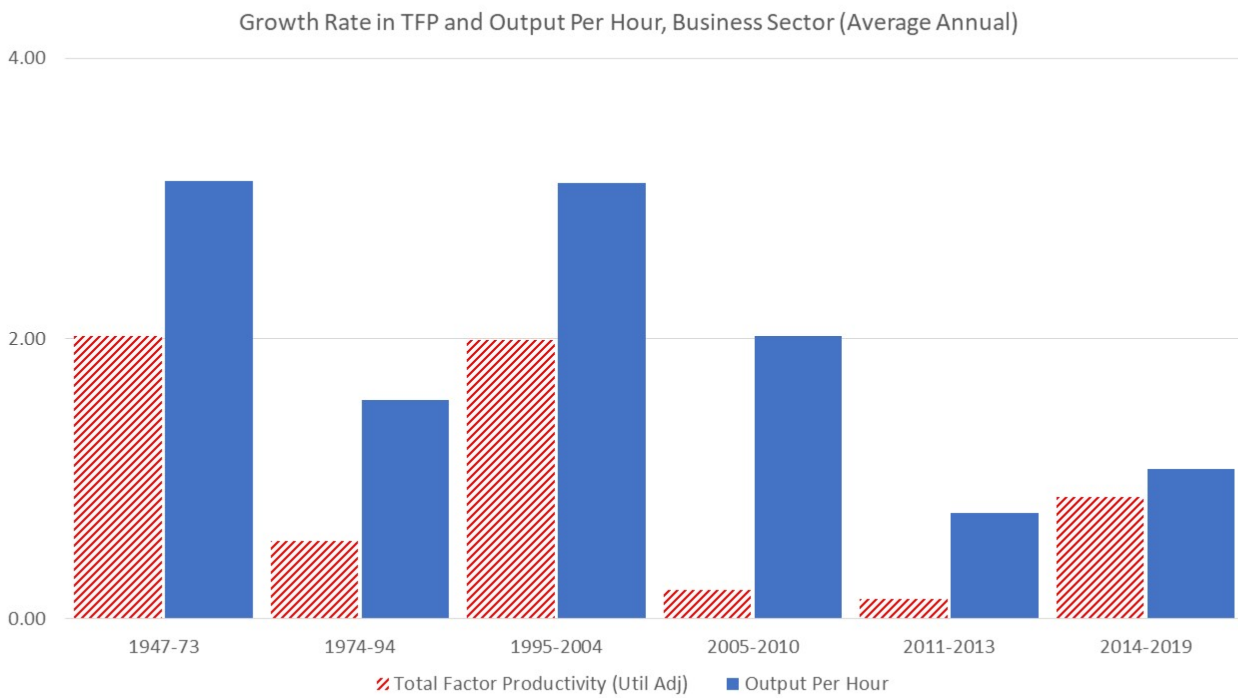


Figure A17: Productivity Growth Pre-Pandemic
Source: San Francisco Federal Reserve

