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Surging Business Formation in the Pandemic: Causes and Consequences?

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Abstract

Applications for new businesses surprisingly surged during the COVID-19 pandemic, rising the most in industries rooted in pandemic-era changes to work and lifestyles. The unexpected surge in applications raised questions about whether a surge in actual new employer businesses would follow. Evidence now shows increased employer business entry with notable associated job creation; and industries and locations with the largest increase in applications have had accompanying large increases in employer business entry. We also observe a tight connection between the surge in applications and quits—or close proxies for quits—both at the national and local level. Within major cities, applications, net establishment entry, and our quits proxy each exhibit a "donut pattern," with less growth in city centers than in the surrounding areas, and these patterns are closely related with patterns of work-from-home activity. Reallocation of jobs across firm age, firm size, industry, and geography groupings increased significantly. Relatedly, there is the beginning of a reversal of the pre-pandemic trend toward greater economic activity being concentrated at large and mature firms, but this reversal is quite modest in magnitude.

The analysis and conclusions set forth are those of the authors and do not indicate concurrence by other members of the research staff or the Board of Governors of the Federal Reserve System. We thank Janice Eberly, Jorge Guzman, Ben Pugsley, Scott Stern, and participants at the Annual Research Conference at the Boston Federal Reserve for comments on an earlier drafts of this paper. We thank Aditya Pande and Matilde Serrano for excellent research assistance. We thank Eric Simants and Kevin Cooksey for fielding numerous questions about Business Employment Dynamics data and for providing vintage files, though any errors in data use and interpretation are our own. This paper uses public domain data from the Bureau of Labor Statistics and the U.S. Bureau of the Census. This is an early version of the paper prepared for the Fall 2023 *Brookings Papers on Economic Activity (BPEA)* conference, and the final version of this paper will be published in the Fall 2023 *BPEA* issue.

1 Introduction

The U.S. economic experience during the COVID-19 pandemic featured a surprising surge in applications for new businesses. After dropping in March and April of 2020, applications rose sharply, reaching an all-time high in July 2020; the series declined through the rest of 2020 then surged again in 2021 and have remained historically elevated through mid-2023 (figure 1). These data received widespread attention amidst high unemployment and broader economic volatility, in part because the surge was apparent even among "likely employers," that is, applications with characteristics that predict the hiring of workers and growth.[1] Monthly applications for "likely employer" businesses in mid-2023 are more than 30 percent higher than the 2019 pace. Historically, there has been a tight relationship between "likely employer" business applications and true employer business formation, but questions have remained about whether the pandemic's surging applications would translate into actual employer businesses with broader macroeconomic implications.

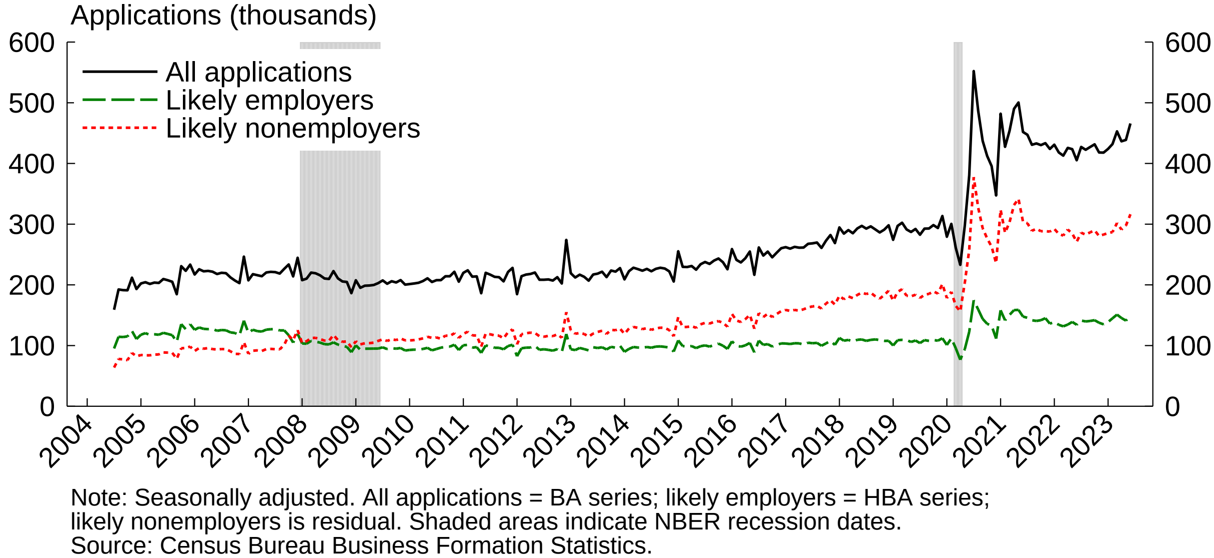
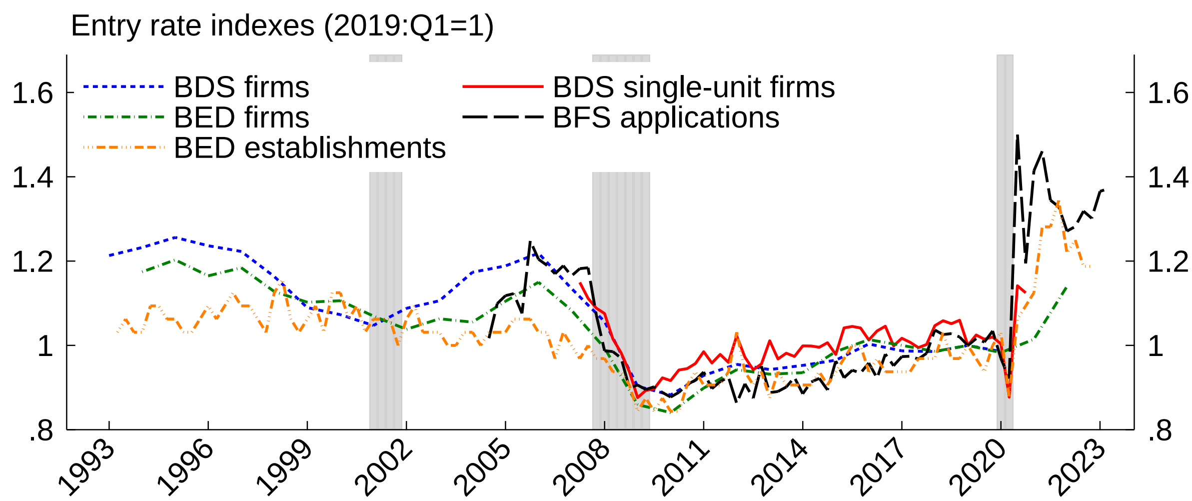


Figure 1: New business applications

In this paper, we describe noteworthy aspects of the surprising surge in applications that point to its genuine economic content. We then draw on a range of data sources to show that the surge in applications was followed—after some lag—by a surge in employer business creation: quarterly data on establishment entry rose substantially starting in the second quarter of 2021, while annual data on firm entry jumped in the year ending March 2022 (figure 2). Moreover, we document a close empirical relationship between applications and employer business entry across industry and geography, with hallmark patterns from the

[1] We more completely describe "likely employer" applications and the data from which they are derived in section 2 and appendix A.

application data appearing in employer entry data. We relate the surge in business formation to pandemic labor market stories such as the "Great Resignation" (that is, the rise in worker quit rates starting in early 2021). Finally, we describe the striking resilience of small and young firms through the pandemic period, and we highlight modest hints of a reversal of pre-pandemic trends in "business dynamism"—though we note that it is too early to declare an end to those trends.



Note: BDS and BED annual firm births are age-0 firms as of March. BFS applications are likely employers (HBA). All series expressed as rates except BFS. Quarterly series are seasonally adjusted. Gray bars indicate NBER recession dates (2001:Q1-Q4, 2007:Q4-2009:Q2, 2020:Q1-Q2).
Source: Business Dynamics Statistics, Business Employment Dynamics, Business Formation Statistics.

Figure 2: New business entry and new business applications

This set of facts lends itself to a compelling narrative of pandemic business and labor market dynamics. The pandemic sparked rapid, dramatic changes to the composition of consumer demand and to preferences for work and lifestyle, and these patterns have continued to evolve through mid-2023. From the standpoint of potential entrepreneurs, these dramatic changes presented opportunities—both to meet newly formed consumer and business needs and to change the career trajectories of the entrepreneurs themselves. Entrepreneurs made plans and applied to start businesses both early on and through mid-2023; some of these plans have resulted in new firms and establishments that hired workers in large numbers. Entrepreneurial opportunities and the demand for employees at these new firms appear to have played an important role in the "Great Resignation," as some quitting workers likely flowed toward new businesses (as either entrepreneurs or new hires). Taken together, these patterns imply significant economic restructuring across industry, geography, and the firm size and age distribution. The extent to which these changes will be long lasting has yet to be seen.

The surge in applications started in the second half of 2020, but it has taken time to determine the implications for new employer (and nonemployer) businesses. One reason for the delay may be that the initial surge in the summer of 2020 was relatively short lived, with the more sustained surge in applications commencing later—in early 2021. Moreover, "likely employer" applications take up to eight quarters to yield the first hire—even conditional on making that transition. And in the U.S., data on the creation of actual employer businesses—that is, businesses with paid workers—are published with a lag since such measures derive from administrative data with long processing time. The timeliest data on new employer businesses are for *establishment* births from the Bureau of Labor Statistics (BLS) Business Employment Dynamics (BED); as of September 2023, BED data on establishment births are available through 2022:Q4, while BED data on (annual) *firm* births are available through March 2022.[2] The gold standard annual firm birth data from the Census Bureau Business Dynamic Statistics (BDS) are available through March 2020 for all firms, though quarterly data on single-establishment firms go through 2020:Q4. Between these and other sources, we now have sufficient data to characterize patterns of employer business formation and related job and worker flows in the pandemic.

We observe strong sectoral and geographic correlations between business applications and employer business entry (we measure the latter by either firms or establishments, and in either gross or net terms, depending on data availability). The rise in applications and employer entry is highly concentrated in a few industries that are conducive to pandemic patterns of work and life (such as online retail and other high-tech industries), consistent with the changing sectoral structure of the economy. We also observe substantial spatial variation in the surge in applications and business entry, consistent with geographic restructuring. The surge in applications and business entry is especially notable in the South, with states such as Georgia standing out. Within large cities we observe a "donut effect" with applications surging more in the suburbs of metropolitan areas than in central business districts.

The pandemic and its aftermath have been associated with increased churn of workers as found in (initially) elevated layoffs (many of them temporary, e.g., Cajner et al., 2020) and, through much of the pandemic, elevated quits. We find a tight spatial correlation—at the state and county level—between surging business applications and quits (or excess separations, a close proxy for quits), with a much weaker correlation between applications and layoffs (or job destruction, a close proxy for layoffs). Among other possible explanations, these results are consistent with workers quitting their jobs to start or join new businesses—and somewhat less consistent with job loss being a key driver of business formation.

This pandemic surge in entry occurred after decades of declining business dynamism in the U.S. The pace of job reallocation had fallen by about 25 percent from the 1990s to just before the pandemic. This decline in the pace of job reallocation was driven in part by the decline in employer business entry over this same time period, which can be seen in figure 2 or, for a longer view, appendix figure C1; closely related is the shift of the firm distribution toward large and mature firms. While the sources of this decline have been widely debated in the literature, there is evidence that it has been associated with a decline

[2] An "establishment" is a single business operating location—such as your local Starbucks location—while a "firm" is a group of one or more establishments under a common tax identifier (in BLS measures) or under common operational control or ownership (in Census Bureau measures).

in productivity-enhancing reallocation and is likely one of the factors underlying sluggish productivity growth in the U.S. since the early 2000s.[3]

We show that the pandemic featured a surge in job reallocation, including reallocation between cells defined by industry, geography, firm size, and—especially—firm age. We also document a pandemic pause—and modest reversal—of the longer-run shift in activity toward large, mature businesses. The share of activity accounted for by young and small firms has risen; young and small firms exhibit a higher pace of dynamism than large and mature firms, so one might anticipate an ongoing increase in the pace of dynamism. In other words, we find early hints of a revival of business dynamism; but in many respects it is too early to ascertain whether a durable reversal of pre-pandemic trends is occurring. Such a reversal—that is, a persistent rise in the pace of reallocation and a substantial shift of activity away from large, mature firms—will require a long-lasting continuation of elevated business entry as well as substantial growth among at least a subset of the pandemic entrants.

It is useful to state our view of our contribution—and the limits to that contribution. A key contribution of our work is that we draw on a wide range of data sources: BLS BED, Quarterly Census of Employment and Wages (QCEW), and Job Openings and Labor Turnover Survey (JOLTS), and the Census Bureau's BFS, BDS, and Quarterly Workforce Indicators (QWI). While none of these data sources alone can tell a comprehensive story of pandemic business entry, each contributes a different perspective in terms of timeliness, industry and geography detail, or measurement concept. We provide an initial assessment of the potential causes and consequences of the surge in business applications by supplying a rich set of empirical facts pointing to substantive pandemic economic stories, but we do not provide identified causal empirical results or new formal theory; rather, we hope our results can direct and discipline future causal analysis. We also hope our approach of exploiting an eclectic combination of datasets can help other researchers better understand the range of available business dynamics and labor market data that can inform timely analysis.

A study of actual application-to-employer transitions, post-entry dynamics, and job-to-job flows of workers must wait for the availability of administrative microdata.[4] Such

[3]As discussed in Davis and Haltiwanger (2015) there are likely both benign and adverse factors underlying this decline in business dynamism. However, as discussed in Decker et al. (2020) there has been a decline in the responsiveness of businesses to idiosyncratic productivity shocks and a widening of revenue productivity dispersion—both consistent with rising distortions and frictions in the economy. Alon et al. (2018) present related evidence that the shift in activity to more mature firms has contributed to the decline in productivity growth. Moreover, Akcigit and Kerr (2018) and Acemoglu et al. (2018) show evidence that young and small firms are more likely to make radical innovations, while mature incumbents make more incremental innovations in order to avoid cannibalizing their market share. Akcigit and Goldschlag (2023) presents evidence that in the post-2000 period inventors are more likely to join large incumbents than young firms; moreover, they find that inventors that join large firms obtain higher earnings but are less innovative. They argue that this is due to strategic considerations for the same argument made above—to avoid cannibalizing their market share. De Loecker et al. (2020) and Autor et al. (2020) present evidence of rising markups associated with the shift to larger firms.

[4]Dinlersoz et al. (2023) features pre-pandemic cross-sectional analysis of the BFS microdata; it will be feasible to extend that work to the pandemic era once the administrative microdata tracking transitions and post-entry growth become available. This will require the confidential Longitudinal Business Database (LBD), which is currently available through 2020 and will be updated through 2021 in September 2023.

microdata can also facilitate rigorous causal analysis and provide empirical moments of relevance to theoretical investigations. Separately, while we focus on new *employer* businesses, the likely surge in new *non*employer businesses appears important and interesting as well; unfortunately, the nonemployer economy is measured with less detail and timeliness than the employer economy, so we leave that investigation for future work (but we provide some additional discussion near the end of this paper and in appendix A).

Our work complements Fazio et al. (2021), which documents similar aggregate patterns using zip code-level 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 registration 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. Duguid et al. (2023) document similar within-city patterns for retail establishments using credit card merchant data and relate these patterns to population flows and remote work considerations. We also expand on Decker and Haltiwanger (2022), which provided a first look at the relationships between business applications and establishment births (and exits) in official data and initially documented the increase in small firms' share of activity during the pandemic.[5]

In section 2 we briefly describe our main data sources, with much more detail in appendix A. We review and document patterns of business applications in section 3 then explore employer establishment and firm entry and its empirical relationship with applications in section 4. We examine the relationship between worker churning—especially quits—and applications in section 5. In section 6 we document changes in the firm size and age distribution and consider implications for business dynamism. We take stock in section 7 then speculate about potential implications for the future in section 8.

2 Data

We exploit a variety of data sources, all of which are publicly available tabulations. Appendix A describes each source in detail; here we simply list our main sources with brief descriptions.

- **Business Formation Statistics (BFS)**, U.S. Census Bureau: Monthly data on IRS Employer Identification Number (EIN) applications. All employer businesses and nonemployer corporations and partnerships must have an EIN, and many nonemployer sole proprietors choose to obtain one for business reasons. The *total applications* series (called "BA" in BFS files) counts all EIN applications that are potential employer or nonemployer (zero-employee) businesses (this implies excluding applications for trusts,

[5] An even earlier first look at the BFS surge in new business applications is in Haltiwanger (2022). This analysis focused on the surge in new business applications in the first year of the pandemic before data on actual employer business entry were available.

estates, and financial instruments). Our main interest is employer businesses; therefore, where possible we focus on what we call *likely employer* applications ("high-propensity applications" or "HBA" in the BFS files). This subset of the total applications series is based on Census Bureau modeling using application characteristics that have a high propensity for transitioning into an actual employer business with paid workers; these characteristics include planned hiring and corporate legal form, among others. However, at narrow levels of industry (3-digit NAICS) or geography (county) detail, only *total applications* are publicly available, so we use the total applications series as a proxy for our preferred likely employer series. As shown in figure 1 (and below at more disaggregated levels by industry and geography), *total* and *likely employer* applications have tracked each other closely in the pandemic, which mitigates concerns about using the total series as a proxy for likely employers where necessary.

The BFS also includes series reporting, in any given time period, the number of applications that actually transition to genuinely new employer firms within four or eight quarters. These series use microdata linkages tying applications to actual employer firm births; the four-quarter and eight-quarter series are currently populated through 2019:Q4 and 2018:Q4, respectively, and relate to new employer firm microdata available through 2020:Q4. Since these transition series end relatively early (constrained by actual employer firm data timing in Census data), the BFS also features series for *projected* transitions at four- and eight-quarter horizons, where projections are based on application characteristics and include all applications (not just those labeled as likely employers). The motivation for the four- and eight- quarter horizons for actual and predicted transitions is that, as discussed further below, there is often a lag between applications and transitions.

- **Quarterly Census of Employment and Wages (QCEW)**, Bureau of Labor Statistics: Quarterly establishment and employment counts by detailed industry and geography; the QCEW is derived from the main business register of the BLS and is based on state unemployment insurance administrative data. We use the QCEW to measure net establishment growth at the national, industry, and local (e.g., county) level. The QCEW microdata also underly the Business Employment Dynamics.

- **Business Employment Dynamics (BED)**, Bureau of Labor Statistics: Quarterly data on establishment openings, closings, births, exits, expansions, and contractions, with associated job flows. The BED also features a "research" product with *annual* employment, firm, and establishment counts by *firm* age, where a firm is defined by an EIN. We use quarterly BED data extending through 2022:Q4 and annual firm age data through 2022:Q1. Importantly, in the BED, an establishment (firm) birth represents an establishment (firm) that did not previously exist; a new firm requires a new business application, while a new establishment of an existing firm does not require but may obtain a new EIN. Notably, new EINs acquired by existing firms would *not* count as employer firm transitions in the BFS 4-quarter and 8-quarter transition series mentioned above but may appear as new establishments (or firms) in BED data.

- **Quarterly Workforce Indicators (QWI)**, U.S. Census Bureau: Quarterly data on employment and job and worker flows (i.e., hires and separations) by firm age with detailed industry (4-digit NAICS) and geography (county) tabulations. The QWI is the public-use version of the Longitudinal Employer-Household Dynamics (LEHD) data based on state unemployment insurance records and collected on a state-by-state basis; we use a balanced panel of 45 states that covers just over 80 percent of private employment as of 2020.

- **Job openings and labor turnover survey (JOLTS)**, Bureau of Labor Statistics: Monthly survey-based estimates of hires, separations, quits, and layoffs with state-level detail. We use JOLTS data through mid-2023 with a focus on quits and layoffs.

- **American Community Survey (ACS)**, U.S. Census Bureau: Annual survey-based data on work-from-home (WFH) prevalence for large counties. ACS data are available in two samples: 5-year samples including the entire U.S., and 1-year samples including large counties. We use the 1-year sample for 2019-2021 and focus on changes in WFH prevalence across counties within large cities. ACS WFH measures are based on location of worker residence; we discuss existing literature on WFH using other data (Hansen et al., 2023) in appendix A.

Additionally, we use data from the Census Bureau's Business Dynamics Statistics (BDS) on certain figures (e.g., figure 2); these data do not currently cover the pandemic period, so we do not use them in most of the exercises that follow. In appendix A, we provide a discussion of the BDS and its relation to the BLS data sources listed above.

3 Business application patterns

3.1 The early pandemic period

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).[6] But, as shown in figure 1, applications quickly recovered and surged to historic levels in July 2020. The surge is apparent in every application series including total applications and likely employer applications (both shown in figure 1) as well as applications with planned wages and applications for corporations.[7] Applications did fall off in August 2020 through December 2020 (albeit still higher in December 2020 than prior to the pandemic) but then surged again in early 2021. This second wave has been more resilient, with monthly applications in 2023 so far averaging about 30 percent higher

[6] 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., 2021), we do not explore CPS data in this paper.

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

than the 2019 pace. Total applications are about 40 percent higher in 2023 relative to 2019 reflecting the even larger surge of "likely nonemployers."

The sharp rise in the likely employers series is in 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.[8] Flat or even rising nonemployer entrepreneurship during a recession can easily be rationalized in light of lack of opportunities for wage and salary employment, which may push many individuals into "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 pursuing 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 the pandemic surge in applications has persisted even as unemployment has fallen toward historic lows.

A number of factors could 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. The pandemic provided new market opportunities given the changing nature consumer demand and of work and lifestyle, and financial conditions—including house prices—were robust compared to the Great Recession (at least through early 2022). The potentially supportive role of stimulus programs—which included sizeable support for aggregate demand and household balance sheets—is an open question. On the other hand, programs like the Paycheck Protection Program (PPP)—along with other business support facilities—may have dampened new business formation since it provided support for incumbents and thus deterred exit.[9]

Even though some factors have been more favorable for business formation in the pandemic than in the Great Recession, an open question has been whether genuine employer business creation would result. Historically, high-propensity applications have been strongly predictive of actual firm entry, with a national correlation of 0.93 and an elasticity roughly centered on one at the aggregate level, within states, and within industries.[10] But one might

[8]Data on actual nonemployer activity during the Great Recession broadly confirm the relative resilience of the likely nonemployer applications data in that episode. The total number of actual 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).

[9]There has been some speculation that sole proprietor nonemployer applicants for the Paycheck Protection Program (PPP) had incentives to acquire an EIN to facilitate processing the paperwork requirements of the PPP. However, Breaux and Gurnani (2022) matched PPP and BFS microdata and found that only a very small fraction of PPP applicants applied for an EIN in 2020 and 2021. 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. In any case, applications have remained elevated well past the end of the PPP program.

[10]The (pre-pandemic) elasticity of actual startups within eight quarters to applications is above one in the national data and ranges from 0.8 to 1.2 in state-by-quarter regressions, depending on specification choices

fear that the transition rate from applications to actual businesses could change in the pandemic. Perhaps especially in the early months of the pandemic, maybe there was a surge in nascent entrepreneurship—individuals *thinking about* doing starting a business—without necessarily making the transition to an actual new business. This is a core question we address by providing available evidence on actual employer business formation below, but first we delve further into the applications themselves.

3.2 Sectoral patterns of applications

One clue about the economic substance of surging applications is the pattern across industries. For likely employer applications, data are only available at the broad sector level; while interesting (and discussed below), this level of industry detail misses important stories. For more detail, we use total applications, which are available at the 3-digit NAICS industry group level (published as a special tabulation after the end of each calendar year—currently these data are available through end-2022). We use the total applications series with some caution given our focus on employer business entry, but we note that there has been a coincident surge in likely employer and likely nonemployer applications at observable national, state, and industry levels.[11]

The surge in total applications was highly concentrated among 3-digit industries; a Herfindahl-Hirschman index of industry-level applications jumped by more than 10 percent in 2020 versus 2019 and remained historically elevated through 2022 (appendix figure C4). Indeed, more than 20 percent of the jump in applications from 2019 to 2022 was accounted for by nonstore retailers (NAICS 454), which includes online retail; and more than half of the overall surge was accounted for by just five 3-digit industries, shown in figure 3.

The industries making large contributions to overall application growth can plausibly be related to pandemic patterns of work and life. Nonstore retailers (NAICS 454) include online retail businesses facilitating shopping from home. Professional, scientific, & technical 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);[12] business formation in these industries may be related to facilitating the transition to work-from-home and related changes in patterns of work and life. 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

(see appendix tables D2 and D3).

[11] At the broad sector level, the correlation in the growth in total applications and likely employer applications (from pre-pandemic to pandemic) is 0.86.

[12] Many artificial intelligence (AI)-related businesses are classified in this industry (https://www.loc.gov/rr/business/BERA/issue31/codes.html); AI firms may also be classified in the Information sector (51).

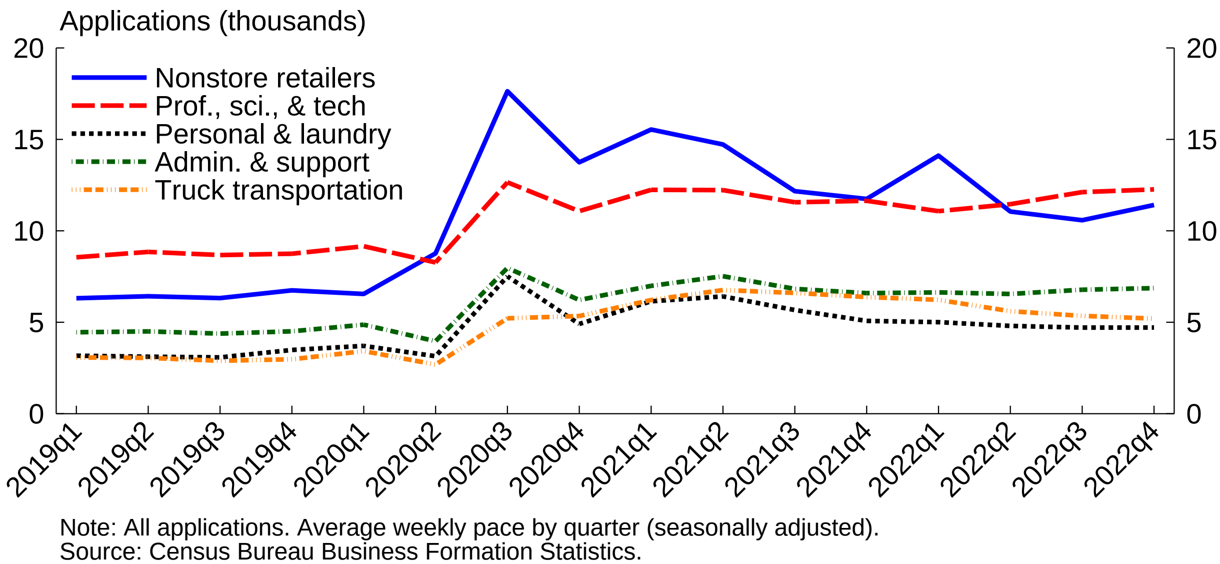


Figure 3: New business applications, selected 3-digit industries

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"); such businesses 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.

The patterns in figure 3 also hint at interesting changes over the course of the pandemic and its aftermath. Applications for nonstore retailers exhibited the most dramatic surge early in the pandemic, and while this remains elevated it has declined substantially from its 2020:Q3 peak. By mid-2022 the highest industry was professional, scientific, & technical services; this tech-intensive industry has exhibited a sustained surge since the beginning, with 2022:Q4 being at about the same pace as 2020:Q3. Truck transportation had a smaller initial surge, peaked in mid-2021, then declined gradually, a pattern consistent with new businesses entering to address supply chain constraints along with the surge in goods consumption, both of which have receded somewhat in recent quarters.