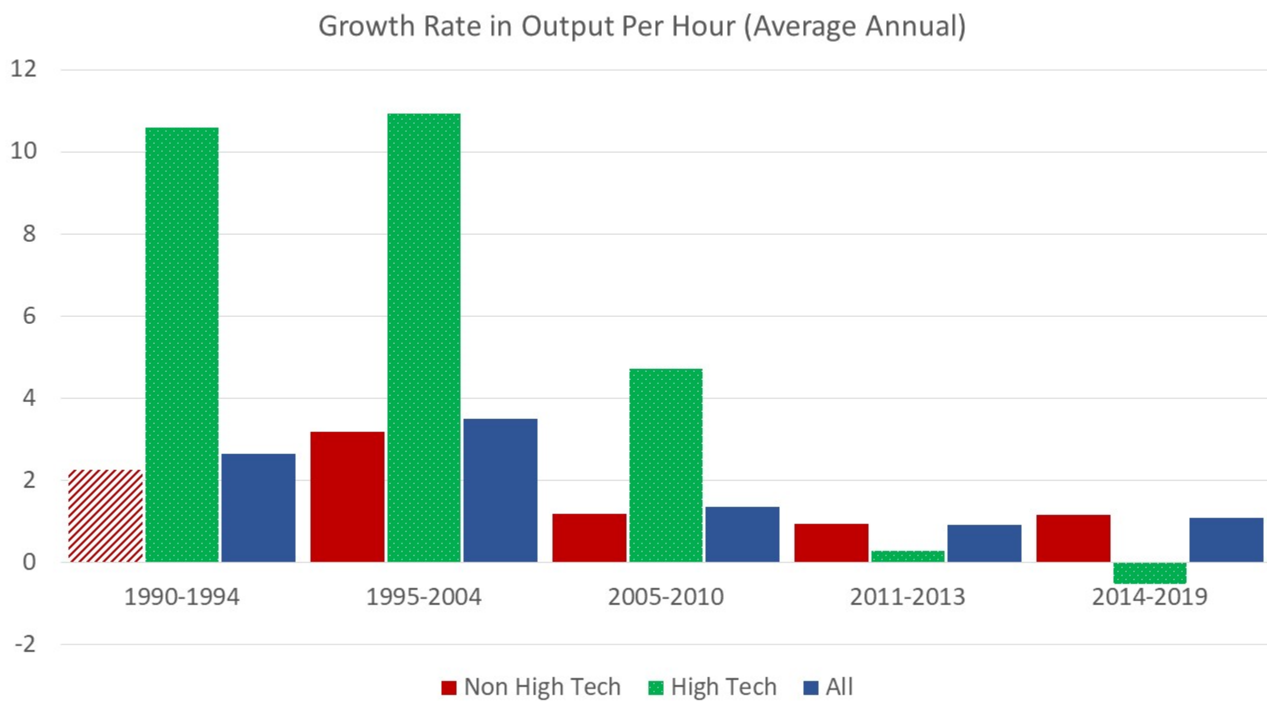


Figure A18: Productivity Growth Pre-Pandemic: High Tech vs. Non High Tech
Source: Tabulations from BLS data

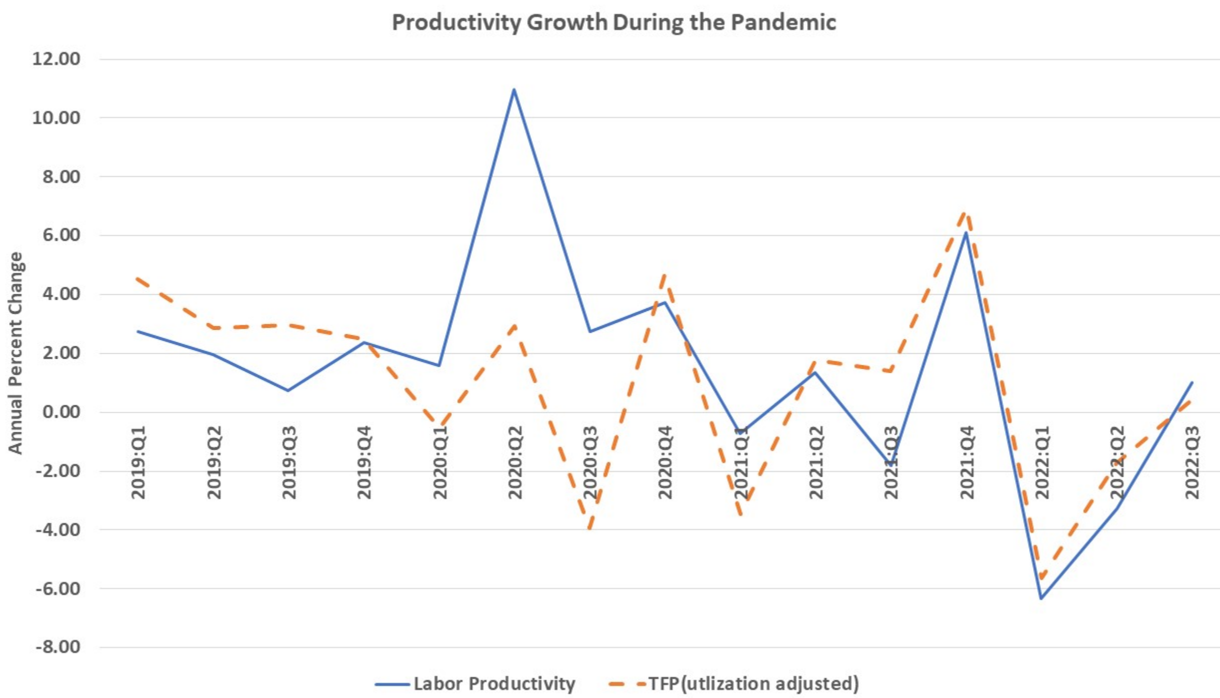


Figure A19: Productivity Growth During the Pandemic
Source: San Francisco Federal Reserve

B Supplemental tables

Table B1: Applications and population density

	Dependent variable: Application growth
ln(population density)	-1.719***
	(0.364)
ln(population density)^2	0.156***
	(0.034)
ln(population density)^3	-0.005***
	(0.001)

Note: County-level regression of change in (log) applications per capita, 2020-2021 versus 2010-2019 (see equation 1) on population density. CBSAs with 2019 population at least one million. Includes CBSA fixed effects. Population density measured in 2019.
***denotes statistical significance with $p < 0.01$.
Source: Author calculations from BFS and Census Bureau population estimates.

Table B2: Applications, population density, and establishment density; own and adjacent counties

	Dependent variable: Application growth		
	Own county	Adjacent county	Indirect Impact
ln(population density)	-1.678**	-1.844**	-1.237**
	(0.668)	(0.818)	(0.549)
$ln(\text{population density})^2$	0.180***	0.243***	0.163***
	(0.064)	(0.080)	0.053
$ln(\text{population density})^3$	-0.005**	-0.008***	-0.006***
	(0.002)	(0.003)	(0.002)
ln(establishment density)	0.100	1.642*	1.10*
	(0.351)	(0.924)	(0.620)
$ln(\text{establishment density})^2$	-0.042	-0.224**	-0.150**
	(0.038)	(0.099)	(0.066)
$ln(\text{establishment density})^3$	-0.001	0.008**	0.005**
	(0.001)	(0.003)	(0.002)

Note: Single county-level regression of change in (log) applications per capita, 2020-2021 versus 2010-2019 (see equation 1) on population density and establishment density in own and adjacent counties (the two columns are from the same regression). CBSAs with 2019 population at least one million. Includes CBSA fixed effects. Population and establishment density measured in 2019. The third column reports the implied indirect impact of the adjacent county effects on the predicted mean of the dependent variable. The direct impact of the own county effects on the predicted mean of the dependent variable are equal to the effects reported in the first column.
***denotes statistical significance with $p < 0.01$, ** denotes $p < 0.05$, * denotes $p < 0.10$.
Source: Author calculations from BFS, QCEW, and Census Bureau population estimates.

C Spatial Analysis

The spatial models we consider in Tables B1 and B2 use data on CBSAs with more than 1 million in population in 2019. The dependent variable is the growth in applications per capita g at the county level. We include CBSA fixed effects in all specifications. Log population density and log establishments per square mile are measure in 2019. The specification in B1 uses only own county population density. The adjacent county specification uses a contiguous county weighting matrix in a spatial regression specification with the own county and adjacent county variables entering in a symmetric manner.

Table B1 provides the estimates underlying the highly nonlinear pattern exhibited in Figure A3. Growth in applications first declines, then rises and then declines again with population density in large CBSAs. The first column of B2 presents the own county patterns. The nonlinear pattern of own county population density is similar to that observed in Table B1. Own county establishment density is not significant. The direct impact of the own county effects on the predicted mean of the dependent variable are equal to the effects reported in the first column. The second column reports the estimated coefficients for the adjacent county effects. The third column reports the implied indirect impact of the adjacent county effects on the predicted mean of the dependent variable. Adjacent county population density has similar effects to own county. Adjacent county establishment density exhibits a significant nonlinear pattern. The linear effect is positive and large, the quadratic effect is negative and cubic effect is negative.

The own county only specification has a R-squared of 0.55 with the within R-squared 0.13. Adding the adjacent county characteristics in B2 increases the R-squared to 0.73 with most of this increase in explanatory power coming from the establishment per capita variation in adjacent counties.