We find similar patterns for likely employer applications at the broad sector level (figure 4); in particular, we observe strong increases in likely employer applications in the retail trade sector and in a proxy for the "high-tech" sector that combines professional, scientific, & technical services and information. Figure 4 has the advantage that it is especially timely—with data through mid-2023—but the disadvantage of coarseness relative to the more detailed data of figure 3.

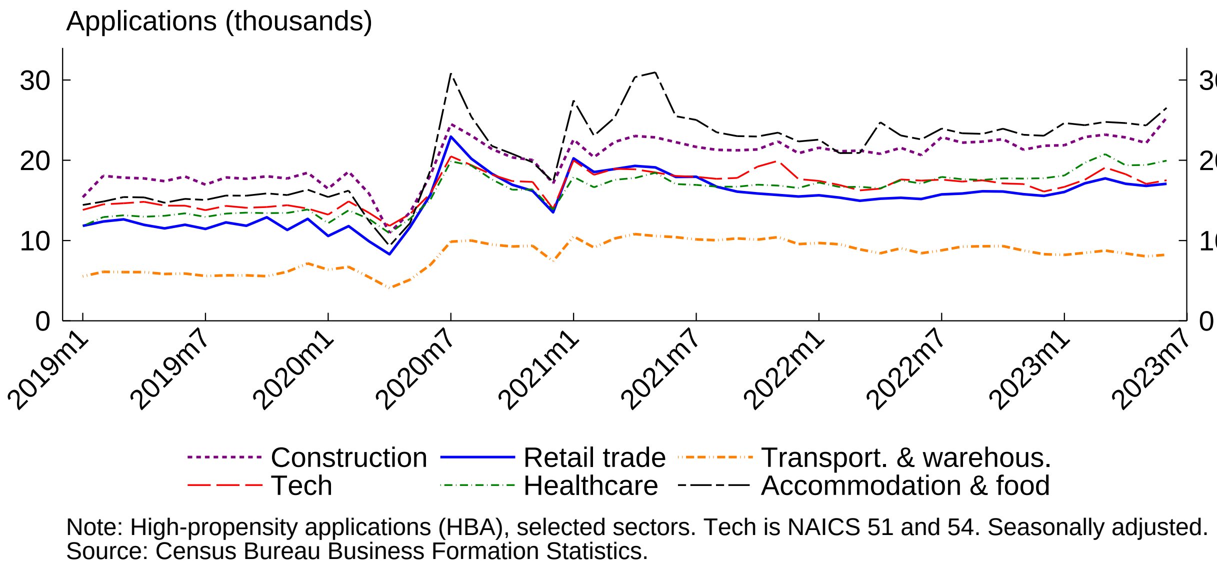


Figure 4: New business applications, selected industries

3.3 Geographic patterns of applications

We next analyze spatial variation in applications, and we introduce a simple measure of growth in applications per capita in the pandemic relative to the pre-pandemic norm which we denote as g. We define g as follows using annual data at various levels of geography:

$$g = \frac{1}{3} \sum_{t=2020}^{2022} ln(x_t) - \frac{1}{10} \sum_{t=2010}^{2019} ln(x_t), \quad (1)$$

where x_t is applications per capita in year t.[13] That is, we study the difference between the average of (log) applications per capita in 2020-2022 and the average of (log) applications per capita during 2010-2019.

Using likely employer applications, figure 5 shows substantial variation across states, with the highest-growth states having growth rates of between 32 and 72 log points while the lowest-growth states exhibit little or no growth. Growth was particularly strong in the South and also parts of the West (i.e., California).

More variation can be seen at the county level, though at this level we must use total applications rather than likely employer applications.[14] Growth in business applications has

[13]In all of our analysis of spatial variation, we focus on per capita variables using Census Bureau county-level population estimates. Karahan et al. (2019) highlights that spatial variation in startups is connected to spatial variation in demographic factors such as population growth. Computing measures using annual population estimates helps take this into account, though investigating population migration and its connection to the patterns of startup dynamics during the pandemic would be of independent interest.

[14]At the state level, the correlation in the growth in total business applications and likely employer applications (pre-pandemic to pandemic) is 0.96.

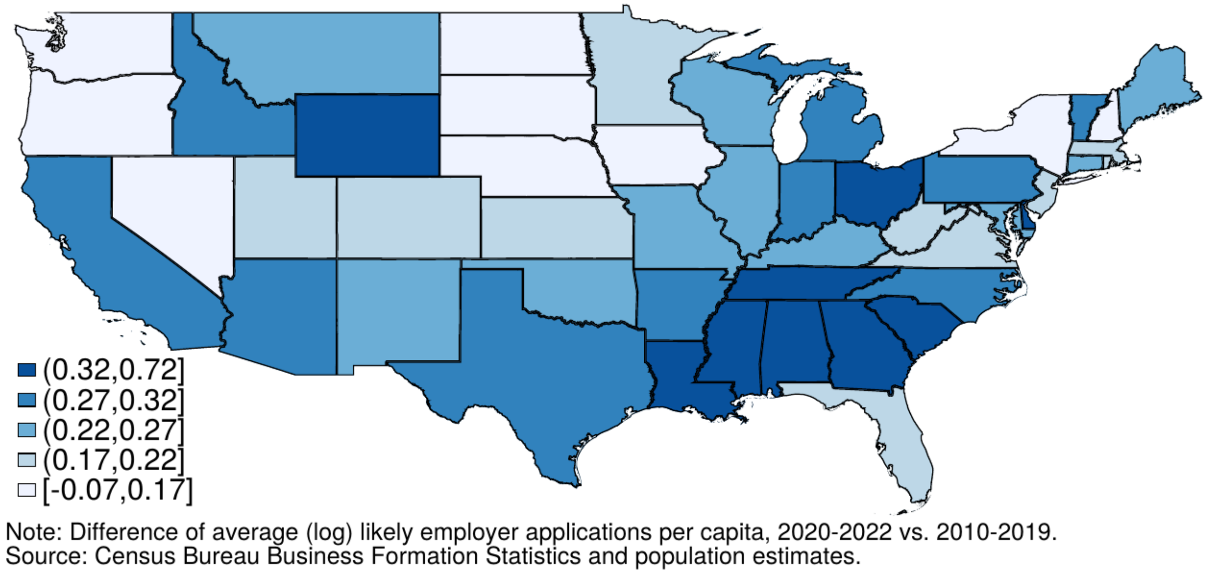


Figure 5: Growth in likely employer applications per capita, 2020-2022 vs. 2010-2019

been widespread across U.S. counties; more than 95 percent of counties saw a higher pace of applications during 2020-2022 than during 2010-2019, on average. Figure 6 provides the county analog to figure 5; the rapid growth in the South is evident in the county map as well, but there are pockets of rapid growth throughout the country.

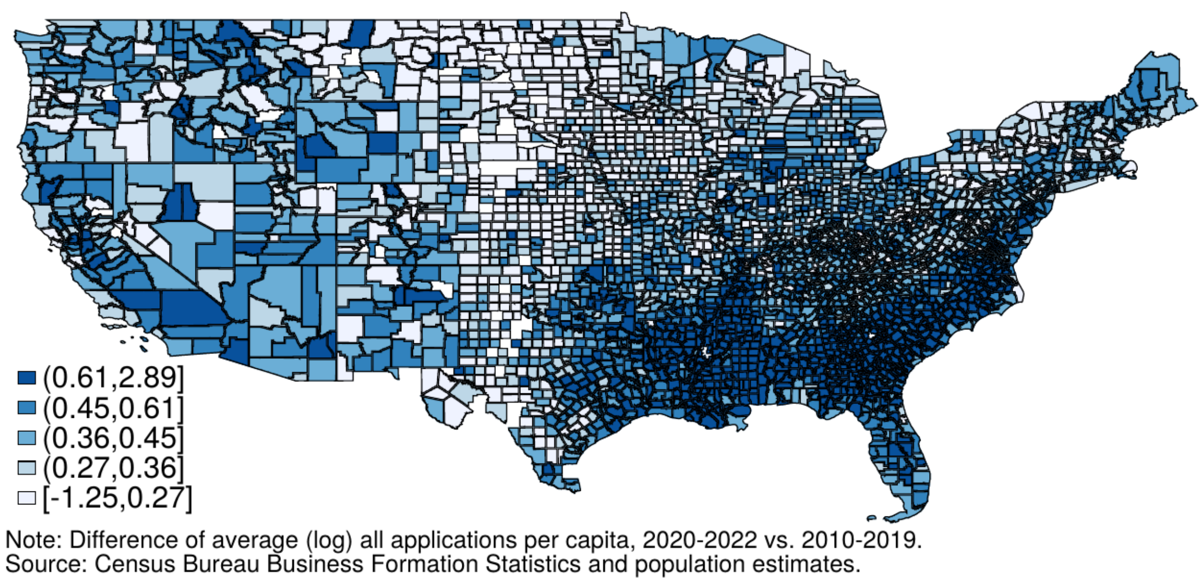


Figure 6: Growth in total applications per capita, 2020-2022 vs. 2010-2019

While a small number of counties actually saw declines in applications per capita, the median county saw an increase of 40 log points, and the highest quintile saw growth of between 61 and 289 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.

Much of the variation across counties reflects larger geographic shifts: Variation between Census divisions accounts for 25 percent, variation between states accounts for almost 50 percent, and variation between commuting zones accounts for 70 percent of the between-county variation in total application growth (reported in appendix table D1). However, counties vary considerably in scale, and even though we are examining growth in applications per capita, the latter is increasing in initial county population (and population density). Among counties that are part of large CBSAs (those with population above 1 million), about 50 percent of the between-county variation is accounted for by between-CBSA effects; over half of U.S. population is in these large CBSAs, so exploring the variation *within* large CBSAs is of independent interest.

As an example of within-city variation, figure 7 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 (total) applications per capita as calculated in equation 1.

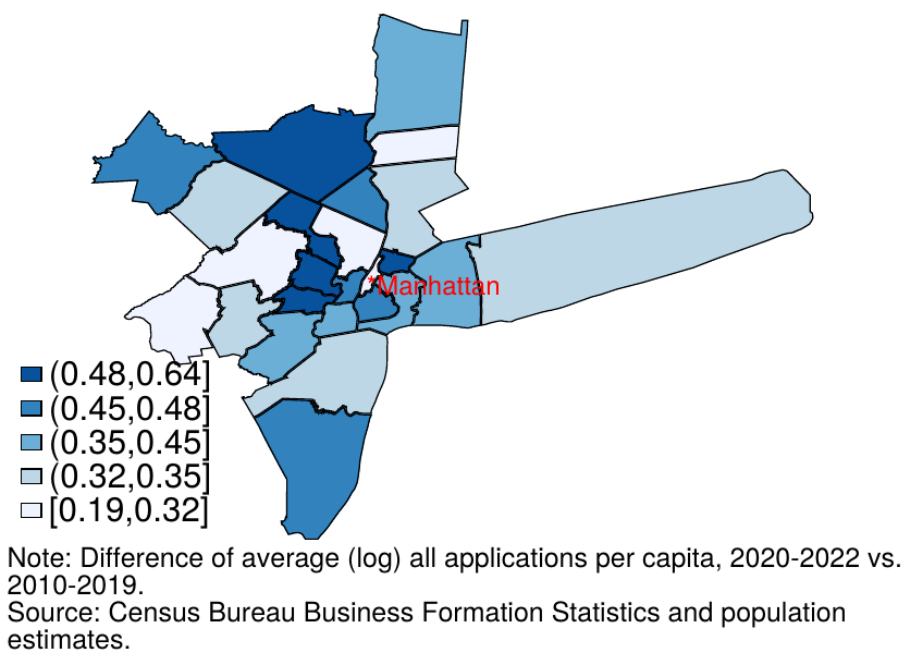


Figure 7: New York City: Growth in applications per capita, 2020-2022 vs. 2010-2019

Growth of applications per capita in New York City counties ranges from 19 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.[15] 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.[16] Duguid et al. (2023) find similar results for retail establishments based on credit card transaction data for the country as a whole; the authors report relatively weak (or negative) establishment growth in core downtown areas, with stronger growth in "inner suburbs" (though not in "outer suburbs").

The donut pattern is apparent in other major cities as well; for example, appendix figure C6 shows the state of Washington, where King County—the central business district for Seattle—shows less application growth than surrounding counties.[17] In unreported results, we visually observe a similar donut pattern in other cities, in the sense that a number of surrounding (close in and outlying) counties within CBSAs exhibit higher growth in applications per capita than the county that contains the central business district.[18]

The donut pattern we observe for applications appears related to popular pandemic themes about high-density downtown areas and the transition of many workers to work-from-home (WFH) activity. We more formally explore the relationship between the growth of applications, density, and WFH within cities using regressions reported in appendix table D7. In particular, at the county level we regress growth of total applications per capita on population density, establishment density (from QCEW data), and growth of WFH activity (from ACS data, where the fraction of workers working from home is based on location of residence). We find highly nonlinear, statistically significant empirical relationships for all three covariates. There is an alternating negative linear effect, positive quadratic effect, and negative cubic effect with magnitudes implying the linear negative term dominates for low values (of density and change in WFH share), the positive quadratic becomes relatively more important for larger values, then the negative term kicks in for very large values. In considering these patterns, it is useful to observe that within New York City, Manhattan has the the highest population density and establishment density and a mid-range growth of WFH.[19]

We also consider a more complex spatial regression specification where we include a cubic of all of these terms for both own and *adjacent* counties (appendix table D8). We find that

[15]Donut-like patterns have been observed on other dimensions such as housing and work as documented by Ramani and Bloom (2021) and others.

[16]Appendix figure C5 shows that prior to the pandemic, Manhattan was one of the top-ranked counties in the NYC CBSA in terms of applications per capita.

[17]Appendix figure C7 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.

[18]We hypothesize this effect would be even more prevalent using tract-level data—an approach that awaits the micro data on applications integrated with the LBD.

[19]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. A nonlinear relationship is consistent with Duguid et al. (2023), who also find nuanced relationships with WFH activity.

each of these covariates have significant own- and adjacent-county effects in this multivariate specification. Given the complexity of this specification, we focus on the overall predictive power; the R-squared of this specification is 0.77, compared to 0.49 in a specification with only CBSA fixed effects. Figure 8 shows that the predicted variation in counties in the New York City CBSA from this spatial model closely correspond to the actual application pattern (compare to figure 7). Put simply, we are able to approximately replicate the within-New York City donut pattern using population density, establishment density, and growth of WFH activity in own and adjacent counties—consistent with the broader high model fit for all cities suggested by the R-squared of 0.77.

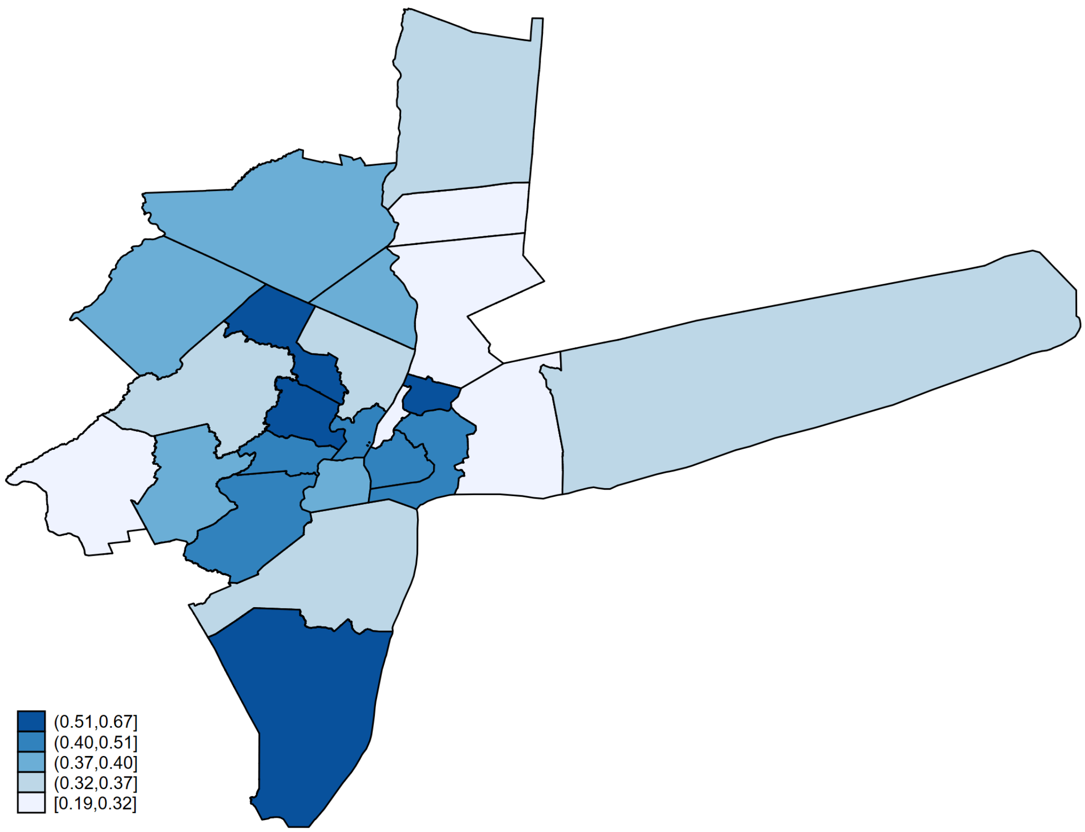


Figure 8: Predicted growth in applications per capita in NYC, spatial model

3.4 The lag between application and employer entry

There is typically a lag between application and new employer firm entry, even conditional on a successful transition. In much of our analysis of employer entry we use quarterly data, annual data, or growth rates based on the difference between pre-pandemic and pandemic averages, mitigating this lag.[20] Appendix figure C3 and tables D2 and D3 show a tight relationship between likely employer applications and employer business formations *within four and eight quarters*. As a rough approximation, the (pre-pandemic) elasticity of new employer firms within 8 quarters with respect to likely employer applications is centered on one in both the aggregate time series and in state-by-time pooled data. These historical relationships would suggest strongly elevated employer entry during the pandemic as well—but with some lag relative to the timing of applications. The lag between application and new employer entry was increasing prior to the pandemic (see appendix figure C2). While the actual transitions are not yet available beyond 2020, we explore these relationships below using a variety of available employer entry rates—but here we simply emphasize that actual births lag applications.

4 New employer businesses

We now turn to data on actual employer business formations, expanding on the data first shown in figure 2. Here we draw on several sources: we use BED quarterly establishment births and openings data through 2022:Q4, BED annual firm births data through March 2022, and QCEW quarterly net establishment births data through 2022:Q4 (which permit finer geographic and industry detail than BED data). Importantly, the gold standard dataset for tracking true employer firm births is the Census Bureau's BDS, which features a more comprehensive firm identifier than the BED (see discussion in appendix A); we report two different BDS series in figure 2, but these data do not currently cover a significant portion of the pandemic period.

The BED and QCEW have the key advantage of timeliness, though the most timely data are on *establishment* entry (gross entry in BED and net entry in QCEW), which include not only new firms but also new establishments of incumbent firms (e.g., new Starbucks locations). While our primary focus is on new firms, new establishments opened as expansions of existing firms are of independent interest, since such establishments are important components of the reallocation of activity across business locations. Moreover, it is likely that new establishments of existing businesses reflect similar incentives of new firms to take advantage of the market opportunities that arose in the pandemic and its aftermath.

4.1 Aggregate establishment and firm entry: Gross and net

Figure 9 shows quarterly data on high-propensity business applications (left panel), BED establishment births and exits (middle panel), and jobs created (destroyed) by births (exits).

The surge in establishment births is especially pronounced starting in 2021:Q2 – several quarters after the initial surge in applications in July 2020 but also after the second wave of the surge in applications in early 2021. It is not surprising there is some lag since,

[20] Dinlersoz et al. (2023) show that in the same quarter as the application, the transition rate of applications with planned wages has been historically about 14 percent then rises to a cumulative 35 percent after four quarters and 40 percent after eight quarters.

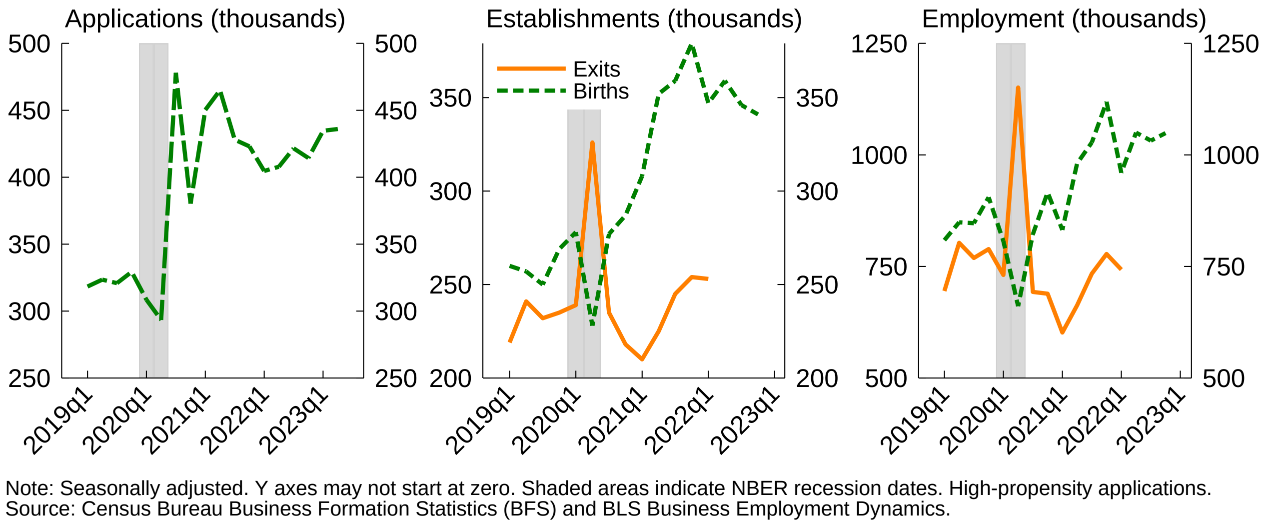


Figure 9: Business applications, establishment births and exits

as discussed above, it can take up to 8 quarters for applications to transit to employer businesses—conditional on transiting at all. Like business applications, establishment births have reached record levels during the pandemic. Note also that births have been well in excess of exits, aside from the initial exit surge in 2020:Q2.

As shown on the right panel, job creation from establishment births has been above 1 million per quarter, on average, during 2021:Q2-2022:Q4—a historically high pace. Establishment birth has played a significant role in the pandemic job recovery, accounting for more than more than 10 percent of gross private job creation from 2020:Q3 through 2022:Q4; at a quarterly frequency, in 2022:Q4 establishment births' share of gross job creation reached 13 percent for the first time since 2004. While this increase in job creation from births is striking, the surge in the number of establishment births (center panel) is proportionally greater than the surge in birth employment; the average size of a new establishment birth declined from about 3.3 jobs in 2019 to 2.9 jobs in 2022. As we discuss in section 6.2 below, average firm entrant size also stepped down in the pandemic—though incumbent size declined as well.

The elasticity of establishment births with respect to likely employer applications has, if anything, strengthened in the pandemic—at least at the national level; we obtain this evidence with simple regressions of births per capita on applications (appendix table D2). For the aggregate series we actually find a higher elasticity of establishment births when we include the pandemic period than if we end the sample in 2019. Appendix table D4 reports state-by-quarter regressions, in which the pre-pandemic elasticities (shown on the top panel of the table) are generally similar to those estimated on pandemic-inclusive data (bottom panel). We also examine the relationships between establishment births and the *projected* startup series from the BFS. Given timing issues, for this purpose we focus on the predicted startup transitions over a four-quarter horizon. Appendix table D5 illustrates two findings, with discussion in appendix B. First, there is a strong positive historical (pre-pandemic) relationship between BFS *predicted firm births* and *actual establishment births*. Second, this relationship remains strong during the pandemic. We discuss these analyses more in appendix section B.[21]

It is clear from the BED data in figure 9 that *net* establishment entry surged in the pandemic; this fact is corroborated in other data sources and for firms as well. Figure 10 shows annual net growth of firm and establishment counts from the BDS, BED, and QCEW. Reassuringly, the various series track each other well through March 2020, after which the BDS becomes unavailable. Net establishment growth was strong in 2021 and, especially, 2022, when establishment growth reached nearly 5.5 percent—a pace not seen since the 1980s.[22] Firm growth was similarly impressive, as the total number of firms (in BED data) increased by more than 250 thousand from March 2020 through March 2022, from under 5.3 million to more than 5.5 million. The largest surge is from March 2021 to March 2022 – broadly consistent with the finding that the increase in establishment births is especially pronounced starting in 2021:2. In appendix figure C8 we report similar results if growth is calculated on a per capita basis.

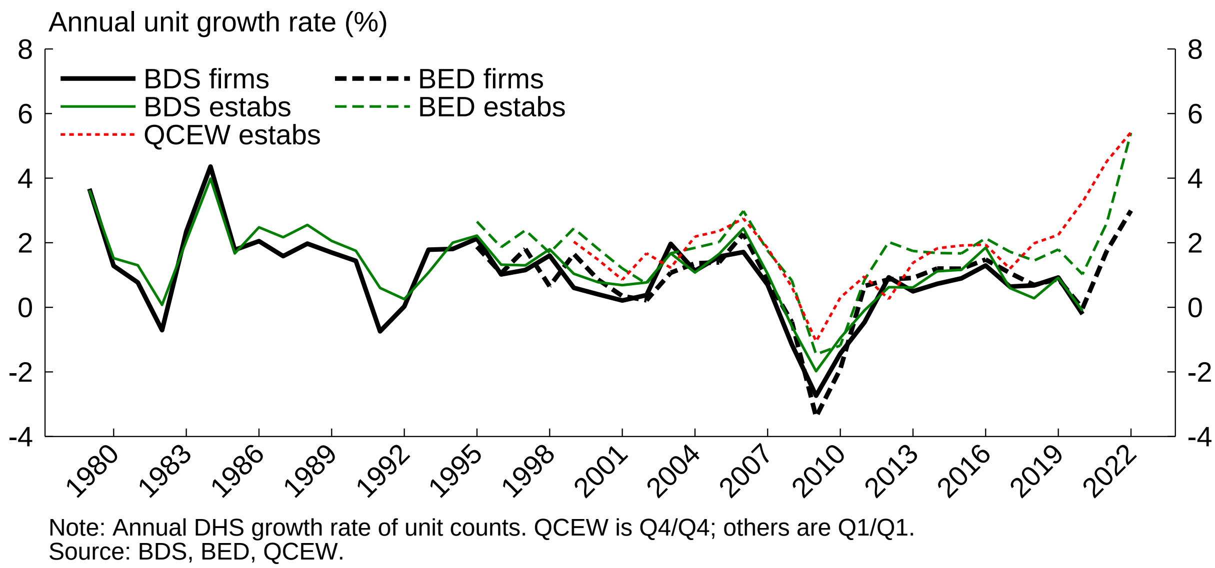


Figure 10: Net increase of establishments and firms

Here we have focused on true establishment birth and exit; *temporary* closings and

[21]Notably, the pandemic-inclusive elasticities are even higher if we exclude the year 2020. See the appendix section B for more discussion.

[22]The QCEW line in figure 10 refers to growth from Q4 of the prior year to Q4 of the current year, which allows us to feature relatively recent data, but for other data sources we report growth from Q1 to Q1; in unreported results we find that the chart looks similar if QCEW is calculated on a Q1 basis. We are not the only researchers to notice the striking surge in establishment counts; for example, O'Brien (2022) highlights the net growth of establishments and explores cross-city variation.

*re*openings of establishments also played a large role in early pandemic labor market dynamics. In the appendix figure C9 we report total establishment openings and closings, and figure C10 shows reopenings (i.e., openings minus births) and temporary closings (i.e., closings minus exits). In 2020:Q2, more than 400,000 establishments closed temporarily, with nearly 1.8 million associated jobs. Reopenings jumped in the following quarter, accounting for 1.2 million jobs in 2020:Q3 and nearly 800,000 jobs in 2020:Q4. These patterns imply a need for caution in the use of establishment openings out of context—especially in 2020:Q3; the patterns also highlight the large role of temporary job dislocation in the early pandemic labor market.

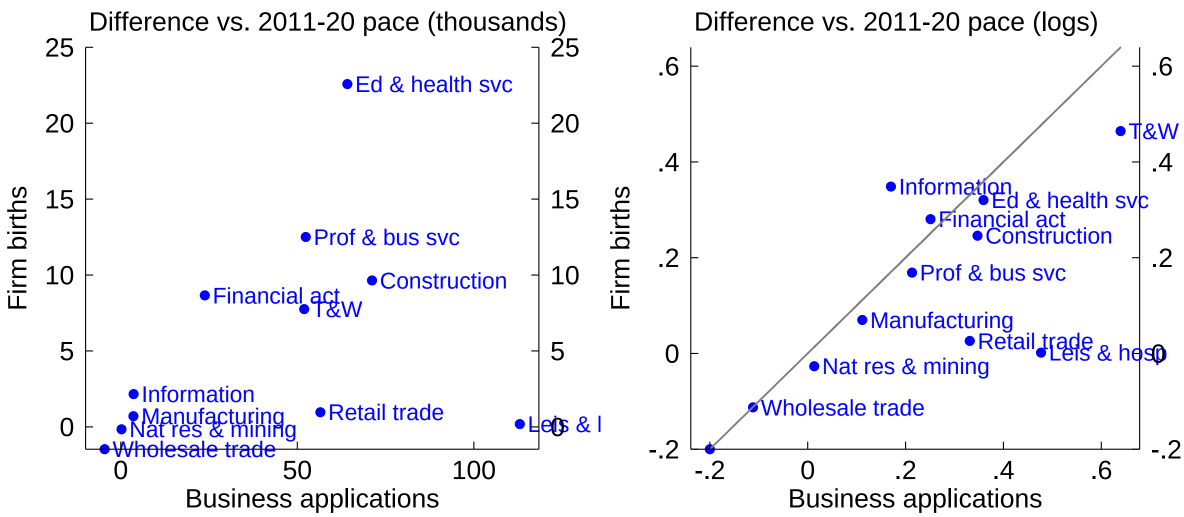
While establishment reopening and temporary closure was a significant feature of the pandemic—particularly in early quarters—the *cumulative* job reallocation associated with births and deaths is even a bit larger. Over the 2020:2-2022:4 period, job reallocation from births and deaths cumulated to 18.7 million jobs with births contributing 10.5 million and deaths 8.3 million. Reallocation from births and deaths necessarily reflects permanent job reallocation. During the same period, temporary closings and reopenings cumulated to 17 million jobs with temporary closings contributing 9.2 million and reopenings 7.9 million. In contrast to births and deaths, this reflects transitory reallocation—although it may be that some workers who lost their jobs to temporary closings did not return to the same employer since reopenings took some time. We discuss the implications of these dynamics for job and worker reallocation further below.

4.2 Sectoral patterns of employer business entry

As noted in section 3.2, the industry 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 actual employer business formation. Annual firm births by broad sector are available from the BED through March 2022; the scatterplots in figure 11 compare pandemic firm births with likely employer applications by sector, where we focus on pandemic growth relative to pre-pandemic norms as described in equation 1.

The left panel of figure 11 gives insight into the contribution of different sectors to the aggregate surge in firm births and likely employer applications by measuring the average *level* of births or applications—in thousands—during the pandemic versus the pre-pandemic pace. Educational and health services, professional and business services, and construction are sectors with large increases in both firm births and high propensity applications, accounting for a large share of the aggregate surges in both. The right panel is more informative about growth *within* sectors, as it is based on the log difference between pandemic and pre-pandemic norms. Sector-level growth in firm births and business applications is strongly positively related, with most sectors lining up reasonably close to the 45-degree line. Transportation and warehousing, information, education and health services, financial services, construction, and professional and business services are all sectors with large (approximately 20 percent or larger) growth of both applications and firm births.[23]

[23] In appendix figure C12 we show analogous scatterplots for establishment (rather than firm) births;



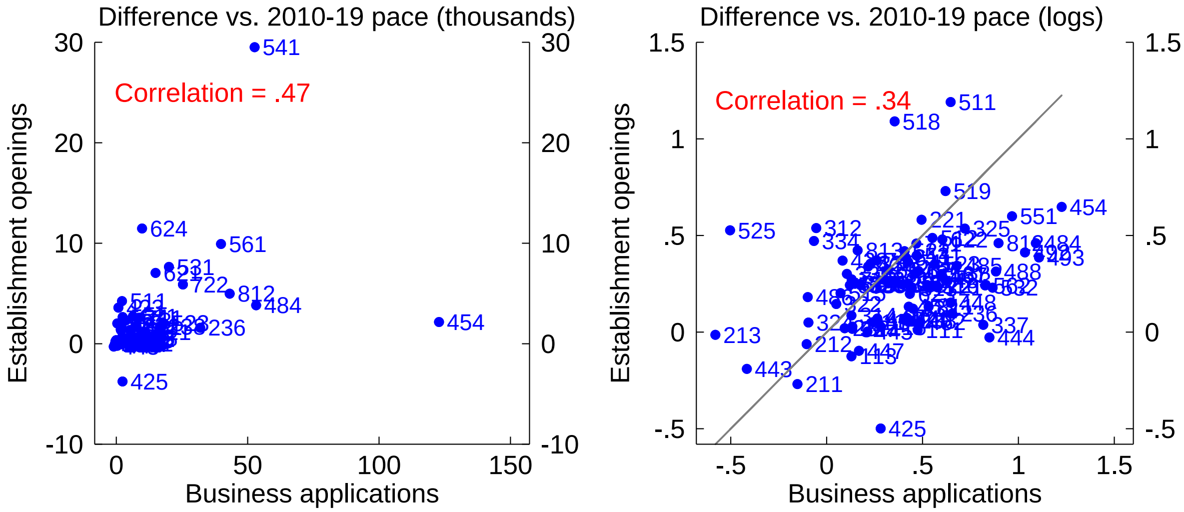
Note: 2021-2022. Left panel expressed in average annual pace. Solid line is 45-degree line. T&W is transportation & warehousing. Years end in March. High-propensity applications.
Source: Business Employment Dynamics (BED), Business Formation Statistics (BFS).

Figure 11: Firm births and business applications, industry detail

Drilling down further, the BED provides establishment *openings* at the 3-digit industry level (and, as noted above, the BFS provides *total* applications at this industry detail). Unfortunately we must end this comparison in 2021:Q4, as the BED switched to the NAICS 2022 format in 2022 while the BFS is still based on the NAICS 2017 taxonomy (see appendix A for more discussion). Moreover, to avoid the spike of reopenings in 2020:Q3, we start the pandemic period 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), again following equation 1. This is shown in figure 12, where the left panel shows the change in levels (thousands) while the right panel shows the ratio of the pandemic pace to the pre-pandemic pace.

The left panel of figure 12 gives insight into the contribution of different industries to the aggregate surge in establishment openings and business applications. See appendix tables D9 and D10 for a full list of industry codes and their titles; here we summarize certain noteworthy industries. 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 reports the log change of pre-pandemic to 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

establishment data have the advantage of more time coverage (through 2022:Q4). Those results are broadly similar to the firm-based results of figure 11, though the within-sector growth relationship appears a bit less strong in the establishment birth data (it is difficult to judge given the sample size).



Note: 2020:Q4-2021:Q4. Left panel expressed in average seasonally adjusted quarterly pace. Solid line is 45-degree line. Correlations are statistically significant at p<0.01.
Source: Business Employment Dynamics (BED), Business Formation Statistics (BFS).

Figure 12: Establishment openings and business applications, industry detail

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 (0.34 and highly statistically significant); that is, 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 distinction between openings and births (of establishments or firms), the role of establishment births within incumbent firms, and industry variation in the propensity of applications to convert to employer businesses. Overall, however, the industry-level data on establishment openings and business applications are broadly consistent.

Figures 11 and 12, taken together, point to similar industry patterns of applications and actual employer business formation, adding to the aggregate evidence relating applications and true business entry.

4.3 Geographic patterns of employer business entry

Given the striking geographic pattern of business applications described in section 3.3, we next explore county-level correlations. Data limitations continue to bind, however, as BED establishment birth (or opening) data are not available at the county level, so we focus on *net* establishment entry (that is, change in the number of establishments) in QCEW data. To start, we consider the spatial variation in growth of establishments per capita between the pre-pandemic and pandemic periods using the same measure as implied by equation 1. Figure 13 highlights substantial variation in the growth of establishments per capita across counties (this figure can be usefully compared with figure 6, the analogous map for business applications). In the top quintile, establishments per capita increased between 13 and 52 log points while in the bottom quintile establishments per capita declined.

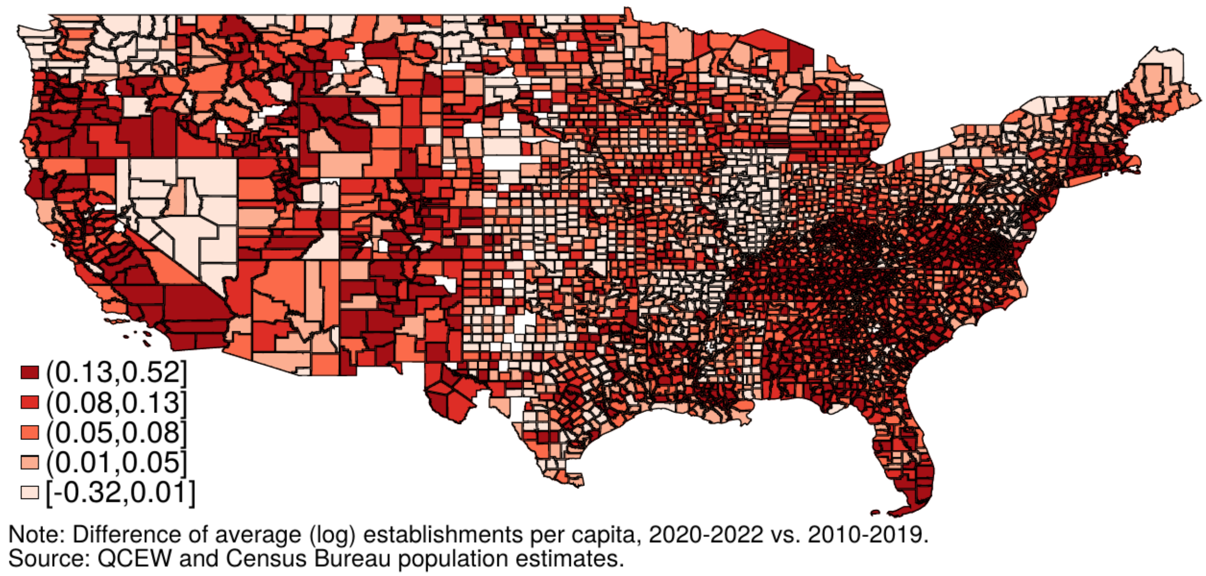


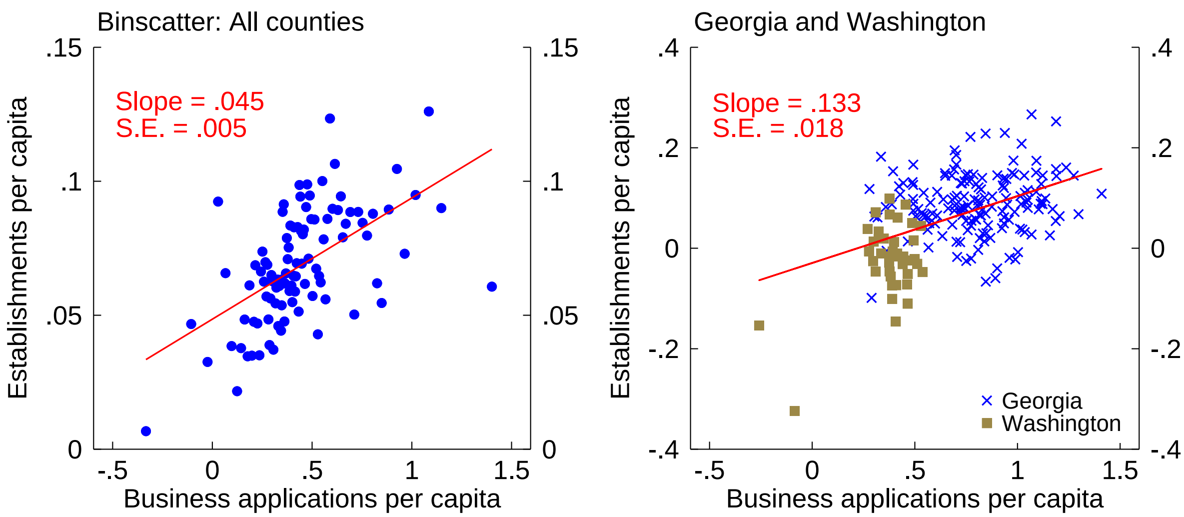
Figure 13: Net establishment growth from Pre-Pandemic to Pandemic

The spatial patterns in figures 13 and 6 are broadly similar, with the South and parts of the West standing out as having especially high growth in both applications per capita and establishments per capita. We can see this more formally on the left panel of figure 14, which is a binscatter plot relating county-level growth in total establishments per capita to growth in applications per capita (2020-2022 versus 2010-2019, following equation 1).

We observe a tight, highly statistically significant relationship between establishment growth and applications. Of course, net 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 (though recall that figure 9 shows that establishment death was not materially elevated after its initial spike in 2020:Q2). Moreover, as in our 3-digit industry scatterplots above, at the county level we have *total* business applications, not the narrower category of high-propensity applications, though recall that total applications and high-propensity applications have moved together in the pandemic. The strong spatial relationship between net establishment entry and total applications suggests that that surging business applications is related to growth in net entry in the geographic cross section.[24]

We provide some concrete perspective into our county maps and the binscatter just mentioned by focusing on the counties in two states: Georgia and Washington (state). The

[24]The small slope coefficient reflects the much greater variation in the growth of applications per capita relative to growth of establishments per capita, which is apparent from the chart axes.



Note: County-level log differences of 2020-2022 vs. 2010-2019 levels. Red line is regression line with reported slope and standard error. Total applications. Left panel is binscatter with 100 bins.
Source: QCEW and BFS.

Figure 14: Net establishments growth vs. applications growth

right panel of figure 14 depicts the growth in applications and establishments for counties in just these two states; Georgia (blue crosses) is a state with high growth on both margins, while Washington (brown squares) is not. Interestingly, this between-state pattern holds pervasively across counties within these respective states.

As another specific example, figure 15 shows net establishment growth for counties of New York City in the same manner as figure 7. While not identical to the pattern of application growth, we still observe a donut pattern of strong growth in establishments per capita in the city suburbs, with less growth in the city center of Manhattan.

We take advantage of these two examples to dig further into the sectoral differences in the growth of establishments per capita. In figure 16, the left panel compares sector establishment growth in Manhattan (vertical axis) and Kings County (i.e., Brooklyn, right axis), illustrating within-city patterns, while the right panel compares Georgia and Washington (state). In both cases, the high-growth areas (Kings County and Georgia, respectively) exhibit higher growth in almost all sectors; that is, the geographic growth pattern is broad-based across sectors.[25]

Sectors that stand out in Kings County relative to Manhattan include information (51), arts, entertainment, & recreation (71), professional, scientific, & technical services (54), and food & accommodations (72). These patterns are consistent with economic activity moving away from downtown areas both for high-tech industries (such as 51 and 54) and for household support industries (such as 71 and 72); it is worth noting, for example, that

[25] In appendix figure C13 we show the growth in establishments per capita in Manhattan relative to the average for high growth counties in the NYC CBSA (including the Bronx, Brooklyn, Essex, Hudson, Kings, Middlesex, Passaic, and Queens). Patterns are broadly similar to those in Figure 16.

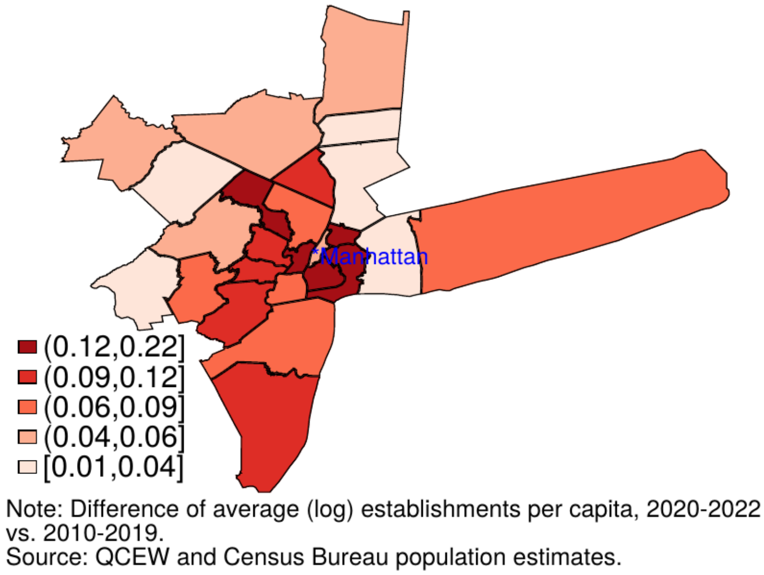


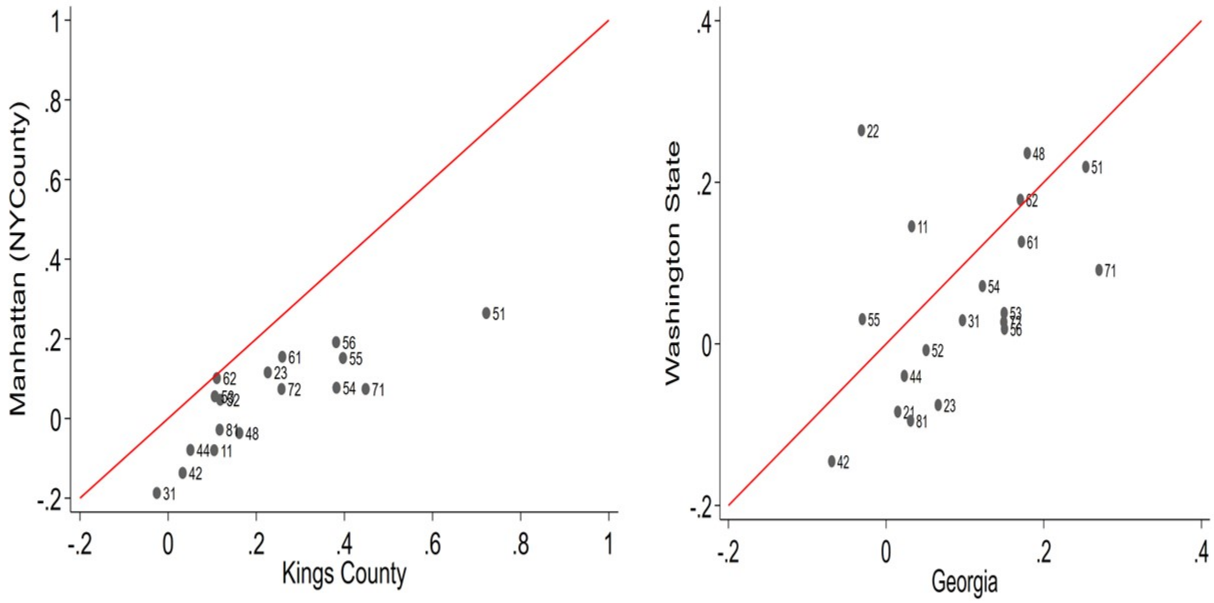
Figure 15: Net establishment growth, New York City

fitness gyms are in 71. As for Georgia vs Washington, Georgia features 14 of 19 sectors having notably higher growth in establishments per capita than in Washington. The sectors with especially high growth in Georgia relative to Washington include construction (23), the professional services industries (54, 55 and 56), arts, entertainment, and recreation (71), and food and accommodation (72). The information sector (51) features the highest growth in establishments per capita in Georgia; it is also a high-growth sector for Washington, which is perhaps not surprising given the important role of that high-tech sector in Washington in recent decades. However, it is interesting that Georgia—which is less well known for being an information sector hub—exhibits higher net establishment growth per capita.

Our geographic exercises, like our industry exercises, suggest a strong relationship between business applications and actual employer business growth. Moreover, these patterns are consistent with thriving business creation in industries that complement pandemic changes in work and lifestyles as well as movement of some forms of economic activity from city centers to outer areas. Notably, our geographic analysis is all done on a per capita basis, so these flows of businesses do not simply reflect underlying population flows.

5 Worker flows and business formation

The pandemic labor market has featured several notable patterns including mass layoffs followed by rapid job growth, migration, and a large number of workers quitting their jobs (which has been called the "Great Resignation"). A natural question is whether these labor market patterns have any relation to the surge in business formation. In section 4.1 we described the significant role of firm and establishment birth in gross and net job growth in



Notes: Source QCEW. Growth rate in establishments per capita from pre-pandemic to pandemic following equation (1). Industries labeled with 2-digit sectoral detail.

Figure 16: Differences in sectoral net establishment growth: Two examples

the pandemic; and in section 4.3 we reported striking geographic patterns consistent with popular stories about migration flows (north to south, inner cities to outer cores) but that reflect flows above and beyond simple population moves.

In this section, we focus specifically on quits and layoffs or, where necessary, close proxies for quits and layoffs. The early pandemic period was characterized by a massive spike in layoffs; while many of these proved temporary (see, e.g., Cajner et al., 2020), the 2020:Q2 spike in establishment deaths (figure 9) indicates that there was also considerable permanent job destruction; separately, the pace of quits rose to record levels—and well above its pre-pandemic trend—in late 2021 and early 2022.

Workers that experience a permanent separation through either quits or layoffs may be joining a new business either as the entrepreneur or as an early employee. Indeed, since quits are dominated by job-to-job flows, workers who quit likely had a job to go to at the time of the quit.[26] But the administrative microdata required to track these flows on a comprehensive basis are not yet available. Instead, we examine patterns at the aggregate and spatial levels as we have in previous sections.

For this purpose, we exploit data from the Census Bureau's Quarterly Workforce Indicators (QWI) and other sources. The QWI provide information on hires (i.e., new worker-firm

[26]Elsby et al. (2010) finds that layoffs, not quits, account for cyclical flows from employment into unemployment. Davis et al. (2012) find a tight connection between job destruction and layoffs, and job-to-job flows are tightly linked with quits (see Molloy et al., 2016, including comment by Haltiwanger).

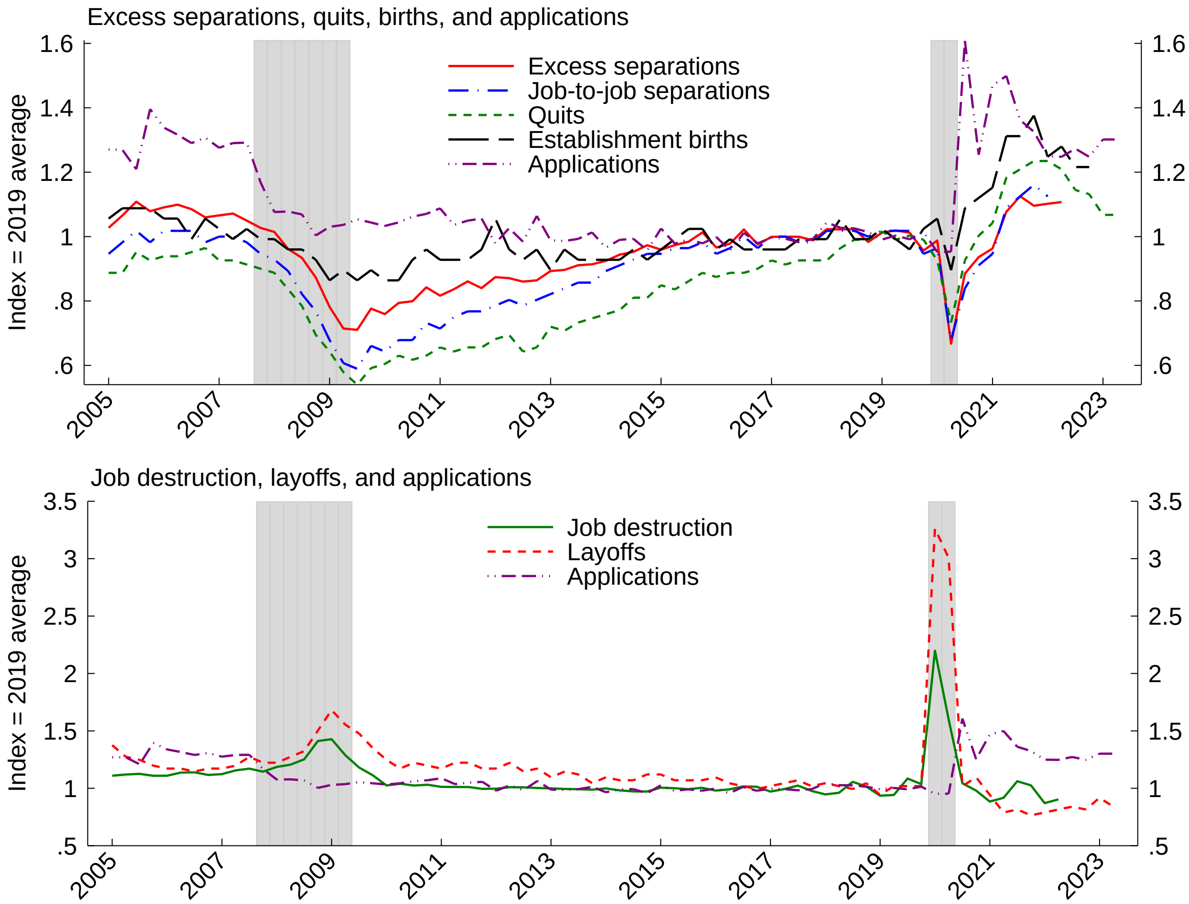
matches), separations (broken worker-firm matches), job creation (growth in firm employment), and job destruction (contraction of firm employment) in various granular tabulations (see appendix A for detail about the QWI and how we use it). We take advantage of that granularity to decompose separations into job destruction and what we denote—following Davis and Haltiwanger (1992)—as *excess separations* (the difference between separations and job destruction).

It is important to grasp the intuition of excess separations. Separations include both layoffs and quits. 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. Both conceptually and historically, job destruction and layoffs track each other well, and excess separations and quits track each other well (Davis et al., 2012).

Figure 17 reports worker flows (i.e., quits and layoffs and their proxies), establishment births, and business applications. The top panel shows excess separations from QWI (solid red line) and the standard quits series from the BLS Job Openings and Labor Turnover Survey (JOLTS), along with BED establishment births and BFS high-propensity business applications (all series indexed to 2019 rates). Prior to the pandemic, quits and excess separations moved in similar patterns (albeit with some level shift), consistent with their close conceptual relationship. This comovement continued in the pandemic, with an initial drop in quits and excess separations followed by a recovery to historic levels (admittedly more dramatic for quits). Over the same period, business applications and actual establishment births surged as well. The top panel shows one other series as well: job-to-job separations from the Census Bureau's J2J product, which is closely related to the QWI. This series measures separations of workers in which the worker quickly starts a new job with a different firm; as suggested by the discussion, excess separations closely track job-to-job separations in figure 17, as both are closely related to quits.

The bottom panel of figure 17 shows the spike in job destruction and layoffs in the second quarter of 2020. Both spikes are short lived and, as noted previously, the layoffs in particular reflect a surge in temporary layoffs. Using the Current Population Survey (CPS)-based inflows to unemployment from employment (using those entering unemployment in a month based upon duration data), about 85 percent of the massive surge in inflows in 2020:2 was due to temporary layoffs (see appendix figure C14). Both series drop to low levels after mid-2020, even while business applications surged.

The two panels of figure 17, taken together, are suggestive of a relationship between quits (or their proxy, excess separations) and business formation, consistent with a theory in which workers quit their jobs to start, or join, new businesses; on the other hand, such a relationship between layoffs and business formation is obviously apparent, as if the surge in business creation does not simply reflect laid off workers starting businesses due to weak labor market opportunities. Still, these are simply aggregate series.



Note: Index of series expressed relative to employment or, for births, to establishments; seasonally adjusted.
Applications are likely employers (HBA). Shaded areas indicate NBER recession dates.
Source: QWI, JOLTS, BED, BFS, and CES.

Figure 17: Worker flows and applications

We therefore turn to spatial variation. We start at the state level, where Job Opening and Labor Turnover Survey (JOLTS) data on quits and layoffs as well as BFS likely employer applications are available; we employ the same approach as prior analyses to study the pandemic relative to pre-pandemic norms. As shown on the left panel of figure 18, states with especially large surges in likely employer applications also saw especially large surges in quits during the 2020-23 period; while there is much variation in both series, there is a substantive positive relationship that is statistically significant.[27] As seen on the right panel, there is little or no association between layoffs and high-propensity applications across states, consistent with the aggregate data of figure 17.

We next drill down to the county level, where we can examine related patterns using

[27]We apply equation 1 using monthly data for this purpose, computing the mean of the log of series per capita for the pre-pandemic (2010-19) and pandemic (2020-23) periods.

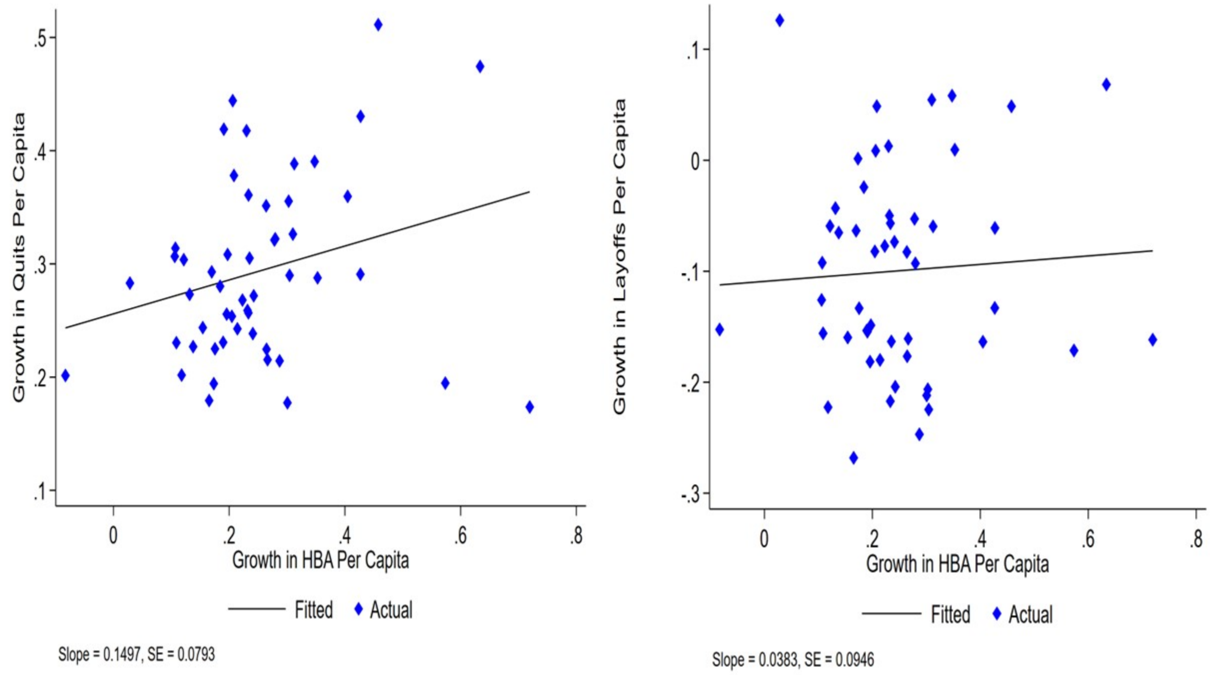


Figure 18: Growth of quits, layoffs, and applications per capita, 2020-2023 vs. 2010-2019

Note: State level. High Propensity Applications. Source: JOLTS and BFS. 2023 data through June 2023

excess separations and job destruction from the QWI (our proxies for quits and layoffs) and total applications from the BFS. In figure 19, the left panel 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 again constructed as in equation 1. We observe a tight, statistically significant spatial relationship between growth in excess separations and growth in business applications. In contrast, as shown on the right panel, we find a much weaker relationship between job destruction and applications.

While we might imagine multiple mechanisms underlying the observed spatial relationships, one possible 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 aggressively poach 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 9 that job creation by establishment births during 2021 was substantial; 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 similar to the pattern for applications (and net establishment births). In the appendix, figure C15

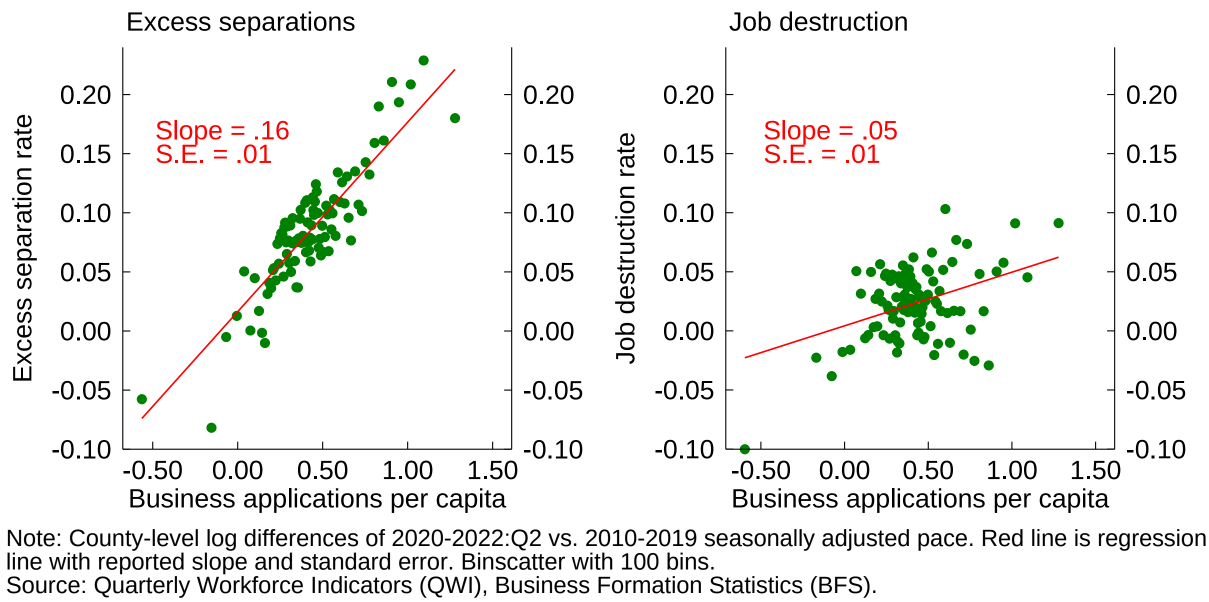


Figure 19: Excess separations, layoffs, and applications, 2020-2022 vs. 2010-2019

shows county-level growth in excess separations for New York City are greater in the counties surrounding Manhattan than in Manhattan itself.

6 Business dynamism revived?

A large literature explores "declining dynamism," or the slowing of job, worker, and business flows in recent decades, including a decline in the firm entry rate and the share of activity accounted for by young and small firms. The evidence above suggests that the pandemic has been a period of increased dynamism relative to the 2010-19 period. In this section, we consider the possibility of a return of the higher dynamism pace of the past (e.g., pre 2000). While we find noteworthy evidence of substantial economic restructuring during the pandemic—including reallocation of jobs and changes in the firm age and size distribution—we conclude that more time (and data) are needed for a material reversal of pre-pandemic trends.

6.1 Job reallocation

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 and is often used as a measure of business "dynamism." The denominator in equation 2 is the "DHS" denominator after Davis et al. (1996). The top panel of figure 20 shows gross job creation, gross job destruction, and job reallocation; the top-left panel zooms in on the pandemic period, while the top-right panel shows a longer view.

As has been extensively documented in the literature, job reallocation exhibits a downward trend over the last few decades and especially since the early 2000s. More recently, job reallocation spiked early in the pandemic; as shown on the top-right panel, the pandemic spike was historic. The 2020:Q2 spike in reallocation was driven by the surge of job destruction; in the following quarter, reallocation moved down some but remained elevated. Initially this reflected the surge of job creation as temporarily destroyed jobs returned. However, both job creation and job reallocation remain elevated through 2022:Q4.

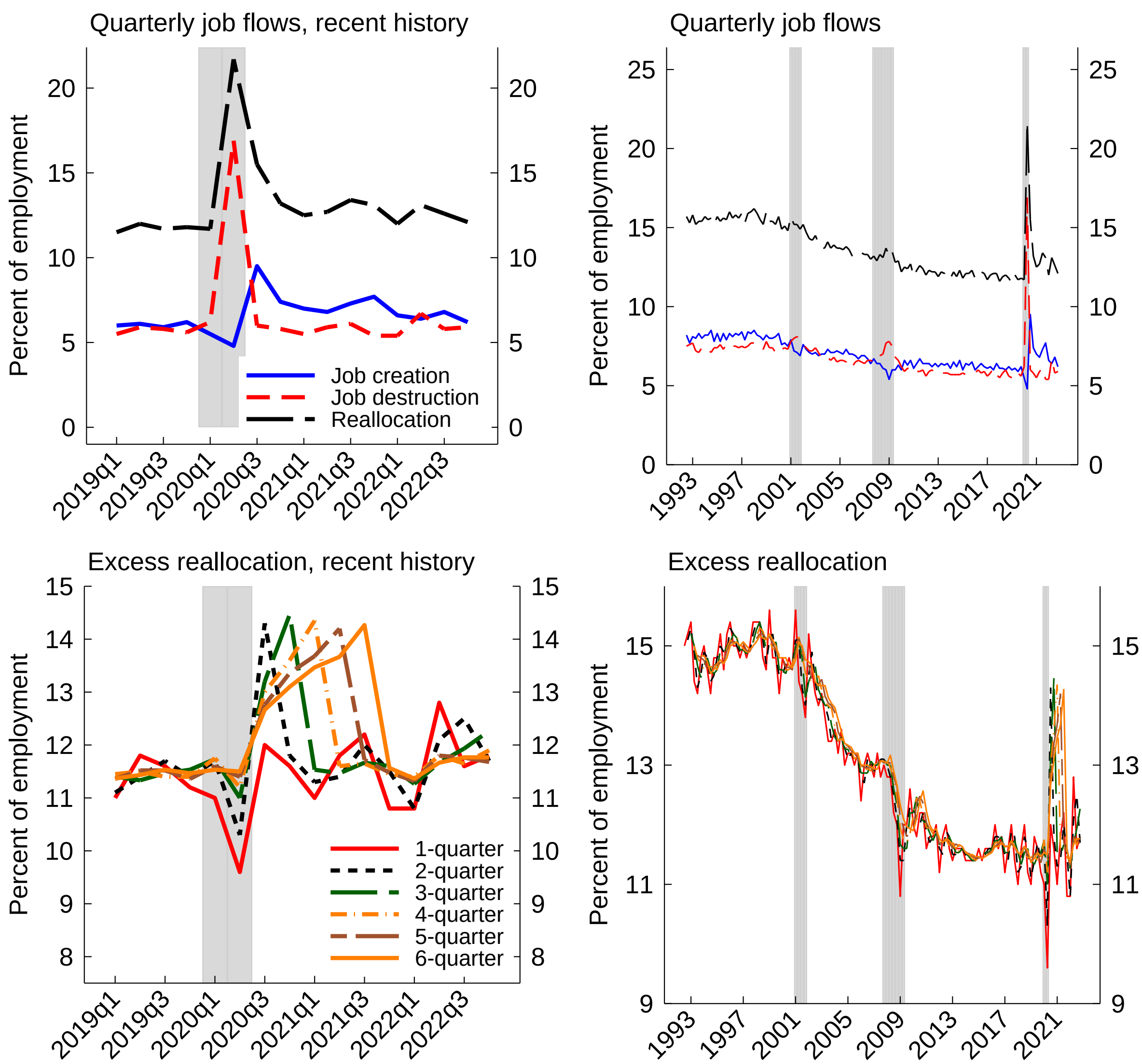
There are two critical points to make about the early pandemic spike in reallocation. First, as just noted, the 2020:Q2 spike was driven entirely by surging job destruction and therefore simply reflects net (negative) job growth in that quarter rather than a "dynamism" phenomenon of simultaneous job 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 had been 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 (this can be seen in the red line of the bottom-left panel of the figure, which we discuss more below).

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 when creation and destruction are decoupled or staggered in terms of timing. A clearer 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 pace not seen in more than a decade, as can be seen in the lower panels of figure 20 (which also shows the dip in 1-quarter excess reallocation).[28] Excess reallocation measured at multi-quarter horizons (e.g., the 6-quarter orange line in figure 20) was elevated for an extended period in the pandemic though came down again in 2022.

[28] 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.



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

Figure 20: Perspectives on job reallocation

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 return to the rich QWI data and 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.[29] 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 evenly distributed 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, $\frac{1}{2}(e_{t-1} + e_t)$.

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
- Counties
- Broad NAICS sectors
- 3- or 4-digit NAICS industries
- Interactions of some of the above as permitted by the public-use data

Figure 21 shows the between-cell excess reallocation rate for the pre-pandemic period (2010-2019, red bars) and the pandemic period (2020:Q1-2022:Q2, blue bars) 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). We use a 6-quarter horizon to permit offsetting net changes within cells to cancel out.

[29] *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 $br_t + wr_t$.

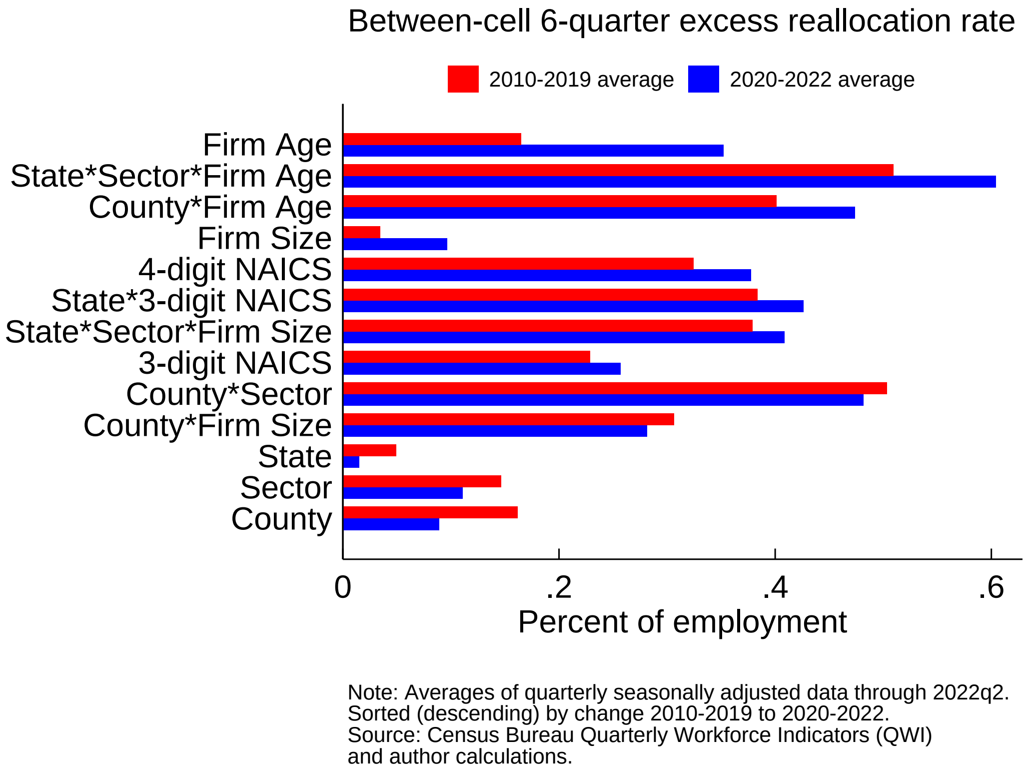


Figure 21: Between-cell reallocation rate (6-quarter horizon)

The chart is sorted in descending order of the change from 2010-2019 to 2020-2022 (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 of employment per quarter (for 2010-2019 on average) to about 0.4 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.

We also note that simple reallocation across simple firm age categories is not the only story told by figure 21: reallocation across firm age categories appears to have important geographic and industry dimensions as well.

6.2 Changes in the firm age and size distribution

The evidence on reallocation—and especially between-cell excess reallocation—implies an increase in the reallocation of activity across businesses in the pandemic. While the changes in the magnitudes of between-cell excess reallocation are large in percentage terms, they are relatively small in terms of absolute flows of jobs. We know from Decker et al. (2016), Decker et al. (2020), and Karahan et al. (2019) that an important source of the decline in indicators of business dynamism is the shift in activity toward large, mature firms: young and small firms are inherently more dynamic, so the decline in the share of the economy accounted for by young and small firms underlies a significant fraction (albeit far from all) of the decline in the pace of reallocation. In this context, it is instructive to explore any changes in the age and size distribution of activity that occurred in the pandemic; we use annual BED data on activity by firm age and size through March 2022.

Figure 22 reports the *change* in the firm age distribution from March 2020—the very beginning of the pandemic—through March 2022. The top panel shows the percentage-point change in the share of firms (blue bars) and employment (hollow bars) accounted for by each firm age group. Young firms' share of activity has risen a bit during the pandemic (after decades of trend decline); the shift in the share of firms is greater than the shift in employment, which is not surprising since pandemic entrants have been smaller than before the pandemic, and because the effect of the surge of business entry on employment shares will inherently take time depending on survival rates and post-entry growth patterns of the new firms. The surge in entry has clearly left a mark on the firm age distribution, but even the share of firms 5-9 years old increased; these are not pandemic births but are instead relatively young firms that were born *before* the pandemic. While the activity share changes in the top panel of figure 22 must sum to zero, the bottom panel of the figure shows the percent growth in the number of firms (blue bars) and employment over this period; for the 2020-2022 period as a whole, all firm age groups saw absolute growth, but the rate of increase was much higher for younger firms (though the growth rates are not quite monotonic). Again, even the oldest young firm category—those aged 5 to 9—saw rapid growth, with 5 percent more firms and 2 percent more employment than at the beginning of the pandemic (do not forget, though, that firms naturally progress through the age distribution via the process of aging).

We also examine changes in the firm size distribution. This is more challenging since firms can move both directions through the size distribution; firms with net job destruction may move into smaller size bins, while growing firms may move into larger bins. With this caution in mind, figure 23 reports changes in the size distribution in a manner analogous to figure 22. The top panel shows a shift in the share of firms and employment accounted for by small firms with fewer than 20 employees; but this shift has not been monotonic—firms between 50 and 499 workers have seen large declines in their share of employment and, especially, firms. In contrast, firms with at least 500 employees have exhibited a modest decline in their share of firms—possibly reflecting firm exit but, more likely, reflecting firms downsizing into lower bins—but actually saw an increase in their share of employment, as some large firms likely benefited from the pandemic. The middle panel, which reports growth in the level of firms and employment, tells a somewhat similar story, with all but the smallest size class seeing a decline in the number of firms but with the largest size class adding jobs. It is important to note that the 1 percent employment growth rate among large firms is substantial given that these firms account for roughly half of all employment, compared with the smallest size class whose share of employment is closer to one-sixth; at the same time, the smallest size class accounts for roughly 90 percent of all firms, so its 3 percent firm count growth rate reflects a large gain in the number of small firms.

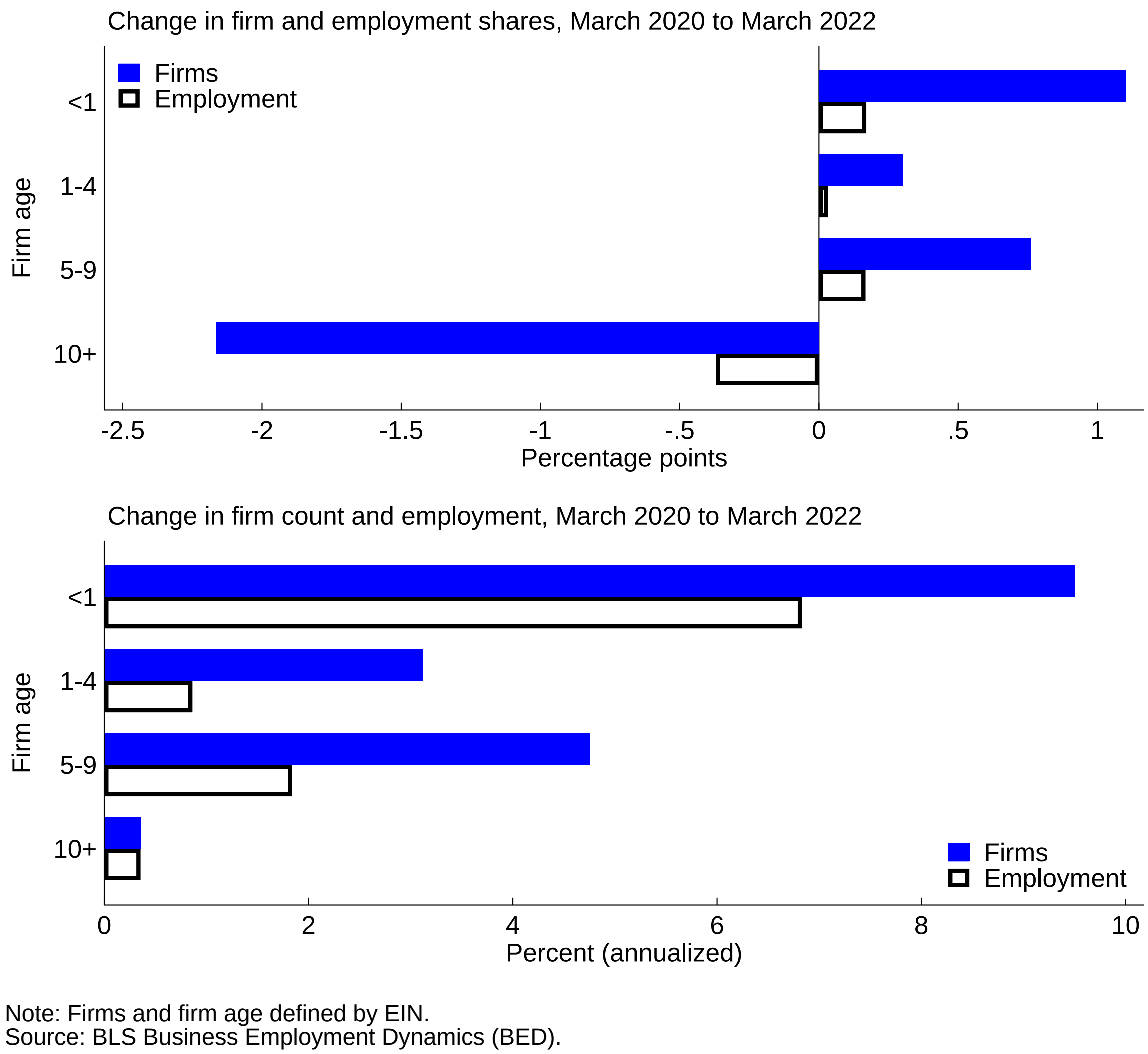
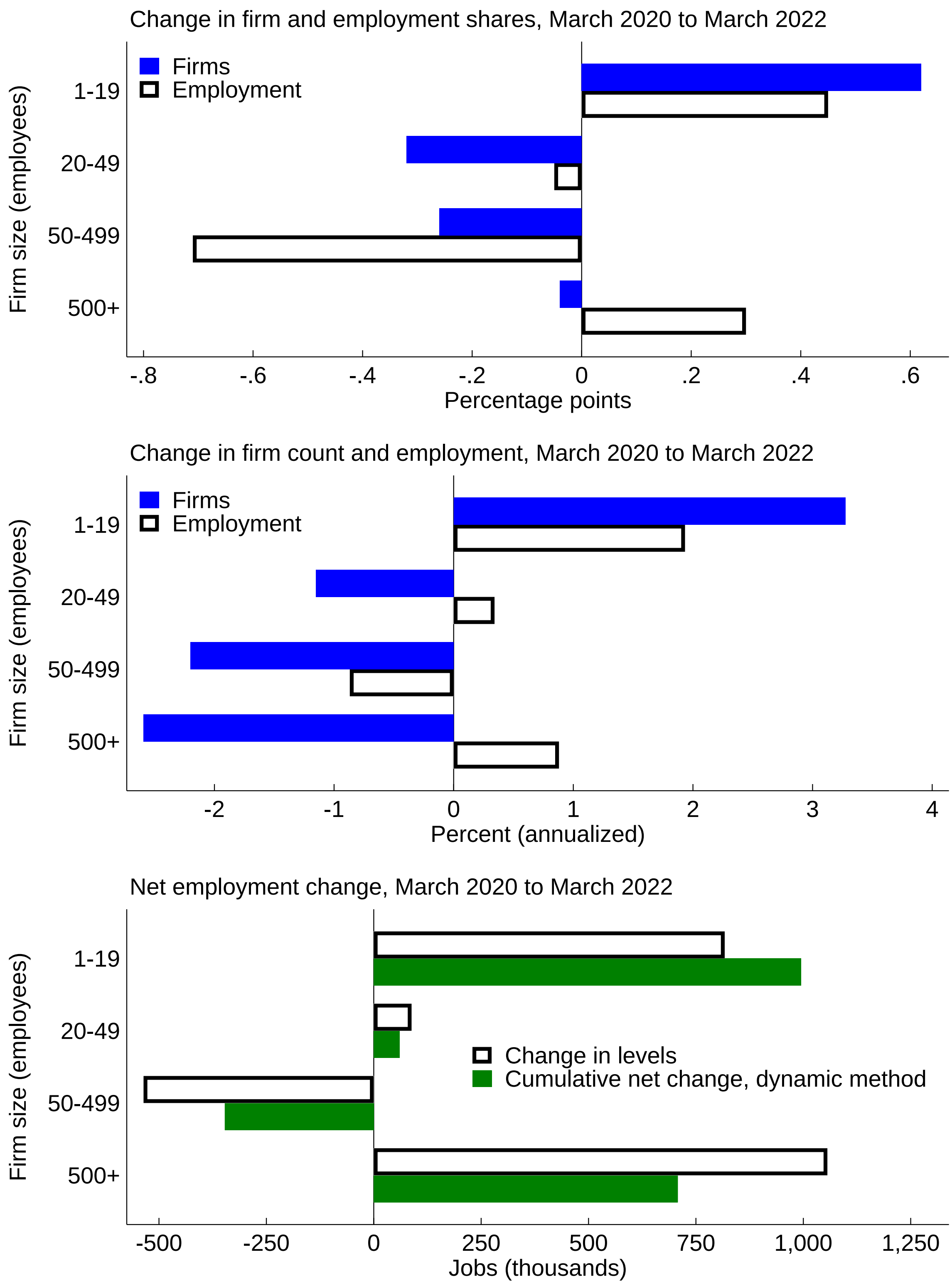


Figure 22: Changing firm age distribution

As just noted, a challenge associated with firm size distribution analysis is that firms may move either direction across the distribution. But an attractive feature of the BED is that statistics on what BLS denotes as *dynamic sizing* are provided. Dynamic sizing assigns firm job growth to the size bin in which it occurred. For example, if a firm increases from 0 (i.e., is a firm birth) to 35 over a window of time, the first 19 jobs added are attributed to the $1-19$ size class, and the increase from $20-35$ jobs is attributed to the $20-49$ size class. Thus, dynamic sizing provides insights into how much of the change in employment observed by size class is due to firms moving across size classes relative to changes within size classes. The BED provides dynamic sizing-based job growth by firm size bin on a quarterly basis.[30]

The third panel of figure 23 reports both the actual change in the level of employment

[30]See Helfand et al. (2007) for discussion of the BLS dynamic sizing methodology.



Note: Firms defined by EIN. Dynamic method distributes net growth across size categories in which it occurs.
Source: BLS Business Employment Dynamics (BED).

Figure 23: Changing firm size distribution

associated with each size bin (hollow bars), which is based on comparing employment levels in March 2022 and March 2020, and the cumulative dynamic sizing-based employment change (green bars, constructed by summing quarterly dynamic job flows, by size class, from March 2020 through March 2022). Consider the smallest size class; since the green bar (dynamic change) is larger than the hollow bar (change in levels), we can infer that there was net movement of firms up and out of this size bin; job growth of firms that "graduate" out of the size class is (partly) attributed to that size class under dynamic sizing (green bar) but is not attributed to that class when we simply measure the change in static employment levels (hollow bar). This result for the smallest class is consistent with the surge in firm births, which are typically small, and suggests that some of these firm births—and perhaps also some pre-existing small firms—grew out of this size bin. In contrast, for the largest size class, the hollow bar is larger than the green bar, from which we can infer that there was net movement of firms downward out of this size bin; this is consistent with the net decline in the number of firms in this size class shown in the middle panel.

Additional perspective on firm size can be gained by studying the average size of new firm entrants; appendix figure C11 shows that the average size of new firm entrants in BED data stepped down in the pandemic, consistent with our earlier discussion about unit counts versus employment from entrants. But figure C11 also shows that average entrant size *relative to average incumbent size* has remained on its pre-pandemic trend; that is, the drop in average entrant size is similar—relative to trend—to the change in average incumbent size. In other words, the relative small size of entrants in the pandemic is not unique to entrants. (Figure C11 also shows BED average size patterns relative to BDS data in the pre-pandemic period; we discuss this in the data appendix).

These shifts in the firm age and size distribution are remarkable, particularly in a recessionary environment; small and young firms—including young firms born before the pandemic and its dramatic business formation surge—appear to have fared remarkably well during the pandemic. But how much have these shifts reversed the pre-pandemic trends toward mature and large firms? The answer is: "not much." Figure 24 depicts the evolution of indices of employment (left panels) and firm counts (right panels) by firm age (top panels) and firm size (bottom panels). Focusing on the top panels reporting firm age data, the pre-pandemic shift in activity toward mature firms is evident as the indices of mature-firm employment (left) and firm counts (right) rise dramatically during 2000-2020.[31] In contrast, consistent with the decline in employer business entry, the indices for young firms (especially firm births at age zero) decline, on net, over this 20-year period. In the pandemic, these trends begin to reverse—but the decline for mature firms is very modest.

Turning to the evolution of the size distribution (bottom panels of figure 24), the activity shift toward larger firms in recent decades is evident.[32] Again, in the pandemic we have seen some reversal of earlier trends—especially for small firm counts, but not so much on

[31] We have confirmed with BLS staffers that there is not a left-truncation bias in the firm age files starting in 2000, despite public-use BED data only starting in 1992, as the BLS has internal microdata affording full accounting of the age 10+ category starting in 2000.

[32] For firm size, we are able to start in 1994 rather than 2000 given we don't face left truncation of the firm size measure as we do for the firm age measure.

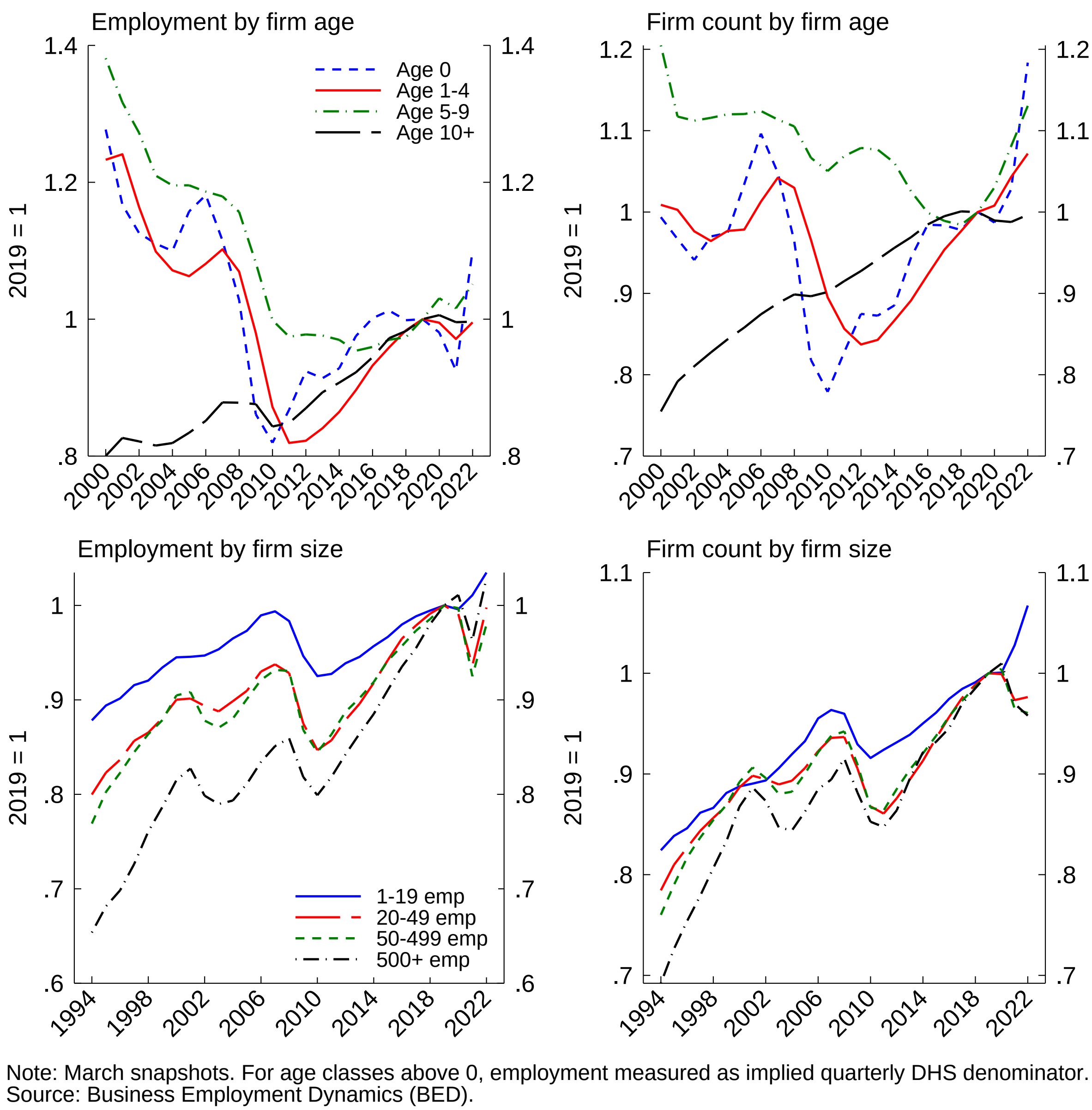


Figure 24: Evolution of firms and employment by age and size

the employment side. Large firms have more employment in 2022 than in 2019, consistent with our evidence above.

Our reading of the data is that there is potentially a beginning of a reversal of the shift in activity to large and mature firms; this is noteworthy and suggests young and small firms weathered the pandemic reasonably well (and, of course, entry has been remarkable), but so far the reversal relative to previous trends is quite modest. A related way to see that the impact has been modest is to compare firm- and employment-weighted entry rates, which we do in appendix figure C1; there is a notable increase in the firm-weighted startup rate, but the increase in the employment-weighted startup rate is less noteworthy.

It is too early to declare an end to the multi-decade decline in business dynamism; such an end will require a *sustained* increase in employer business entry with, in turn, robust post-entry dynamics (i.e., not a decline in survival rates and post-entry growth conditional on survival). A one-time increase of entry and job reallocation—even if spanning a few years—is different from a persistent elevation of dynamism flows. Still, the striking rise in young and small firm activity in the pandemic is noteworthy.

7 Taking stock

Using several official data sources, we document close relationships between business applications, business entry, and job and worker flows during the pandemic. Our findings indicate that the surprising surge in business applications and registrations seen during the pandemic represented genuine entrepreneurial activity and resulted in considerable job creation and reallocation of jobs and workers. This 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. The increase in entrepreneurial activity left its mark on the firm age and size distributions, with a higher share of activity accounted for by young and small firms.

Our findings are consistent with the surging applications yielding increasing new 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, so the pandemic may have provided entrepreneurial opportunities to minority groups that have historically faced challenges to business entry.[33]

A related issue that warrants further attention is the high-frequency dynamics of applications and business entry over the course of the pandemic. As we have noted, the surge in applications came in two waves: an initial short-lived wave in the summer (especially July) of 2020 then a second, still-ongoing wave commencing in early 2021. It may be that these two waves reflect different incentives and dynamics. The first wave may reflect the distinct market opportunities that arose just after the onset of the pandemic (e.g., online retail), but it may also reflect an increase in nascent entrepreneurship or entrepreneurial brainstorming. Many people found themselves with extra *free* time in the summer of 2020 given avoidance

[33] In pre-pandemic data, Dinlersoz et al. (2023) find that Census tracts with higher African American shares of population have higher application rates, but lower transition rates to becoming employers. The latter effect dominates so that Census tracts with higher African American shares of the population have lower employer startup rates per capita. It is of great interest to know whether these distinct patterns of applications and transitions changed in the pandemic.

of high-contact leisure activities and time savings from fewer commutes; some may have used that time—along with broader reassessment of career goals—to consider starting a business. In some cases, these early entrepreneurial ideas may have been overtaken by the (partial) return to more normal patterns of work and leisure later in 2020. In contrast, in 2021, vaccines started becoming available and pathways out of pandemic isolation were becoming increasingly clear as the country gradually transitioned toward a post-pandemic new normal. Potential entrepreneurs had more information to plan and start serious businesses by 2021 and this has continued through 2023. We raise these issues since it may be that the transition dynamics of applications to new businesses are very different across these waves. We still lack the data to rigorously discern this distinction, but we do find preliminary evidence for lower transition rates in the early wave, which we discuss in appendix section B.

Our strongest evidence on the surge in business entry is from data on gross and net *establishment* entry, which includes both new firms and new establishments (new operating locations) of incumbent firms. We find a large and sustained increase in aggregate gross and net establishment entry through 2022:Q4, and the industries and locations with the largest increases in gross and net establishment entry tend to have the largest increases in new business applications. Our evidence on *firm* entry is consistent with these patterns but only available through 2022:Q1 and with less industry and spatial detail. The incentives for new business opportunities induced by the pandemic and its aftermath apply to both new and existing firms, but is the distinction important? Both types of establishment entry are inherent components of reallocation of business activity across the economy; but historically, rapid post-entry growth and innovation are more associated new firms than new establishments of existing firms.[34]

Our findings also raise questions about the role of pandemic policies that strongly supported aggregate demand and eased credit conditions—which may be expected to boost firm entry—while also subsidizing incumbent firms via the PPP, the Main Street Lending Program, and the Federal Reserve's Corporate Credit Facilities; Decker et al. (2021) find that these business support policies included virtually the entire (incumbent) business distribution in their nominal scope for firm size, industry, and legal form. We must leave these and related questions for future research, which we hope will be informed by the large collection of facts we have assembled. In the meantime, our existing results suggest that entrepreneurship has played a key role in pandemic-era labor market dynamics.

One topic that is conspicuously missing from our analysis is an investigation of the surge in business applications that are likely *non*employers. Per Bayard et al. (2018), likely nonem-

[34] We have some preliminary evidence this distinction is important. The BED annual files that currently run through 2022:Q1 permit computing establishment entry for establishments of age<1 year old and for firms of age<1 (where by construction the establishments are also age<1). From 2019:Q1 through 2022:Q1, annual total establishment births (i.e., age< 1) rose by 38 percent, while the annual number of establishments at new firms grew at 21 percent (the latter is consistent with the firm entry rates reported in figure C1). Both are substantial, but the higher growth of total establishment births suggests an important role for new establishments at incumbent firms. Notably, though, we also find total establishment births grew more rapidly from 2020:Q1 to 2021:Q1 than establishments at firm births, suggesting establishment entry for existing firms was more resilient *early* in the pandemic than firm births.

ployer applications have a very low probability of becoming employer businesses (about 3 percent), and prior to the pandemic these applications tracked nonemployer activity reasonably well (Haltiwanger, 2022, and see our appendix A). Given the very large increase in likely nonemployer applications, the increase in entrepreneurship may be substantially greater than we have characterized given the potential increase in new nonemployer businesses. But the Nonemployer Statistics (NES) from the Census Bureau are currently available only through 2020. An alternative path is to use the BLS/Census Bureau Current Population Survey (CPS) or other household surveys that track self-employment activity; but there has been a growing discrepancy between self-employment activity tracked by the administrative data, such as the NES, and household data (Abraham et al., 2021). Relatedly, the nonemployers of relevance to the BFS are those with an EIN, but most nonemployers do not have an EIN. Nonemployers with EINs are substantially larger than those without an EIN (Davis et al., 2009); only 15 percent of sole proprietors have EINs, and the small sole proprietors without EINs are dominated by individuals for whom nonemployer activity is supplemental (often to a wage and salary income) and/or reflects stopgap activity. Published NES statistics do not separately tabulate sole proprietors with and without EINs, and the CPS only distinguishes between incorporated and non-incorporated self-employed. The bottom line is there are challenges to investigating the implied dynamics of the surge in likely nonemployers. But given the magnitude of the increase in likely nonemployer applications (figure 1), exploring this topic is of considerable interest; moreover, there has been much discussion of the pandemic changing attitudes toward work, including the recognition that important tasks can be done remotely. And an argument could be made that the non-pecuniary benefits of *being one's own boss*—as discussed in Hurst and Pugsley (2011)—may have risen. A potential implication is that individuals have increasingly decided to go out on their own as nonemployers, but at this point nonemployer measurement is limited.

8 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. Thus, 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 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; Pugsley et al., 2021). 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 increase 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; as we discuss in section 6, the shock to entry and reallocation seen during the pandemic would have to be very persistent, and the new cohorts of entrants would have to feature a sufficient number of high-growth firms, for past trends to be substantially reversed.

Third, it may be important to consider the dynamics of aggregate productivity prior to the pandemic. In appendix figures C16 and C17, 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 12), with high-tech industries like nonstore retail, software publishing, computer systems design, scientific research and development services (e.g., AI businesses), 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 service industries (e.g., restaurants and gyms) is consistent with this perspective. And the within-city donut effects we (and others) 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—to the extent that the change is persistent—but it is unclear that such reallocation would herald a burst of innovation and productivity growth. A related possibility is that the pandemic presented a shock to entrepreneurial preferences (as in Hurst and Pugsley, 2011); this is consistent with the drop in average entrant size. Whether persistent or not, such a shock is also unlikely to be associated with a burst of innovation and productivity growth.

Finally, we acknowledge the widely speculated upon possibility of an economic slowdown in the coming quarters. Since early 2022, U.S. monetary policy has tightened materially in response to elevated inflation, and financial condition measures are now much more restrictive than they were in the early pandemic period (Ajello et al., 2023). While business applications have remained reasonably stable at their elevated pandemic level through mid-2023 (figure 1), monetary policy is typically thought to operate with "long and variable lags." 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.

References

Abraham, Katharine, John Haltiwanger, Kristin Sandusky, and James Spletzer, "Measuring the Gig Economy: Current Knowledge and Open Issues," in "NBER/CRIW Conference Volume on Measuring and Accounting for Innovation in the 21st Century" 2021.

Acemoglu, Daron, Ufuk Akcigit, Nicholas Bloom, , and William. R. Kerr, "Innovation, Reallocation and Growth," *American Economic Review*, 2018, *108*, 3450–3491.

Ajello, Andrea, Michele Cavallo, Giovanni Favara, William B. Peterman, John W. IV Schindler, and Nitish R. Sinha, "A New Index to Measure U.S. Financial Conditions," Technical Report, FEDS Notes. Board of Governors of the Federal Reserve System June 2023.

Akcigit, Ufuk and Nathan Goldschlag, "Where Have All the "Creative Talents" Gone? Employment Dynamics of US Inventors," Working Paper 31085, NBER 2023.

_ **and William R. Kerr**, "Growth through Heterogeneous Innovations," *Journal of Political Economy*, 2018, *26*, 1374–1443.

Alon, Titan, David Berger, R. Dent, and Benjamin Pugsley, "Older and slower: The startup deficit's lasting effects on aggregate productivity growth," *Journal of Monetary Economics*, 2018, *93.*

Autor, David, David Dorn, Lawrence F. Katz, Christina C. Patterson, and John Van Reenen, "The Fall of the Labor Share and the Rise of Superstar Firms," *Quarterly Journal of Economics*, 2020, *135*, 645–709.

Barnatchez, Keith, Leland D. Crane, and Ryan A. Decker, "An Assessment of the National Establishment Time Series (NETS) Database," Finance and Economics Discussion Series 2017-110, Federal Reserve Board 2017.

Bayard, Kimberly, Emin Dinlersoz, Timothy Dunne, John Haltiwanger, Jarmin Miranda, and John Stevens, "Early-Stage Business Formation: An Analysis of Applications for Employer Identification Numbers," Working Paper 24364, National Bureau of Economic Research March 2018.

Board of Governors of the Federal Reserve System, "Monetary Policy Report," June 2020.

Breaux, Cory and Alisha Gurnani, "PPP-BFS Project," presentation, US Bureau of the Census September 2022.

Cajner, Tomaz, Leland D. Crane, Ryan A. Decker, John Grigsby, Adrian Hamins-Puertolas, Erik Hurst, Christopher Kurz, and Ahu Yildirmaz, "The

U.S. Labor Market during the Beginning of the Pandemic Recession," *Brookings Papers on Economic Activity*, 2020, *Summer*, 3–33.

Chow, Melissa C., Teresa C. Fort, Christopher Goetz, Nathan Goldschlag, James Lawrence, Elisabeth Ruth Perlman, Martha Stinson, and T. Kirk White, "Redesigning the Longitudinal Business Database," Working Paper 28839, National Bureau of Economic Research May 2021.

Crane, Leland, Ryan Decker, Aaron Flaaen, Adrian Hamins-Puertolas, and Christopher Kurz, "Business Exit During the COVID-19 Pandemic: Non-traditional Measures in Historical Context," *Journal of Macroeconomics*, June 2022, *72.*

Davis, Steven and John Haltiwanger, "Labor Market Fluidity and Economic Performance," in "Re-Evaluating Labor Market Dynamics, 2014 Jackson Hole Symposium Volume" 2015, pp. 17–108.

_ and _ , "Dynamism Diminished: The Role of Housing Markets and Credit Conditions," Working Paper 25466, National Bureau of Economic Research January 2021.

Davis, Steven J. and John Haltiwanger, "Gross Job Creation, Gross Job Destruction, and Employment Reallocation," *The Quarterly Journal of Economics*, 1992, *107* (3), 819–863.

Davis, Steven J, John C Haltiwanger, and Scott Schuh, *Job Creation and Destruction*, The MIT Press, 1996.

Davis, Steven J., R. Jason Faberman, and John Haltiwanger, "Labor market flows in the cross section and over time," *Journal of Monetary Economics*, 2012, *59* (1), 1–18.

Davis, Steven, John Haltiwanger, C. J. Krizan, Ron Jarmin, Javier Miranda, Al Nucci, and Kristin Sandusky, "Measuring the Dynamics of Young and Small Businesses: Integrating the Employer and Non-Employer Businesses," in "Producer Dynamics: New Evidence from Micro Data," NBER/University of Chicago Press, 2009, p. 329–366.

Decker, Ryan A, John Haltiwanger, Ron S Jarmin, and Javier Miranda, "Where has all the skewness gone? The decline in high-growth (young) firms in the US," *European Economic Review*, 2016, *86*, 4–23.

_ , _ , _ , and _ , "Changing Business Dynamism and Productivity: Shocks vs. Responsiveness," *American Economic Review*, 2020, *110* (12), 3952—-3990.

Decker, Ryan and John Haltiwanger, "Business entry and exit in the COVID-19 pandemic: A preliminary look at official data," Technical Report, FEDS Notes. Board of Governors of the Federal Reserve System May 2022.

_ , _ , Ron Jarmin, and Javier Miranda, "The role of entrepreneurship in US job creation and economic dynamism," *Journal of Economic Perspectives*, 2014, *28* (3), 3–24.

_ **, Robert Kurtzman, Byron Lutz, and Christopher Nekarda**, "Across the Universe: Policy Support for Employment and Revenue in the Pandemic Recession," Working Paper 2020-099r1, Board of Governors of the Federal Reserve System 2021.

DeSalvo, Bethany, Frank Limehouse, and Shawn D. Klimek, "Documenting the Business Register and Related Economic Business Data," Working Paper 16-17, Center for Economic Studies 2016.

Dinlersoz, Emin, Timothy Dunne, John Haltiwanger, and Veronika Penciakova, "Business Formation: A Tale of Two Recessions," *American Economic Association: Papers and Proceedings*, May 2021.

_ **,** _ **,** _ **, and** _ , "The Local Origins of Business Formation," working paper CES-23-34, Center for Economic Studies 2023.

Duguid, James, Bryan Kim, Lindsay Relihan, and Chris Wheat, "The Impact of Work-from-Home on Brick-and-Mortar Retail Establishments: Evidence from Card Transactions," Working Paper 2023.

Elsby, Michale W. L., Bart Hobijn, and Aysegul Sahin, "The Labor Market in the Great Recession," *Brookings Papers on Economic Activity*, 2010, *Fall.*

Fairlie, Robert, "The Impact of COVID-19 on Small Business Owners: The First Three Months after Social-Distancing Restrictions," *Journal of Economics & Management Strategy*, 2020, *29*, 727–740.

Fazio, Catherine E., Jorge Guzman, Yupeng Liu, and Scott Stern, "How is COVID Changing the Geography of Entrepreneurship? Evidence from the Startup Cartography Project," Working Paper 28787, National Bureau of Economic Research May 2021.

Fazio, Catherine, Jorge Guzman, and Scott Stern, "New Business Needs a Big Rescue, Too," *Forbes*, Apr 2020.

Foster, Lucia, Cheryl Grim, John C. Haltiwanger, and Zoltan Wolf, "Innovation, Productivity Dispersion, and Productivity Growth," in "Measuring and Accounting for Innovation in the Twenty-First Century," NBER/University of Chicago Press, 2019, pp. 103–136.

Guzman, Jorge and Scott Stern, "Nowcasting and placecasting entrepreneurial quality and performance," in "Measuring Entrepreneurial Businesses: Current Knowledge and Challenges," University of Chicago Press, 2017, pp. 63–110.

_ **and** _ , "The State of American Entrepreneurship: New Estimates of the Quantity and Quality of Entrepreneurship in 32 US States, 1988-2014," *American Economic Journal: Economic Policy*, 2020, *12* (4), 212–243.

Haley, Shane and Kennedy Keller, "The NAICS 2022 Update and Its Effect on BLS Employment Estimates in the Retail Trade Sector," *Monthly Labor Review*, September 2023.

Haltiwanger, John, "Applications for New Businesses Contract Sharply in Recent Weeks: A First Look at the Weekly Business Formation Statistics," mimeo, University of Maryland 2020.

_ , "Entrepreneurship During the Covid-19 Pandemic: Evidence from the Business Formation Statistics," *Entrepreneurship and Innovation Policy and the Economy*, 2022, *1*, 9–42.

_ **, Henry Hyatt, Lisa Kahn, and Erika McEntarfer**, "Cyclical job ladders by firm size and firm wage," *American Economic Journal: Macroeconomics*, 2018, *10* (2), 52–85.

_ **, Ron S. Jarmin, and Javier Miranda**, "Who Creates Jobs? Small versus Large versus Young," *Review of Economics and Statistics*, 2013, *95* (2), 347–361.

Handwerker, Elizabeth Weber and Lowell G. Mason, "Linking Firms with Establishments in BLS Microdata," *Monthly Labor Review*, June 2013, pp. 14–22.

Hansen, Stephen, Peter John Lambert, Nicholas Bloom, Steven J. Davis, Raffaella Sadun, and Bledi Taska, "Remote Work Across Jobs, Companies, and Space," Working Paper 32007, National Bureau of Economic Research March 2023.

Helfand, Jessica, Akbar Sadeghi, and David Talan, "Employment Dynamics: Small and Large Firms over the Business Cycle," *Monthly Labor Review*, March 2007, pp. 39–50.

Hurst, Erik and Benjamin Pugsley, "What Do Small Businesses Do?," *Brookings Papers on Economic Activity*, 05 2011, *Spring.*

Jarmin, Ron and Javier Miranda, "The Longitudinal Business Database," Working Paper 02-17, Center for Economic Studies 2002.

Karahan, Fatih, Benjamin Pugsley, and Ayşegül Şahin, "Demographic Origins of the Startup Deficit," working paper 25874, NBER 2019.

Loecker, Jan De, Jan Eeckhout, and Gabriel Unger, "The Rise of Market Power and the Macroeconomic Implications," *Quarterly Journal of Economics*, 2020, *135*, 561–644.

Molloy, Raven, Christopher L. Smith, Riccardo Trezzi, and Abigail Wozniak, "Understanding Declining Fluidity in the U.S. Labor Market," *Brookings Papers on Economic Activity*, 2016, *Spring.*

O'Brien, Connor, "More Physical Places of Businesses Open Now than Pre-Pandemic, Led by Sun Belt Metros," `https://eig.org/more-physical-places-of-businesses-open-now-than-pre-pandemic-led-by-sun-belt-metros/` April 2022. Accessed: September 27, 20220.

Pugsley, Benjamin, Petr Sedlacek, and Vincent Sterk, "The Nature of Firm Growth," 2021.

Ramani, Arjun and Nick Bloom, "The Donut Effect: How COVID-19 Shapes Real Estate," Policy Brief, Stanford Institute for Economic Policy Research (SIEPR) January 2021.

Sadeghi, Akbar, "The Births and Deaths of Business Establishments in the United States," *Monthly Labor Review*, December 2008, pp. 3–18.

A Data appendix

We gather data from a variety of sources, all of which are public-use files from U.S. statistical agencies.

In most cases, we use data that have been seasonally adjusted by the statistical agencies. In certain cases we seasonally adjust the data ourselves, either because seasonally adjusted series are not available (as is the case for the Business Formation Statistics 3-digit NAICS files at weekly frequency) or because doing so is more appropriate given the nature of data transformations we employ (e.g., our Quarterly Workforce Indicators exercises). We use additive seasonal factors, but results are generally similar under multiplicative seasonal factors where possible; and we estimate seasonal factors on all data, not excluding the pandemic period, relying on standard outlier routines to look through large pandemic swings. We use the Census X-13ARIMA-SEATS algorithm implemented through the SAS X13 procedure.

Our county-level analyses are complicated by a recent change in county definitions for Connecticut. New county definitions are present in BFS and Census population data starting in 2022. In most cases, new county definitions roughly approximate old definitions (either in one-to-one or many-to-one fashion). In certain cases we share out population and applications from the new scheme to the old scheme using population shares from the Federal Register notice announcing the change.[35] This issue does not (yet) affect QCEW counties. Our rough mapping is not critical for our results; all county-level results are nearly quantitatively identical if Connecticut is omitted.

We next provide details on each main data source in turn.

A.1 Census Bureau Business Formation Statistics (BFS)

The BFS are based on IRS applications for new EINs integrated with the Census Bureau's Longitudinal Business Database (LBD).[36] The Census Bureau receives the application data from the IRS on a weekly flow basis in almost real time. The *weekly* BFS series is publicly released on Thursday for the prior week (just for total applications), and the *monthly* series (with the narrower series listed below) are released within two weeks of the end of the reference month.

The BFS excludes applications that are not associated with business formation such as applications for tax liens, estates, trusts, or certain financial filings as well as applications lacking geographic information; the BFS also excludes many applications associated with public administration (NAICS 92), farms, private households, and civic or social organizations. Business owners operating under their social security number (rather than an EIN) will not appear in BFS. However, many sole proprietors do obtain EINs; employer sole proprietors need an EIN to file payroll taxes, and even among nonemployers, having an EIN

[35] See `https://www.federalregister.gov/documents/2022/06/06/2022-12063/change-to-county-equivalents-in-the-state-of-connecticut`.

[36] The BFS was initially described by Bayard et al. (2018). BFS data and related technical documentation can be found at `https://www.census.gov/econ/bfs/about_the_data.html`.

facilitates doing business with other businesses and other business needs (e.g., having a business bank account) and can help prevent identity fraud. Nonemployer sole proprietors with EINs have three times the revenue of sole proprietors without EINs, on average (Davis et al., 2009).

There are four main application series published in the BFS; their names as given in the actual data files are:

- **BA: (Total) business applications** (excluding only the items mentioned above, such as trusts).

- **HBA: High-propensity business applications** are those applications deemed (based on internal Census Bureau modeling) to have a high propensity to turn into a business with payroll. **We refer to the HBA series as "likely employers."**

- **WBA: Business applications with planned wages** are applications that feature a planned date of first wage payments to employed workers. We do not use this series in the present paper.

- **CBA: Business applications from corporations** as indicated on the application form. We do not use this series in the present paper.

The likely employer series (HBA) consists of applications with any of the following characteristics: (a) for a corporate entity, (b) that indicate they are hiring employees, (c) that provide a first wages-paid date (planned wages); or (d) that have a NAICS industry code in accommodation and food services (72) or in portions of construction (237, 238), manufacturing (312, 321, 322, 332), retail (44, 452), professional, scientific, and technical services (5411, 5413), educational services (6111), and health care (621, 623). The industry selection is based on industries with a high propensity to transit to employer businesses based on historical patterns.

Additionally, the Census Bureau leverages its internal data on actual employer firm formation (from the LBD) to provide information about likely and actual "transitions" from application to employer business. Among others, the BFS includes the following resulting series:

- **BF4Q/BF8Q: Business formations within 4 (8) quarters** count applications that result in actual employer firm formations within 4 or 8 quarters.

- **PBF4Q/PBF8Q: Projected business formations within 4 (8) quarters** feature predicted employer firm formations resulting from applications, based on internal Census Bureau modeling described in Bayard et al. (2018).

Most of our analysis of transitions focuses on the 8-quarter horizon since it is more complete, but we include some analysis of the 4-quarter horizon in appendix tables. The transition series reflect actual transitions through 2020:Q4, the latest date through which firm births are available in the Longitudinal Business Database at the time of writing. Thus, the actual 8-quarter series features applications through 2018:Q4, and the actual 4-quarter series features applications through 2019:Q4. The *projected* series (PBF4Q/PBF8Q) predictive model is based on application characteristics including whether the application has planned wages and whether the application is for a new corporation, as well as detailed industry information.

Our focus is on employer business formation—and predictions thereof—but we also report "likely nonemployer" or "NHBA" series, which we define as total applications (BA) minus likely employer applications (HBA). As we have noted, Bayard et al. (2018) find that the propensity for likely nonemployer applications to transition to *employer* businesses is very low (about 3 percent). There has been less microdata analysis of the transitions of NHBA applications to *nonemployer* businesses, but aggregate evidence suggests a close relationship between fluctuations likely nonemployer applications and actual nonemployer business activity. We provide a crude, limited analysis here. Generating the projected nonemployer index from likely nonemployer applications is as follows (this is similar to Haltiwanger, 2022):

$$NESPredicted_t = (1 - ExitRate(t))NES_{t-1} + NHBA_t \tag{A1}$$

where $NESPredicted_t$ is the predicted nonemployer index; $ExitRate(t)$ refers to the nonemployer firm exit rate in year t, NES_{t-1} refers to the total number of actual operating nonemployer businesses in year $t-1$—which we obtain from the Census Bureau's Nonemployer Statistics (NES)—and $NHBA_t$ is the number of likely nonemployer applications in year t (obtained, as noted above, by subtracting likely employers from total applications). This is a crude comparison for a number of reasons. First, the actual NES data include all nonemployer sole proprietors—both with and without EINs—whereas we would expect business application data to correspond only to those businesses with EINs; the NES does not separately tabulate business with and without EINs. Second, the $ExitRate(t)$ variable from equation A1 must necessarily be obtained from microdata, as the NES does not provide gross firm flows; we are not aware of recent microdata-based estimates so we obtain the exit rate from microdata-based work of Davis et al. (2009)—with just an average exit rate and no time variation. Third, there are unknown timing issues since we know little about the lag from application to forming a nonemployer business (whereas lags from application to *employer* business formation have been more thoroughly studied).

We show actual and application-predicted nonemployer series on C19; in spite of the limitations just discussed, the figure shows a tight relationship between the indices, with a correlation of 0.98. In the figure, the projected nonemployer series is provided through 2021. Given the increase in likely nonemployer applications in the pandemic, the index of of projected nonemployers is expected to increase substantially in 2021 and beyond. The lack of time series data on exits at high frequency is likely important for some of the year-to-year deviations in the actual and projected series. For example, in 2008 the actual series fell slightly while the projected series rose; it is likely that exits increased in 2008. There might also be timing differences between applications and transition rates (to being a nonemployer) that vary over time.

A strong relationship between likely nonemployer applications and actual nonemployer firms is also apparent in the cross section. The NES and likely nonemployer application data are available at the state level, and figure C20 uses these data for examining five-year growth rates in the NES and likely nonemployer applications per capita for intervals over the 2005-2019 period. It is apparent that these two series are closely related.

A.2 BLS Quarterly Census of Employment and Wages (QCEW) and Business Employment Dynamics (BED)

A.2.1 QCEW

The BLS business register underlies both the QCEW and the BED. The source data are state unemployment insurance records, so the scope of the data products is limited by unemployment insurance program participants; most nonfarm establishments are in scope, though in some states large nonprofit organizations are exempt from mandatory filings and may choose not to participate (see Decker et al., 2021, for extensive discussion of BLS scope with comparison to Census Bureau business register scope).

The QCEW consist of quarterly tabulations of establishment and employment counts (with some monthly detail by quarter); wage data are also included, though we do not use wages in the present paper. The tabulations feature extensive granularity, with detailed (6-digit) industry and geography to the county level. The scope of the QCEW is employer establishments as defined in unemployment insurance programs; as a result, the QCEW can include establishments that, in a given quarter, have zero paid employees. The QCEW is the primary source for annual benchmark revisions to the official U.S. payroll employment statistic, the Current Employment Statistics (which is benchmarked annually to match the March employment level of the QCEW, with some additional sources for establishments outside of unemployment insurance system scope). QCEW data are released with a lag of roughly two quarters, making the QCEW the most timely source of administrative business data. We use the QCEW to track *net* establishment entry: total establishment counts at industry, geography, or aggregate levels are readily available for each quarter, but gross establishment flows (i.e., total entry or exit) are not available in the QCEW.

While the QCEW is a product of administrative data, it is subject to revision in successive releases as the BLS must initially impute information for late-responding unemployment insurance units. We thank Seth Murray for sharing the following unpublished analysis of recent QCEW revision patterns. In the few years leading up to the COVID-19 pandemic, revisions from first to second release of quarterly private employment levels tended to be positive and averaged a bit under 50,000 jobs, but this average rose to nearly 200,000 after mid-2020. Subsequent revisions after the second release tended to be close to zero prior to the pandemic but have become slightly positive more recently. Murray also found that revisions tend to be inversely correlated with initial response rates.

The BLS does not consider the QCEW to be a time series product, but it is used as a time series in many settings. For example, the wage data from the QCEW inform quarterly compensation growth estimates for the National Income and Product Accounts (NIPA) produced by the Bureau of Economic Analysis; NIPA compensation estimates in turn inform compensation per hour growth estimates from the BLS Productivity and Costs statistical product. QCEW microdata are also used as inputs to the Current Employment Statistics net establishment birth-death model, which is used in monthly payroll employment estimates.

A.2.2 BED

More relevant for the present paper is that the QCEW microdata are used to construct the time series BED statistic that we use extensively in our analysis. The BED is based on longitudinally processed QCEW data and features a slightly narrower scope; in particular, establishments with zero reported employment in a quarter are strictly excluded from the BED (and may be counted as closures and openings as they move out of and into actual employer status). BED data are particularly useful for tracking gross flows of establishments and employment, allowing for measurement of establishment entry and exit as well as gross job creation and destruction. The BED facilitates further detail of establishment flows using the following variables:

- **Openings** include all establishments that have positive employment in the (third month of the) current quarter but zero employment (or no presence at all) in the (third month of the) prior quarter. Reopenings of previously operating establishments can be included.

- **Births** include only those establishments that are openings and have not appeared in any of the previous four quarters.

- **Closings** or closures include all establishments that had positive employment in the (third month of the) prior quarter but no employment (or no reporting) in the current quarter. Temporary closures can be included.

- **Exits** (called "deaths" in BLS documentation) are those closings that have no reported employment for four subsequent quarters. Exits are therefore published with a lag; see Sadeghi (2008) for detail and analysis of exit measurement.

Quarterly BED data are published with a lag of roughly three quarters, though reporting of exits are delayed as noted above. Importantly, BED data are only revised once each year in a benchmark revision (associated with the first-quarter estimate of each year); the "current" BED estimate is based on microdata associated with the first QCEW release. As noted above, QCEW revisions can be nontrivial and have been particularly noteable during the pandemic, so the most recent year of data in our analysis above should be thought of as preliminary.

The quarterly BED product does not allow users to distinguish between establishment births associated with incumbent firms and establishment births associated with newly formed firms. However, the BED also features an *annual* (March snapshot) "research" product that identifies employer *firm* births, where firms are defined based on EIN (see Handwerker and Mason, 2013). This firm definition contrasts with the broader definition from Census Bureau data, where firms are defined based on ownership or control and can feature multiple EINs per firm. Therefore, some new firms in the BED research product may actually be new EINs of existing firms by Census Bureau definitions. Still, firm births in the BED closely track the more broadly defined firm births from Census Bureau data (figure C1) and do not appear to overstate birth rates, as might be expected if the firm definition issue were significant. In both sources, a firm birth is defined as a firm with age zero, where firm age is based on the age of the oldest establishment in the firm.

The annual BED firm age product is available at the national and broad sectoral levels. These data are a valuable resource for watchers of U.S. firm dynamics, since the Census Bureau counterpart—the Business Dynamics Statistics—is published with a lag of years. We use BED firm age data extending through March 2022.

It is important to note that the BED made the transition from the NAICS 2017 standard to the NAICS 2022 standard starting with the release of the 2022:Q1 data. This change affected the entire series history. A major change in NAICS 2022 relative to NAICS 2017 is for industry 454, nonstore retailers—which includes increasingly important online retail businesses (and, as noted above, accounted for a disproportionate share of the business application surge); other industries in NAICS 454 are vending machine operators and direct selling establishments. NAICS 454 was a distinct industry group in the NAICS 2017 taxonomy, but for NAICS 2022 establishments from this industry were distributed into the specific industries where their online activity is occurring (e.g., an online retailer for electronic products becomes classified in the electronic products retail industries under NAICS 2022). See Haley and Keller (2023) for a helpful discussion of the NAICS 2017 to 2022 transition for the retail trade sector.

In discussions with BLS staff, we learned that the current vintage of the BED simply dropped the time series of industry groups which do not appear in the NAICS 2022 taxonomy (and newly created industries for 2022 are also omitted) since microdata necessary for full industry mappings were unavailable. We carefully examined the pre- and post-transition vintage data files and found that the total establishment count in 2021:Q4 is nearly 700,000 lower in the post-transition vintage than in the pre-transition vintage, and discontinuities in individual 3-digit industry groups affected by the transition are observable. As a result, in the current vintage the aggregate establishment count found by summing across 3-digit industries is roughly 10 percent lower than the aggregate count reported in high-level tabulations (the employment count discrepancy is similar). For this reason, all 3-digit BED tabulations in this paper are based on the last BED vintage to use NAICS 2017, which covers the period through 2021:Q4. This problem does not materially affect sector-level BED tabulations.

A.3 Census Bureau Business Dynamics Statistics (BDS) and comparison with the BLS business register

Census Bureau data on business dynamics feature slower release schedules than the BLS data described above—with annual snapshots released roughly 2.5 years delayed—but the Census data offer other advantages in terms of concepts and granularity. The Census Bureau's workhorse public use data product for business dynamics is the BDS, which consists of tabulations from the underlying Longitudinal Business Database (LBD).

LBD data derive from the Census Bureau Business Register and cover the near-universe of private nonfarm employer business establishments.[37] The LBD features high-quality firm identifiers based on firm ownership and control, which facilitates the study of firms with multiple EINs (whereas such firms would count as separate firms in BED data). The LBD has been used extensively in the firm dynamics literature; for example, LBD data first facilitated the study of the distribution of firm growth by both firm size and firm age (Haltiwanger et al., 2013) and have been used in the large literature on declining business dynamism (e.g., Decker et al., 2014). The ultimate source data for the LBD derive from federal tax information supplemented with Economic Census and other survey data housed at the Census Bureau. For detail on the LBD and the Census Bureau Business Register see Jarmin and Miranda (2002), Chow et al. (2021), and DeSalvo et al. (2016).

Like the annual BED firm age research product, the main BDS product is annual and features snapshots as of March of each year. Tabulations by firm age and size are available at the detailed industry level (up to 4-digit NAICS) and at the detailed geography level (counties). Additionally, the BDS features a *quarterly* research product on single-unit firms (the "BDSSU"), that is, firms with only one establishment. We use these sources in figure 2 alongside BLS sources and the BFS.

The QCEW/BED and the BDS provide data from independent business registers—state unemployment insurance records and federal tax and census data, respectively. Yet the aggregate figures they produce match reasonably well, albeit with some notable discrepancies. Figure C21 shows the number of firms (left panel) and establishments (right panel) as reported in the BDS and BED. Unit counts in the two data sources generally move together, and firm counts are particularly close. BDS features more firms than BED, though not by a wide margin; the higher firm count in BDS is surprising, though, given that the BDS features a broader firm definition, with multi-EIN firms counting only once in BDS while counting as multiple firms in the BED. As noted above, though, the BED is limited to the scope of the unemployment insurance system, and some nonprofits are not required to participate. This may help explain why the BED has fewer firms than the BDS, though further investigation is needed. Average firm size is somewhat lower in the BED than the BDS; while the two had very similar firm size in the 1990s, as of 2020 the average BDS firm had 25 employees while the average BED firm had just under 24.

Establishment counts show much more divergence; while the BED featured fewer establishments than the BDS in the 1990s, the BED establishment count surpassed the BDS count in the 2000s and there is now a large discrepancy—roughly 1 million establishments in the latest data. The discrepancy is even larger if the QCEW is used instead of the BED; while QCEW and BED are based on the same business register, the BED strictly omits establishments with zero employment and may also reduce counts through longitudinal cleaning.

The large establishment count in BLS sources relative to Census Bureau sources has been described before; for example, Barnatchez et al. (2017) document this discrepancy by comparing QCEW with County Business Patterns (which, like the BDS, is based on

[37] The most notable omission—from both Census Bureau and BLS employer business registers—is railroads; see Decker et al. (2021) for discussion.

the Census Bureau Business Register) and also show that the discrepancy is driven by small establishments. The authors find that in 2014, the number of establishments with fewer than 5 employees in the QCEW exceeds the comparable establishment count in the County Business Patterns by more than 30 percent; most other size categories feature similar establishment counts, though the County Business Patterns actually has more of the largest establishments. Consistent with small establishments being the source of the discrepancy, the QCEW actually has *lower* aggregate employment than County Business Patterns.

Taken together, these various discrepancies imply that the average establishment size has diverged between the two sources; indeed, average establishment size was between 16 and 17 employees in both sources in the mid-1990s, but after that the average size in the BED declined precipitously, reaching just above 15 in 2020, while average size in the BDS actually rose to above 18 in 2020. The establishment size discrepancy is much larger than the firm size discrepancy mentioned above. These establishment data discrepancies require further study, but one likely explanation is that movement of businesses between the employer and nonemployer universes is captured differently in the two sources.

These discrepancies notwithstanding, key patterns of firm dynamics are similar in the two sources, as can be seen from figure C1. Entry rates—both unweighted and employment weighted—exhibit reasonably similar fluctuations and are at roughly similar levels.

A.4 Census Bureau Quarterly Workforce Indicators (QWI)

The Census Bureau QWI combines source data related to both the BLS and the Census Bureau business registers; worker-level data and establishment characteristics come from state unemployment insurance records and the QCEW, while firm characteristics are obtained from the federal tax and census data underlying the BDS.

For our purposes the key advantages of the QWI are twofold:

1. Timely measurement of job flows at the narrow industry and geography level in addition to firm age and size bins; for our between-cell exercises we use up to 4-digit NAICS industry detail and up to county-level geography detail

2. Measurement of worker flows (particularly separations) at the county level

While a national QWI file is available, we obtain more control over coverage by combining state-level files. State files are updated by the Census Bureau with widely varying timing (dependent on state provision of data); we utilize a balanced panel of 45 states ranging from 2004:Q1 through 2022:Q2 and covering just over 80 percent of private sector employment as of 2020. The omitted states are Alaska, Arkansas, District of Columbia, Massachusetts, Michigan, and Mississippi.

In the QWI, we measure separations using the QWI SepBeg variable rather than the Sep variable. The latter measures all separations 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, which tends to be more quantitatively comparable to JOLTS worker flow estimates. 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. When expressing QWI variables as rates, we use the DHS denominator calculated as the average of Emp and EmpEnd, which are the beginning- and end-of-quarter employment, respectively.

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.

We also report data from the J2J product in figure 17 (where we show job-to-job separations). The J2J program is closely related to the QWI and uses the underlying worker linkages to track job-to-job flows.

A.5 BLS Job Openings and Labor Turnover Survey (JOLTS)

JOLTS provides the workhorse statistics for tracking worker flows in the U.S., with data for a given month being released with a two-month lag. JOLTS is the main source of the popular pandemic stylized fact about elevated quit rates (the "Great Resignation"). JOLTS data are based on a monthly survey in a sample of roughly 21,000 establishments. Response rates have trended down in recent years, and while this trend began before the pandemic, it accelerated in the pandemic; recent response rates have been just above 30 percent. Importantly, though, monthly JOLTS data are continually benchmarked against the Current Employment Statistics (CES)—the main U.S. payroll survey—to make net employment changes roughly consistent between the two products.

We use data on quits and layoffs from JOLTS (though the product also features data on hires and on separations other than quits and layoffs). Both quits and layoffs are measured as totals for the entire reference month. *Quits* include all voluntary separations except retirements or within-firm transfers. *Layoffs* include all layoffs and discharges expected to last more than 7 days.

A.6 Census Bureau American Community Survey (ACS)

The ACS is a monthly household survey designed to measure population demographics between decennial censuses and is the workhorse source of annual information about U.S. households by geography. The ACS sample methodology varies between the so-called "5-year" and "1-year" estimates; 5-year estimates feature full geographic coverage of the U.S. while 1-year estimates cover only geographic areas with populations of 65,000 or more. We use the ACS to measure growth in the faction of workers working from home (WFH) at the county level during 2019 through 2021 (the latest available); we use the 1-year estimates, so our exercises are necessarily limited to large counties. As in our "donut" exercises more broadly, we focus on large CBSAs, so our ACS-based exercises are limited to large counties within large cities.

The ACS data are limited in capturing only individuals who only work from home in the reference week of the survey (which differs across individuals); such measures have limitations since "hybrid" WFH home activity (i.e., some days at home and some days in office) will not be captured Still, the ACS WFH data show a large increase in working from home—from 5 to 15 percent at the county level. Even more strikingly, the right tail of the distribution shifts dramatically, with the 99th percentile increasing from 13 to 36 percent.

It is useful to compare the ACS-based WFH statistics to WFH patterns documented by from Hansen et al. (2023). Using vacancy postings, those authors produce data on the share of vacancies that include references to WFH, including hybrid work, and find large increases from 2019 to 2023. The ACS and the Hansen et al. (2023) vacancy data provide correlated patterns—with cities such as New York and San Francisco having very large increases in both sources. However, within-city patterns differ reflecting the fact that the ACS is based on location of residence while the vacancy data are based on location of business. While the vacancy data are more up to date (through June 2023), we use the ACS data given our interest in within-city variation (and in particular our interest in variation by place of residence).

B Applications and employer entry: Further discussion

B.1 Applications and firm births (pre-pandemic)

Our most convincing evidence of the relationship between applications and employer business entry uses the BFS applications and transitions from those applications to actual firm births. We report those results in the first two columns of table D2 using aggregate time series data, and in table D3 using state-by-quarter variation. We note that for the purposes of this analysis we have collapsed the monthly BFS series to the quarterly frequency to make the analysis comparable to our analysis below using the BED establishment births.[38] The elasticity is roughly centered on one across these specifications; for example, the elasticity of aggregate firm birth transitions within 8 quarters to aggregate likely employer applications is 1.230, as shown in the first column of table D2. A major advantage of this analysis is that the public domain series of transitions over the respective horizons are directly linked to the applications in a given month via the internal Census Bureau microdata; the firm births reported in these series are actually associated with the applications occurring in a given month within 4 or 8 quarters. Of course, the major limitation of this analysis is that actual transitions are only available for transitions that occur through the end of 2020; therefore, the 8-quarter transition series tracks applications through 2018:12, and the 4-quarter series tracks applications through 2019:12.

[38]Results are similar if we use the monthly data directly.

B.2 Applications and establishment births, pre-pandemic and pandemic

In the main text we describe a variety of indicators of employer business entry suggesting that that the surge in applications yielded a surge in employer business entry. A related question is whether the relationship between applications and business entry changed during the pandemic relative to pre-pandemic. We cannot directly answer that question with available data given that our measures of employer business entry (unlike the actual transitions found in BFS data) are not directly linked to the applications; in other words, we cannot be sure that the firm and establishment births we document in the main text reflect the same business applications that are represented in the applications data. However, we can explore whether the relationship between our proxies for transitions (establishment births) and applications changes in the pandemic relative to the pre-pandemic period—and even use cross-sectional variation to further describe this relationship. To start, we use quarterly BED establishment births, both nationally and at the state level; establishment births are the most up-to-date indicators of actual employer business entry but, as discussed in the main text and data appendix, appropriate caution needs to be used. Regressions relating quarterly national establishment births with likely employer applications are reported in columns 3, 4, and 5 of table D2; these columns use data ending in 2018:Q4, 2019:Q4, and 2022:Q4, respectively. We find that the elasticity of establishment births with respect to likely employer applications is positive and significant—and the coefficient actually increases when including the quarters from the pandemic (column 5).

The aggregate time series evidence of table D2 is compelling, but in table D4 we examine the elasticity for establishment births using state-by-quarter variation; the top panel reports elasticities for the pre-pandemic period, while the bottom panel includes the pandemic. We again find that the elasticity of establishment births with respect to likely employers is positive and significant; and the results are broadly similar whether or not we include the quarters during the pandemic.

B.3 BFS predicted firm births and actual establishment births, pre-pandemic and pandemic

We also consider the relationship between establishment births and the *projected* transition series; we focus here on the BFS series of predicted transitions within 4 quarters of application (PBF4Q). Again, we collapse the BFS PBF4Q series from monthly to quarterly to be integrated with the establishment quarterly birth series. While PBF4Q is a projected series for transitions within 4 quarters, it is in fact a weighted application series for the current quarter—where the weights are chosen to yield the most accurate prediction of transitions within 4 quarters (the weights are based on a model relating the probability of transition to detailed application characteristics). In this respect, the projected transitions series is based on a richer set of application characteristics than the likely employer series, and one might therefore expect the relationship between projected firm births and actual establishment births to be even stronger than the relationship between likely employer applications and actual establishment births. We report the elasticity of establishment births with respect to projected transitions (within 4 quarters) in table D5, where the top panel is limited to the pre-pandemic period while the bottom panel includes the pandemic. A careful comparison of the results shows the elasticities using the projected transitions series tend to be higher than those using the likely employer series (table D4). [39]

The results just described using establishment births and alternative application series are not the ideal comparison given lags between application and actual business formation. We next study the relationship between establishment births and the average of the PBF4Q over the current quarter *and prior 3 quarters* to account for lag dynamics. Recall again the PF4Q is essentially a weighted application series, so this is an average of this weighted application series over the current and prior 3 quarters. This is a simple way to capture the notion that employer business entry in the current quarter is likely related to applications in the current *and prior* quarters.

These exercises are reported in table D6, where the top panel refers to the pre-pandemic period while the bottom panel includes the pandemic. The elasticities using the multi-quarter lagged average of projected transitions are broadly similar to those using only the current-quarter projected transitions (table D5); this is a bit surprising but may reflect this somewhat crude way to investigate the underlying dynamics.

Our preferred approach to studying this elasticity—and how it may change during the pandemic—would be to use the relationship between applications in a given period and the actual transitions that emerge from those applications over alternative horizons; such analysis awaits the updating of the LBD and BFS data. Without such data, the current analysis in this appendix does not provide much guidance about the high-frequency changes in transition rates over the course of the pandemic.

Notably, we also find that pandemic-inclusive elasticities are uniformly higher when we exclude the year 2020 from the calculations, consistent with our discussion in the main text about the earlier (2020) versus later (2021-2023) waves of business applications. For example, the elasticity reported in column 5 of table D2 increases to 0.90 if we exclude 2020. We might speculate that transition rates exhibited higher-than-usual volatility in 2020 given the overall uncertainty and volatility of that period. We see a hint of lower transition rates in 2020 if we estimate predicted transition rates using the projected transitions relative to applications (PBF8Q/HBA). We find that July 2020, the month with the spike in 2020, has a predicted transition rate that is 12 percent lower than the average transition rate in 2019 (August 2020 has a predicted transition rate 9 percent lower).[40] In contrast, the average predicted transition rate in 2021 is less than 3 percent lower than in 2019, and the average in 2022 and 2023 is the same as in 2019. We note that one of the driving forces of this lower transition rate in mid-2020 is the nonstore retailers industry group (NAICS 454); this

[39]We use the 4-quarter transition series rather than the 8-quarter series in this analysis given our focus on current-period establishment births.

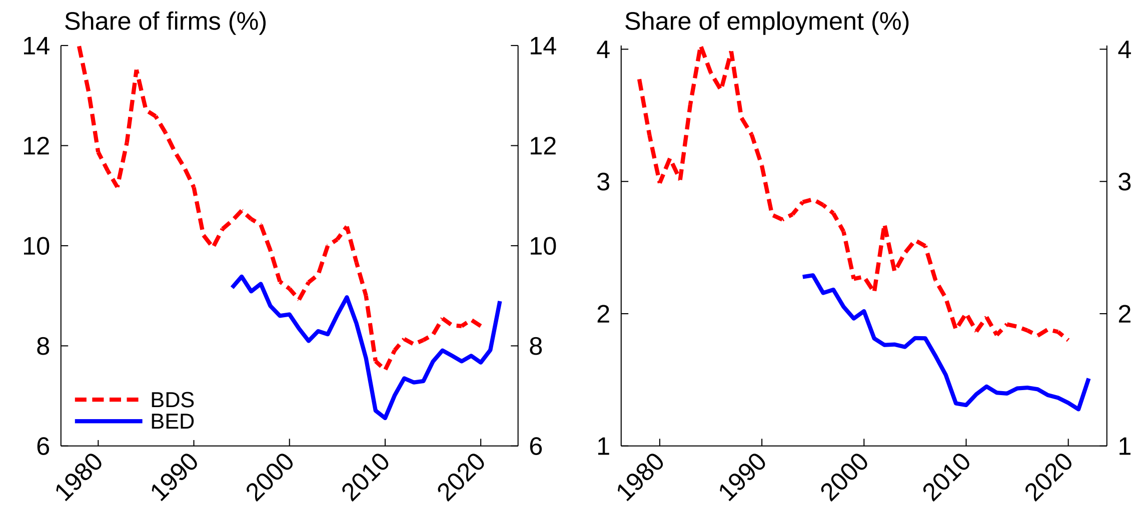
[40]For this discussion of high-frequency predicted transition rates we use the monthly BFS to highlight the volatility in 2020. We find broadly similar patterns using the ratio of PBF4Q/HBA. If we use BA as the denominator we observe an even larger percentage point decline in the predicted transition rate in July 2020 relative to the average transition rate in 2019.

is a nonemployer-intensive industry (prior to the pandemic 92 percent of nonstore retailers were nonemployers), and the dramatic increase in applications in this industry during 2020 reduces predicted rates of transition to employer businesses.

Another perhaps more transparent way of observing these high-frequency dynamics is to examine the patterns in figure C3 for PBF8Q (the dashed line in that figure during the post 2018 period). The dramatic surge in HBA in July 2020 is apparent, but observe that PBF8Q rises in July 2020 but not as dramatically. By December 2020, PBF8Q is not much higher than in 2019. In contrast, in 2021 and beyond there is a sustained increase in PBF8Q. We acknowledge that drawing inferences about changing transition rates over the course of the pandemic from PBF8Q is speculative and needs to be viewed with caution. However, we do find it interesting that the detailed characteristics of the applications changed over the course of the pandemic with implications for predicted transition rates in a pattern consistent with a decline in the summer of 2020 and then a recovery in 2021 and thereafter. Related to this discussion, our findings of increasing business births following the surge in applications become especially notable, as quarterly establishment births beginning in 2021:Q2 and for annual firm births during the year ending March 2022.

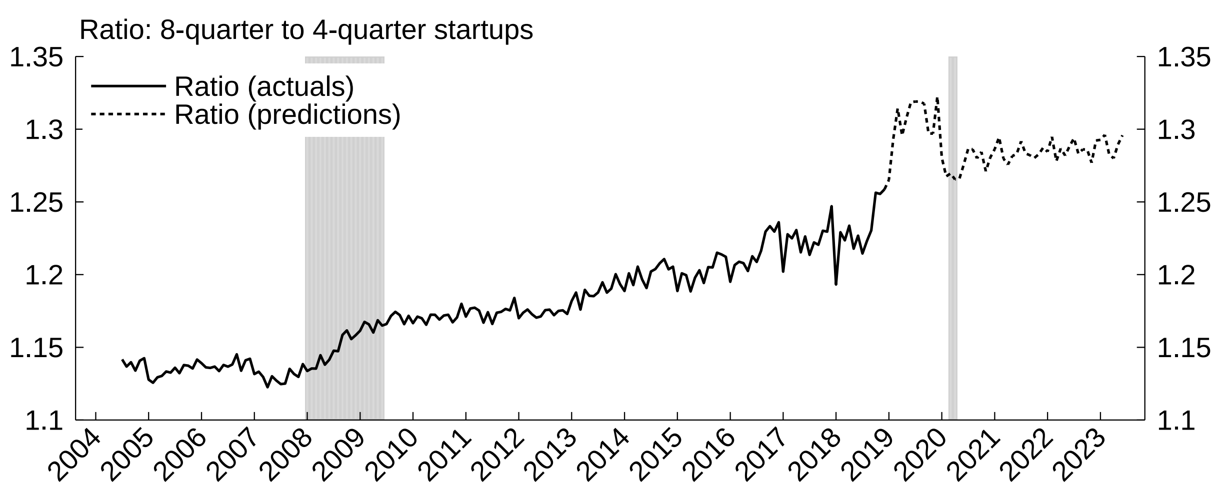
As a closing note for this section, our results suggest that the BFS projected transition series contain important information. For the main analysis in the paper, we focus on likely employer applications rather than projected transitions since the simple application count series are more transparent; this approach has low cost, as the two series are closely related (correlation of 0.9 in the aggregate data). Moreover, while it would be interesting to explore the cross-sectional dimensions of the projected transitions series further, this series is limited—like the likely employer series—to being available only at the national, broad sector, and state level in the public-use BFS data. In the main text, much of our cross-sectional analyses use 3-digit industry and county-level variation, where we are restricted to using total applications, the only BFS series available. In our analysis of the 3-digit and county-level variation we focus on the growth in applications and measures of employer business entry from the pre-pandemic (averaged over 2010-2019) to the pandemic (averaged 2020-2022) periods; this approach has the advantage of focusing attention on the surge in applications and measures of employer business entry in the pandemic without requiring analysis of the detailed timing issues discussed in this section.

C Supplemental figures



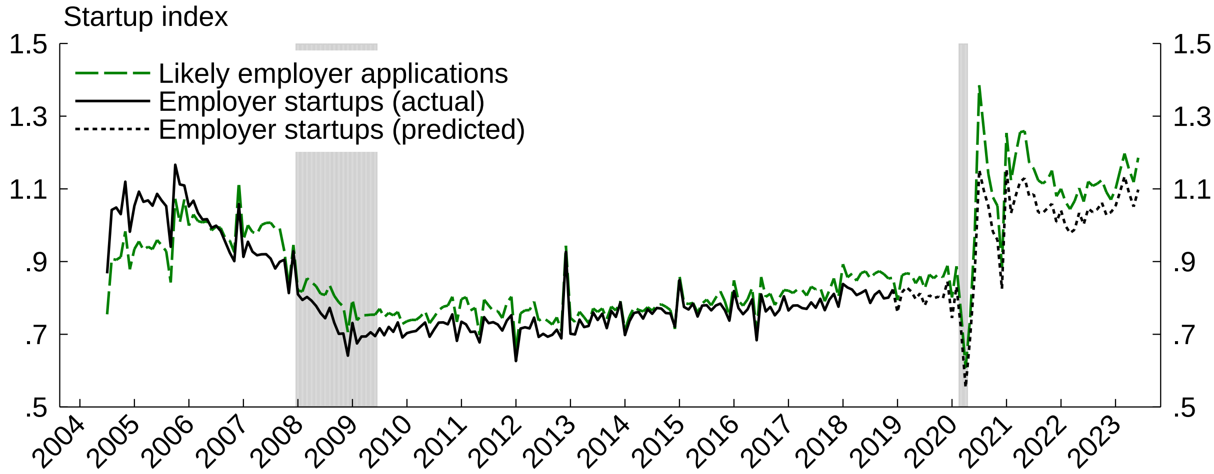
Note: Firm entry rates. Right panel uses DHS denominator.
Source: Business Dynamics Statistics (BDS) and Business Employment Dynamics (BED).

Figure C1: Startup Rates from the BDS and BED, Firm and Employment Weighted



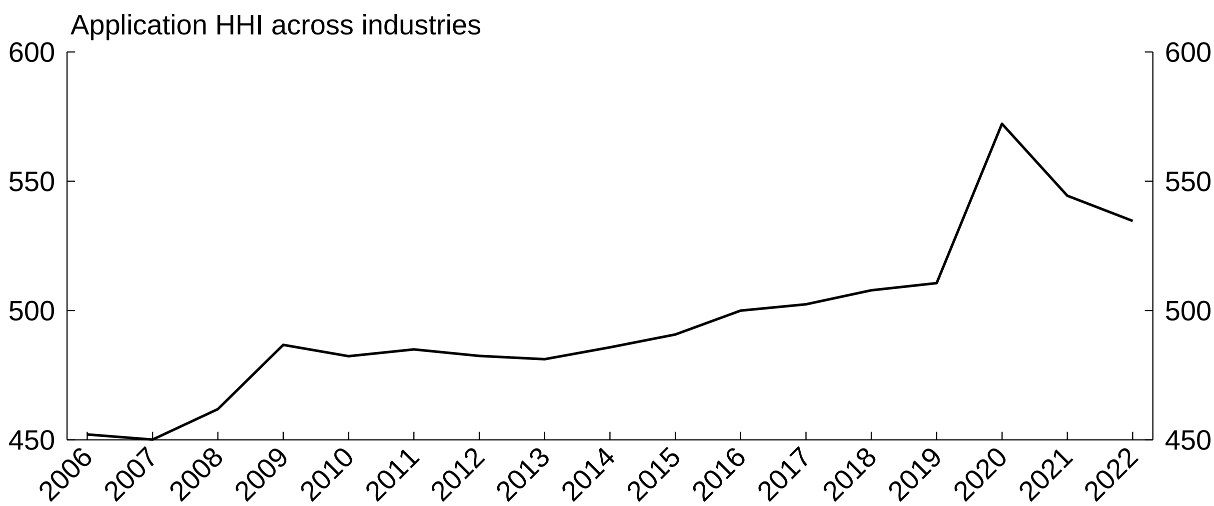
Note: Ratio of startups within 8 quarters of application to startups within 4 quarters of application.
Seasonally adjusted before calculation. Shaded areas indicate NBER recession dates.
Source: Census Bureau Business Formation Statistics.

Figure C2: Ratio of startups 8 quarters after application to startups 4 quarters after application



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 C3: High-propensity business applications and startups 8 quarters ahead



Note: Herfindahl-Hirschman index (HHI) for total applications (BA) across 3-digit industries.
Source: Census Bureau Business Formation Statistics.

Figure C4: Concentration of New business applications, 3-digit Annual

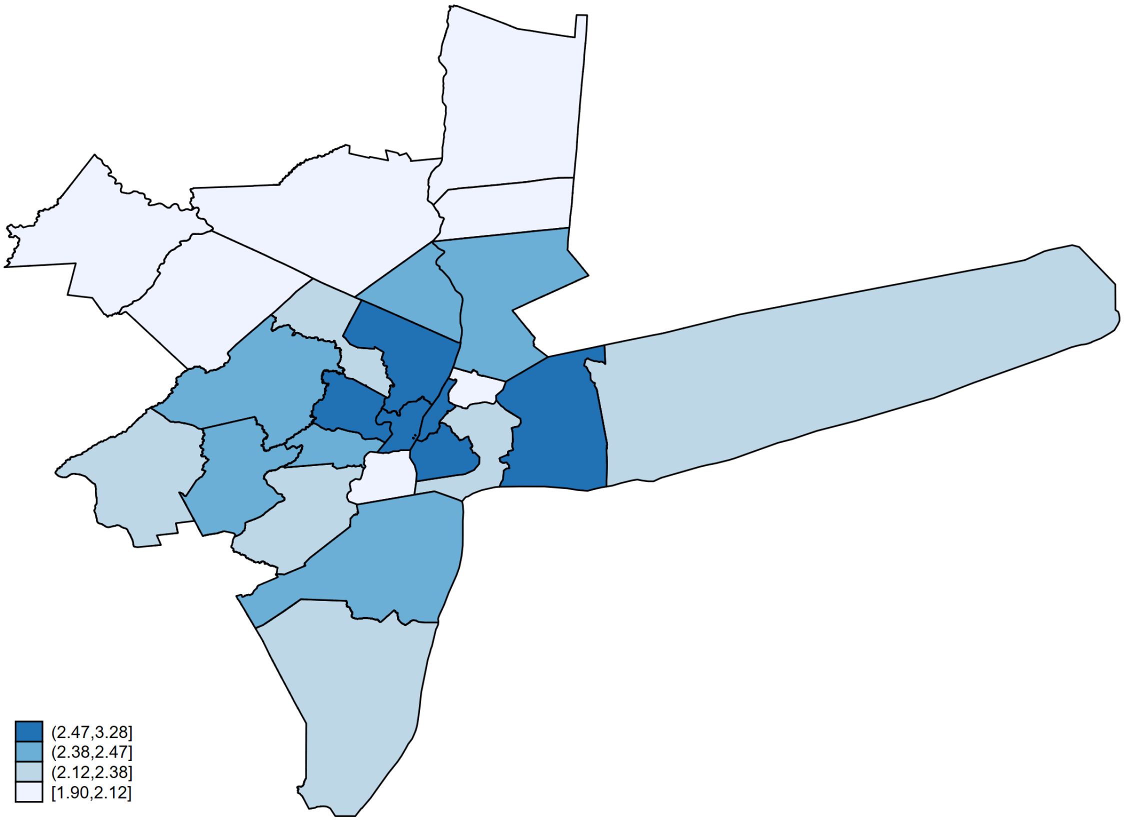


Figure C5: Average Applications Per Capita, NYC, 2010-19

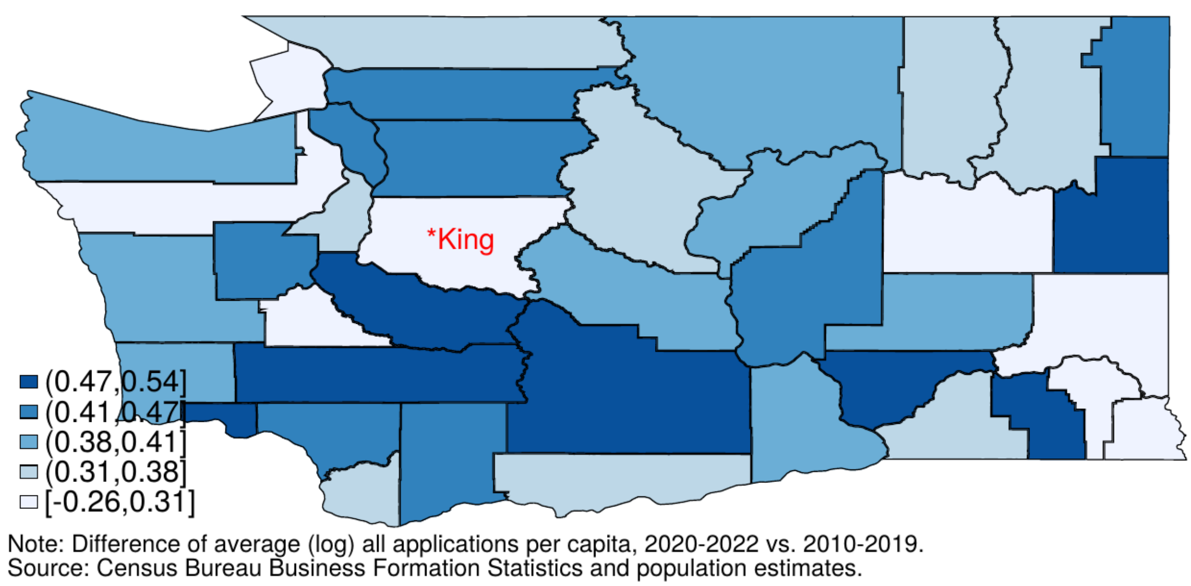


Figure C6: Washington State: Growth in applications per capita, 2020-2022 vs. 2010-2019

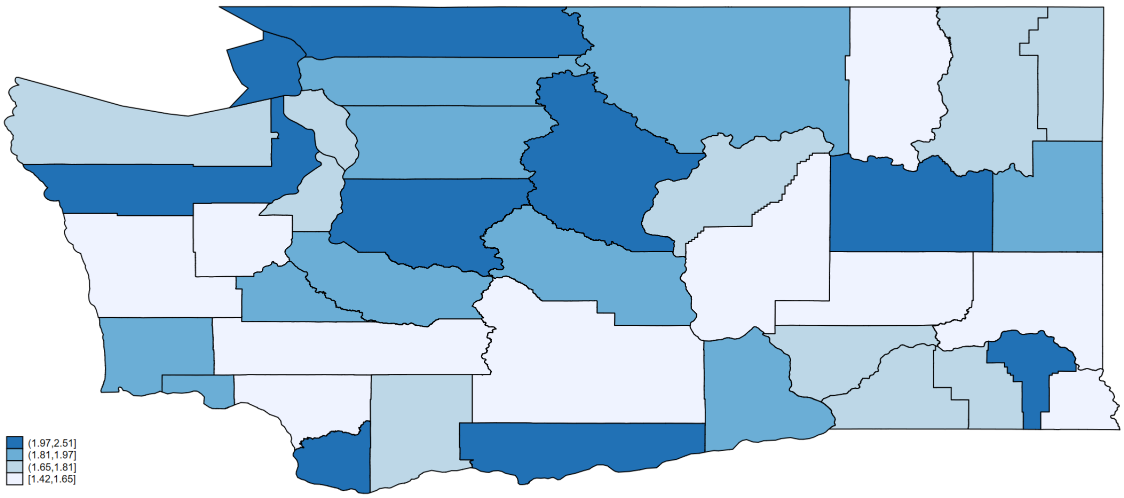


Figure C7: Average Applications Per Capita, Washington State, 2010-19

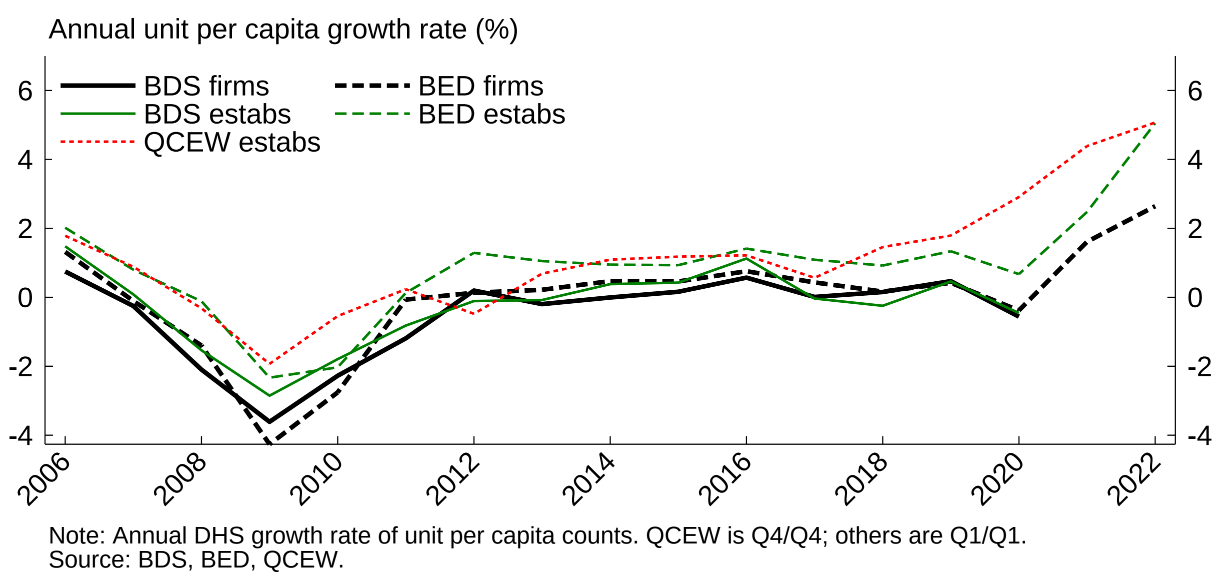
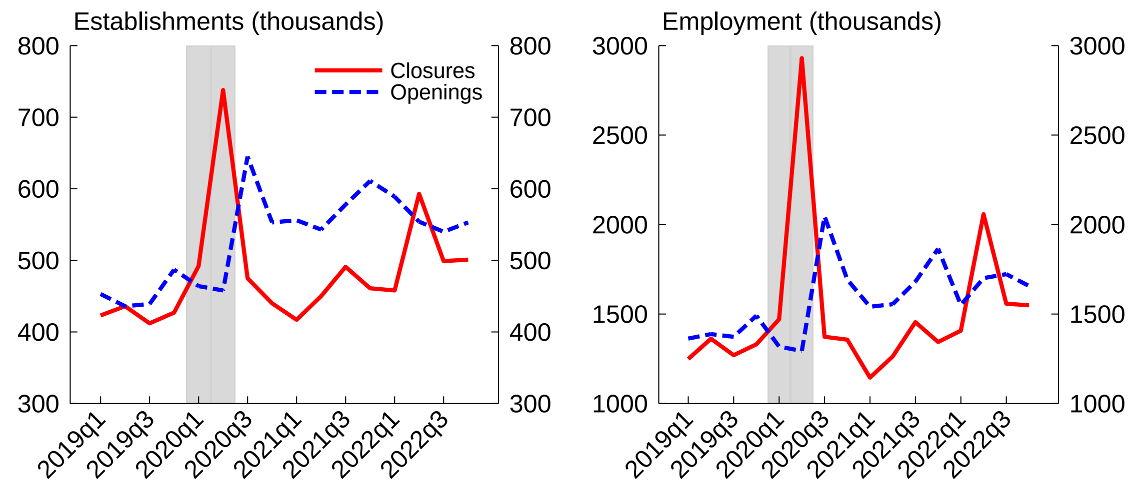
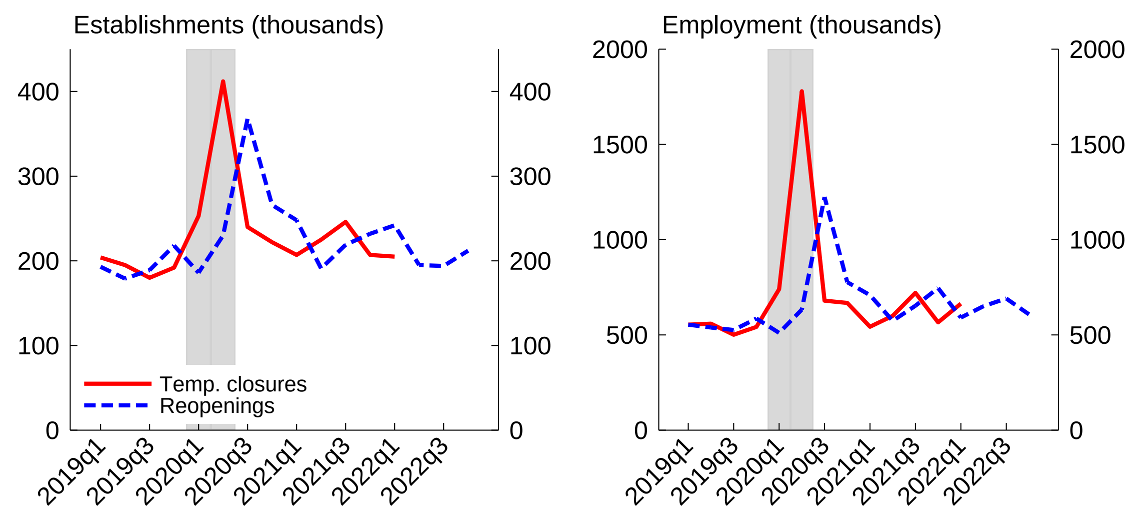


Figure C8: Net increase of establishments and firms



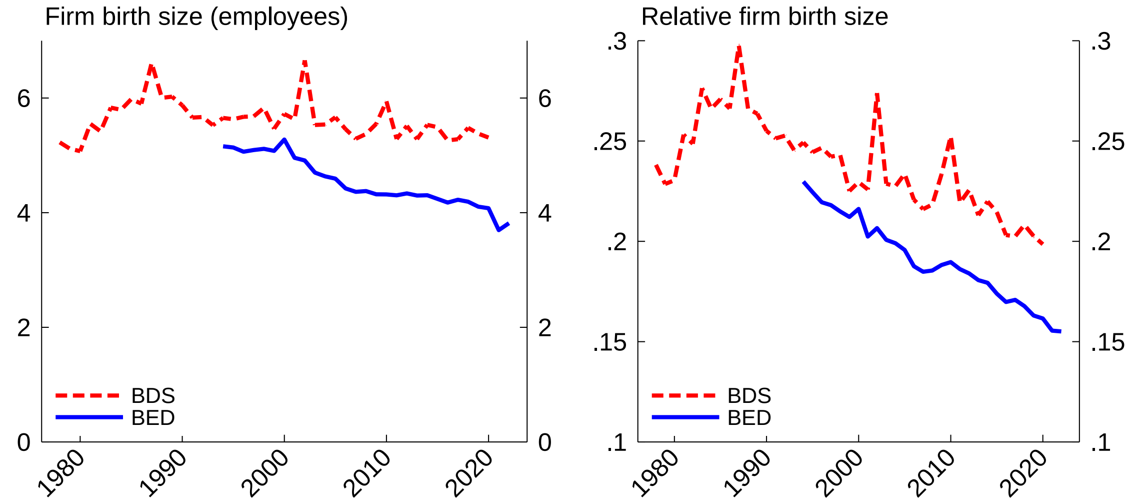
Note: Includes temporary closures and reopenings. Seasonally adjusted. Y axes may not start at zero.
Shaded areas indicate NBER recession dates.
Source: Business Employment Dynamics (BED).

Figure C9: Establishment openings and closures



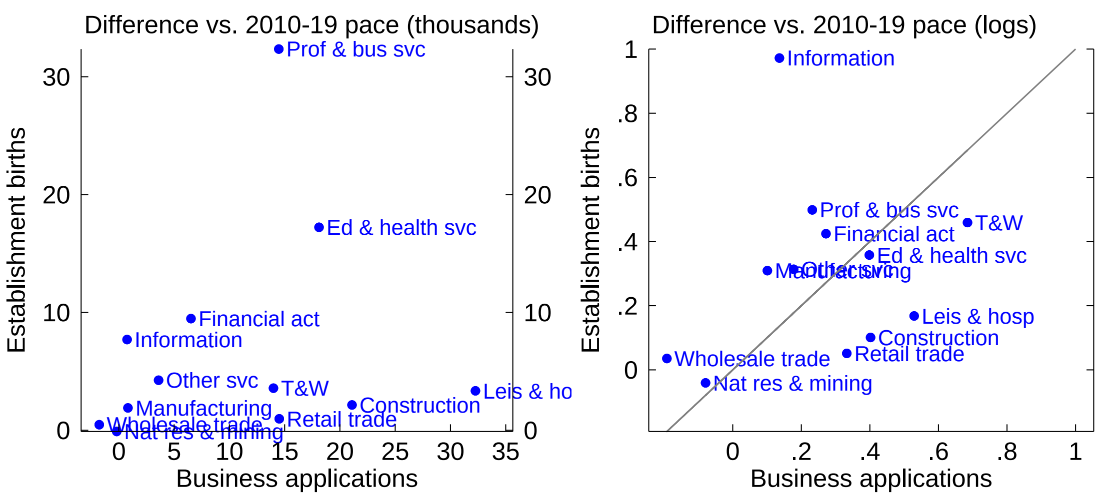
Note: Seasonally adjusted. Shaded areas indicate NBER recession dates.
Source: Business Employment Dynamics (BED) and author calculations.

Figure C10: Establishment reopenings and temporary closures



Note: Average size in first year (left); relative to incumbent average size (right).
Source: Business Dynamics Statistics (BDS) and Business Employment Dynamics (BED).

Figure C11: Average firm entrant size, BDS and BED



Note: 2020:Q3-2022:Q4. Left panel expressed in average seasonally adjusted quarterly pace. Solid line is 45-degree line. T&W is transportation & warehousing.
Source: Business Employment Dynamics (BED), Business Formation Statistics (BFS).

Figure C12: Establishment births and business applications, industry detail

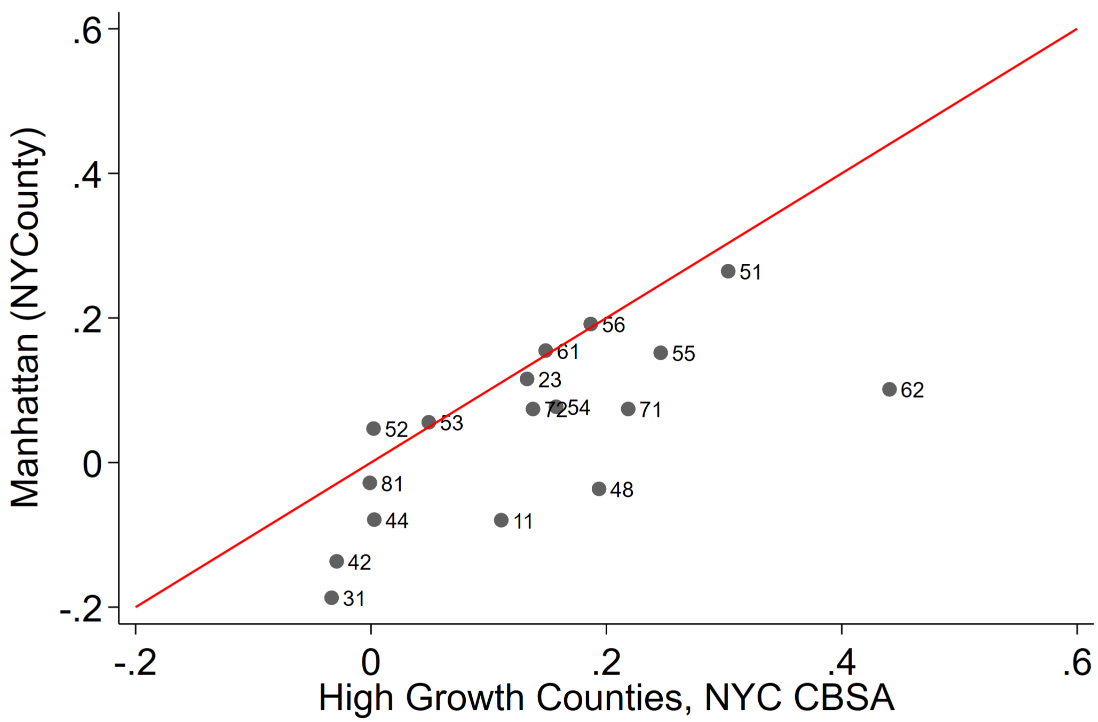


Figure C13: Net Establishment Growth in Manhattan and High Growth Counties in NYC CBSA

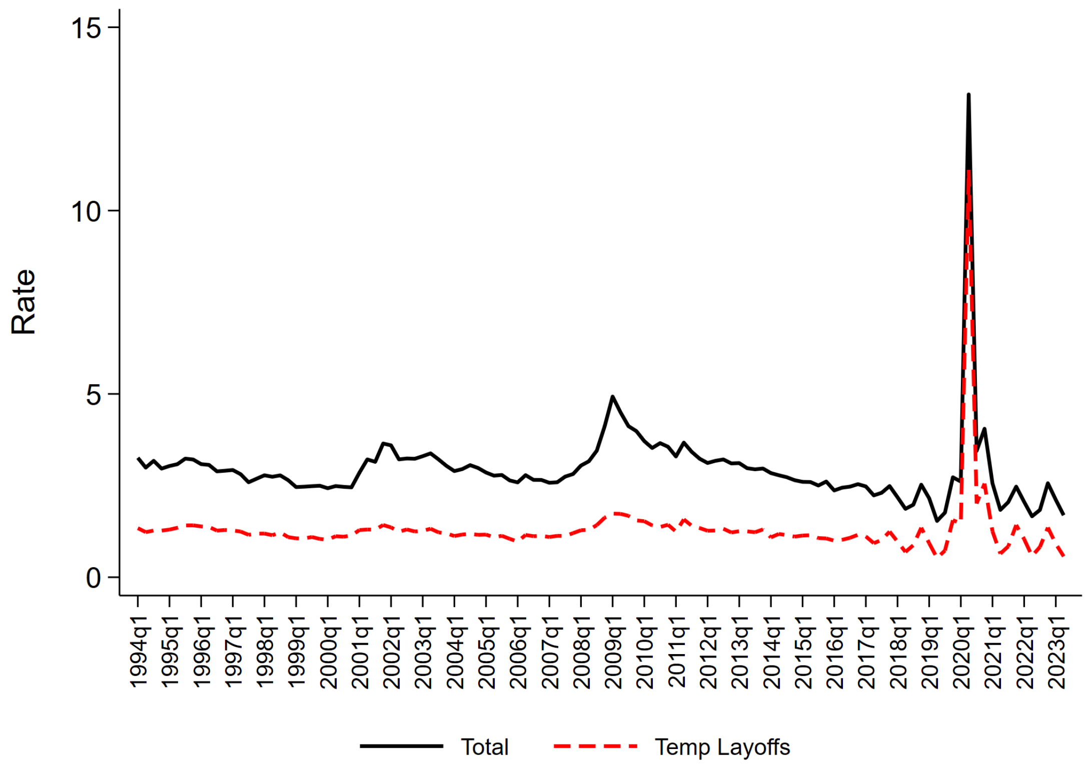
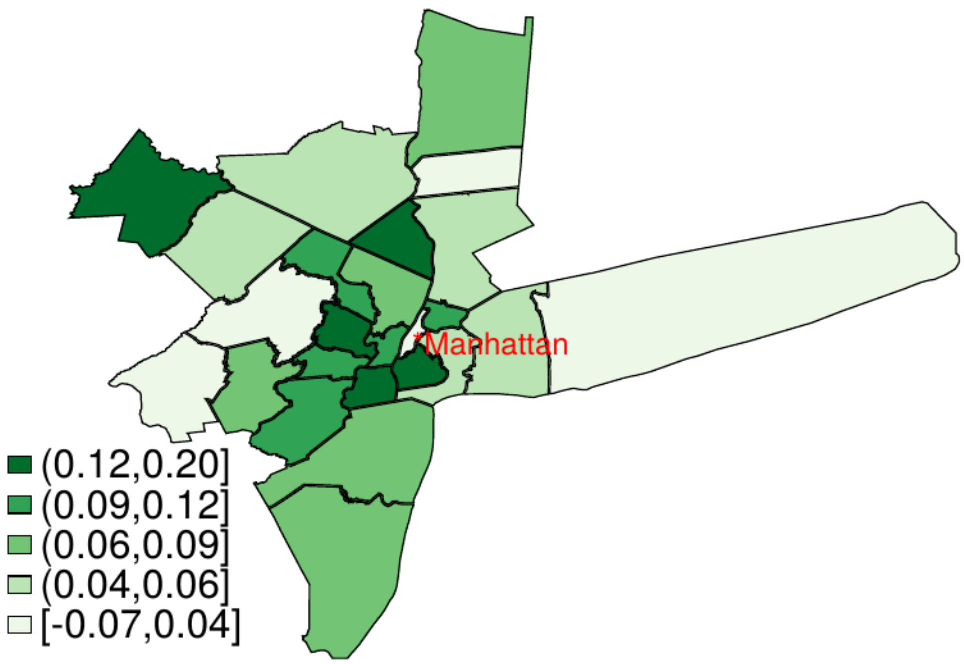


Figure C14: Inflow Rates from E to U, CPS, Quarterly



Note: Difference of average (log) excess separation rate, 2020-2022 vs. 2010-2019.
Source: Census Bureau Quarterly Workforce Indicators.

Figure C15: New York City: Growth in excess separations, 2020-2022 vs. 2010-2019

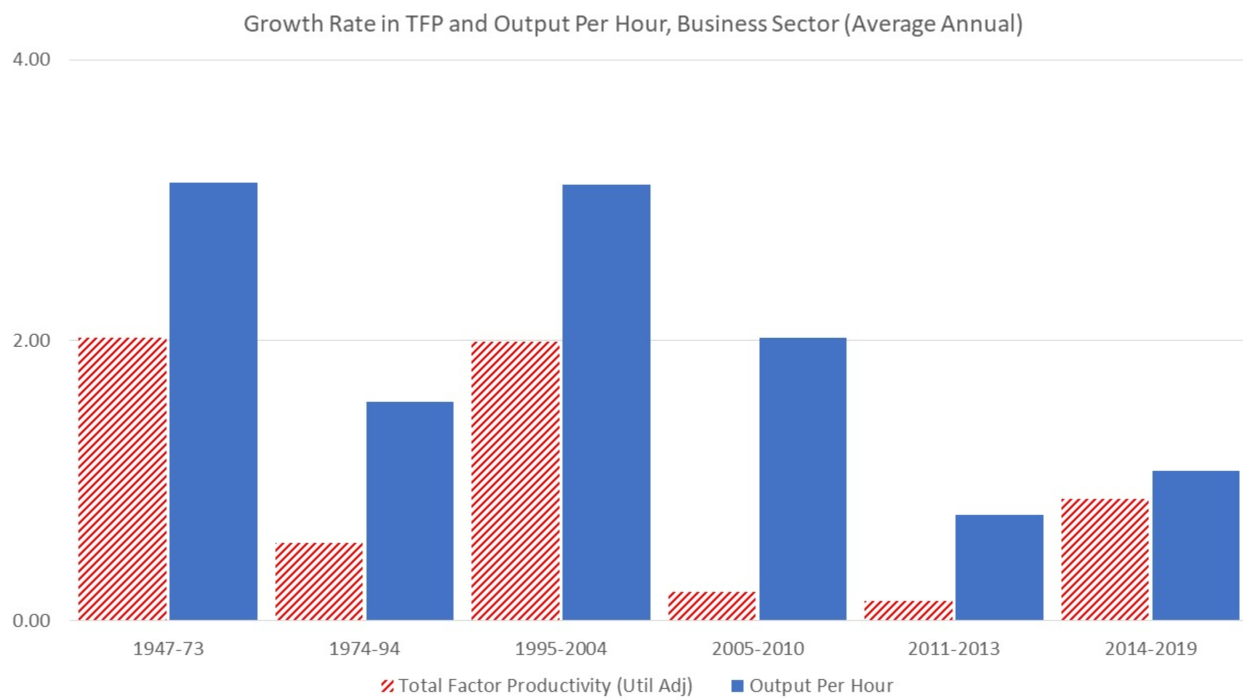


Figure C16: Productivity Growth Pre-Pandemic

Source: San Francisco Federal Reserve

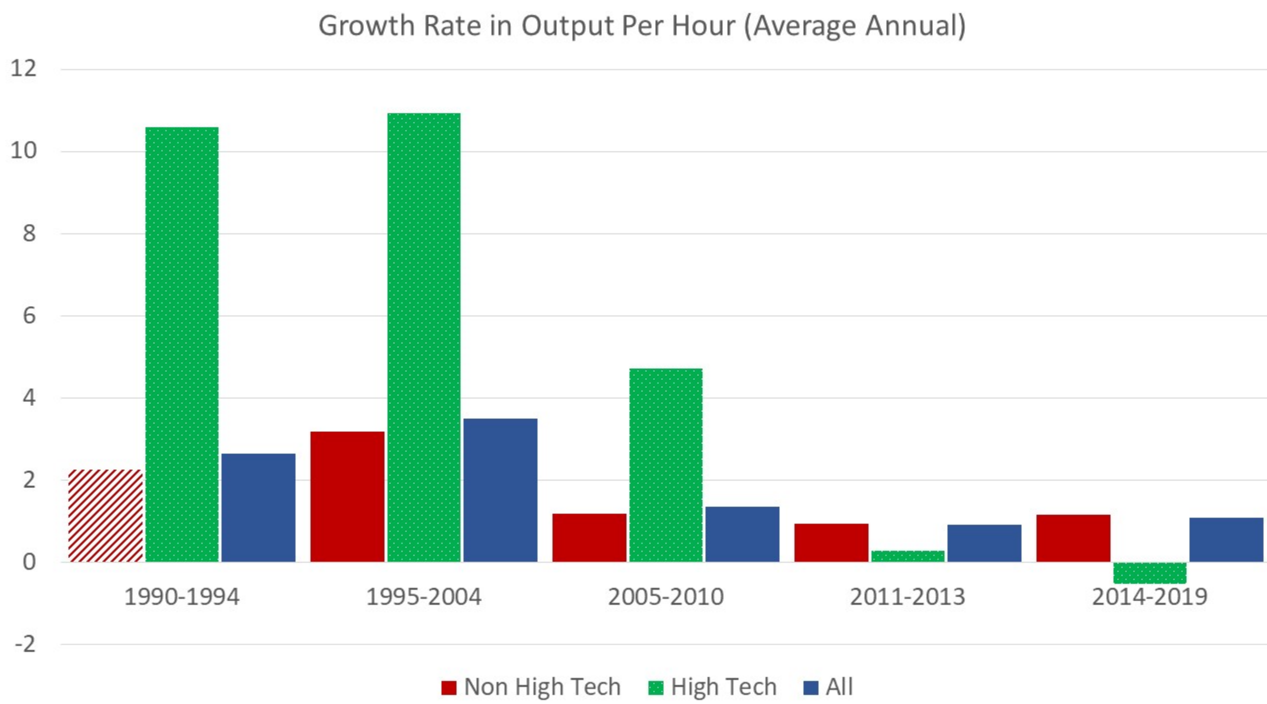


Figure C17: Productivity Growth Pre-Pandemic: High Tech vs. Non High Tech

Source: Tabulations from BLS data

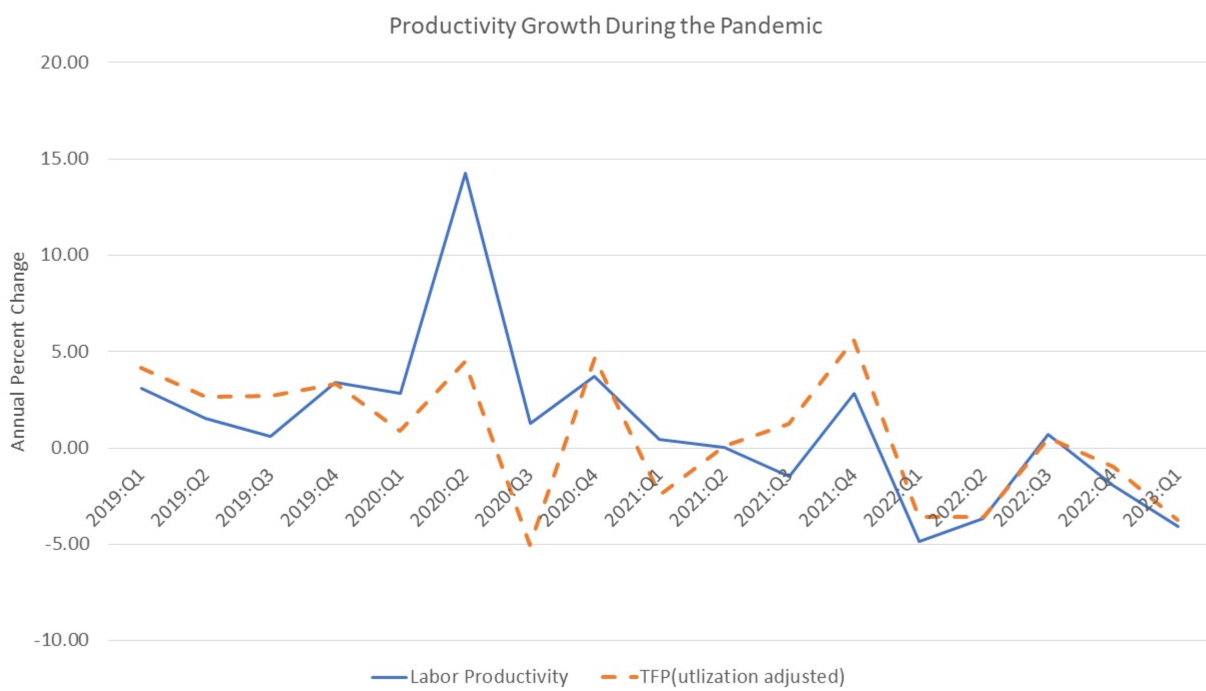


Figure C18: Productivity Growth During the Pandemic

Source: San Francisco Federal Reserve

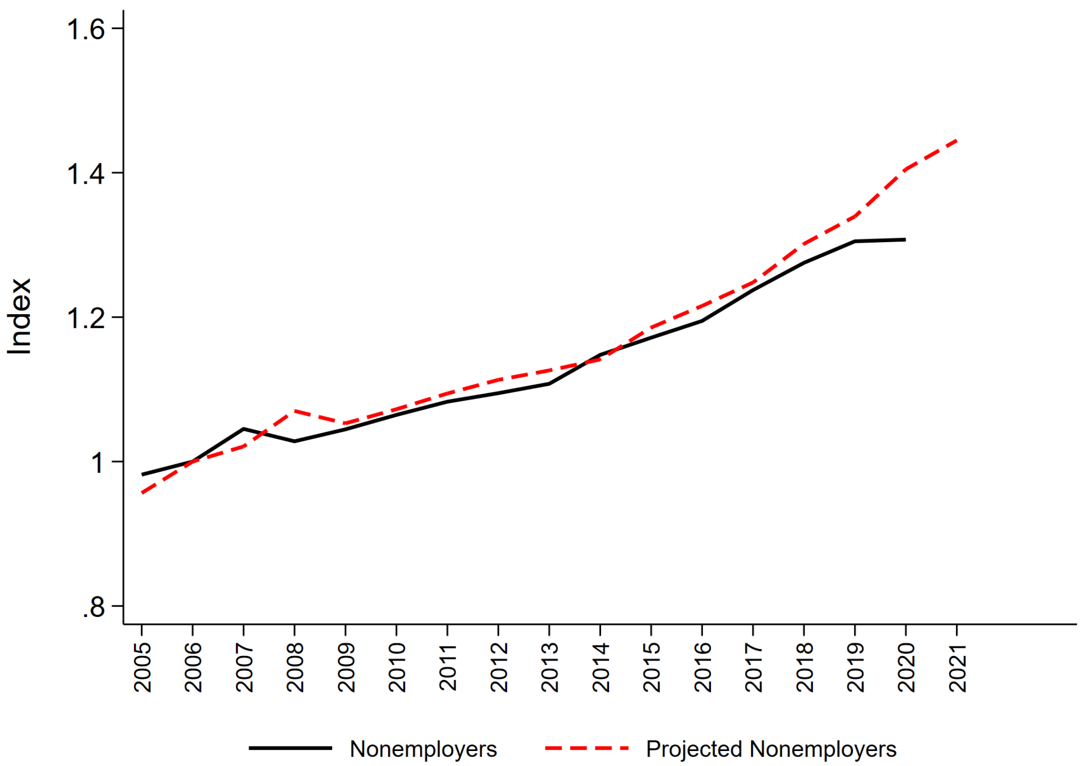


Figure C19: Relationship Between Actual and Projected Nonemployers using NHBA

Source: Census NES data with BFS.

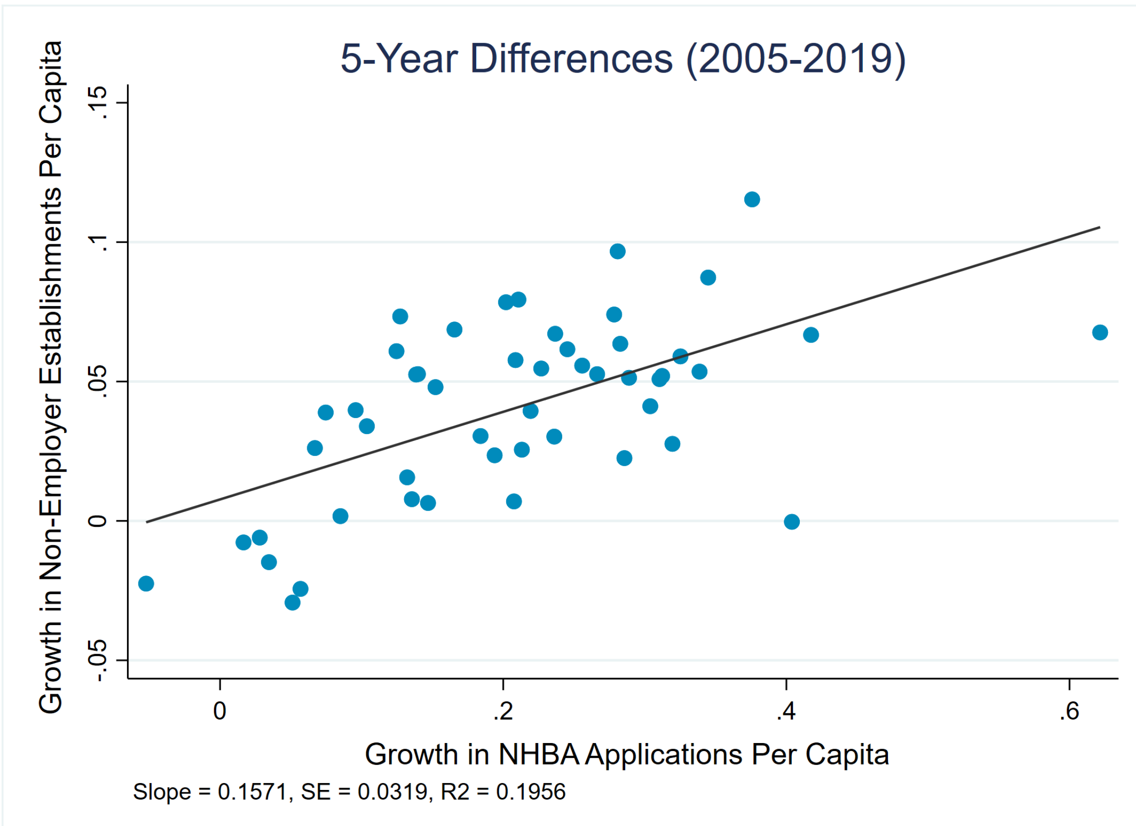
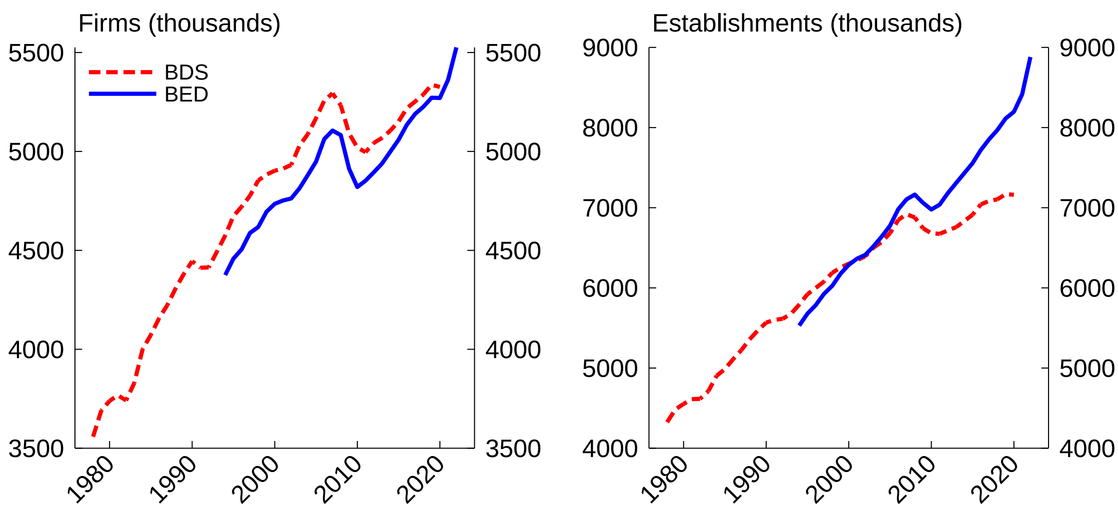


Figure C20: Growth in Nonemployer Businesses and Growth in NHBA, 5-year differences

Source: Census NES data with BFS.



Note: Y axes may not start at zero.
Source: Business Dynamics Statistics (BDS) and Business Employment Dynamics (BED).

Figure C21: Firm and Establishment Counts from the BDS and BED

D Supplemental tables

Table D1: Analysis of Variance of Between-County Variation in Growth in Business Applications

	Dependent variable: Application growth		
	All Counties – Fixed Effects		
	Division	State	Commuting Zone
R-squared	0.25	0.49	0.7
Fixed Effects	9	51	704
Observations	3802		
	Counties Part of Large CBSAs –Fixed Effects		
	CBSA		
R-squared	0.50		
Fixed Effects	53		
Observations	437		

Note: Reported are R-squared from regressions of change in (log) applications per capita, 2020-2022 versus 2010-2019 (see equation 1) at county level on alternative fixed effects. The top panel includes all counties. The bottom panel includes only counties that are part of CBSAs. Source: Author calculations from BFS and Census Bureau population estimates.

Table D2: Elasticity of business births with respect to applications, Aggregate quarterly

	(1)	(2)	(3)	(4)	(5)
	Firms 8Q	Firms 4Q	Estabs	Estabs	Estabs
Applications (HBA)	1.230***	1.336***	0.342***	0.372***	0.843***
	(0.069)	(0.092)	(0.085)	(0.092)	(0.084)
R^2	0.851	0.780	0.226	0.214	0.583
Sample end	2018:4	2019:4	2018:4	2019:4	2022:4
Observations	58	62	58	62	74

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: Quarterly regression of log firm or establishment birth measures on likely employer applications (HBA) in aggregate data; all samples start in 2004:Q3. Column 1 uses actual transitions from applications in subsequent 8 quarters from the BFS which are available for applications made through 2018:4. Column 2 uses actual transitions from applications in subsequent 4 quarters from the BFS which are available for applications made through 2019:4. The next three columns use establishment births from the BED. Column 3 uses the sample for which which actual 8-quarter BFS transitions are available (through 2018:4). Column 4 uses the sample for which actual 4-quarter BFS transitions are available (through 2019:4). The last column uses the sample through 2022:4, the latest available data.
Source: Author calculations from BFS and BED.

Table D3: Pre-pandemic elasticity of firm births per capita with respect to likely employer applications per capita, state/quarterly

	(1) Firm births	(2) Firm births	(3) Firm births	(4) Firm births
A. Births within 8 quarters				
Applications (HBA PC)	0.791***	1.222***	0.683***	1.034***
	(0.123)	(0.064)	(0.138)	(0.172)
R^2	0.330	0.725	0.393	0.757
Observations	2802	2802	2802	2802
B. Births within 4 quarters				
Applications (HBA PC)	0.722***	1.206***	0.610***	0.626***
	(0.076)	(0.058)	(0.077)	(0.105)
R^2	0.577	0.906	0.691	0.967
Observations	3006	3006	3006	3006
Controls	*None*	*State*	*Time*	*State, Time*

Standard errors in parentheses, clustered at state level.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: All variables expressed in per capita terms. State-by-quarter regressions of log firm births per capita over 8- or 4-quarter horizon on log likely employer applications per capita. Column 1 uses no controls, column 2 uses state effects, column 3 uses time (year-by-quarter) effects, and column 4 uses state and time effects. The sample is 2004:3-2018:4. Variables winsorized at 99% and 1%.
Source: Author calculations from BFS.

Table D4: Elasticity of establishment births per capita with respect to likely employer applications per capita, state/quarterly

	(1) Est Births	(2) Est Births	(3) Est Births	(4) Est Births
A. Pre-pandemic (2004:Q3 through 2019:Q4)				
Applications (HBA PC)	0.512***	0.315***	0.552***	0.305***
	(0.065)	(0.035)	(0.079)	(0.104)
R^2	0.355	0.803	0.410	0.843
Observations	3006	3006	3006	3006
B. Pandemic-inclusive (2004:Q3 through 2022:Q4)				
Applications (HBA PC)	0.533***	0.569***	0.498***	0.188*
	(0.064)	(0.040)	(0.076)	(0.094)
R^2	0.325	0.708	0.462	0.842
Observations	3618	3618	3618	3618
Controls	None	State	Time	State,Time

Standard errors in parentheses clustered at the state level.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: All variables expressed in per capita terms. State-by-quarter regressions of log establishment births per capita on log likely employer applications per capita. Column 1 uses no controls, column 2 uses state effects, column 3 uses time effects (year-by-quarter), column 4 uses state and time effects. Variables winsorized at 99% and 1%.
Source: Author calculations from BFS and BED.

Table D5: Pre-pandemic elasticity of establishment births per capita with respect to PBF4Q per capita, state/quarterly

	(1) Estab Births	(2) Estab Births	(3) Estab Births	(4) Estab Births
A. Pre-pandemic (2004:Q3 through 2019:Q4)				
PBF4Q PC	0.654***	0.247***	0.798***	0.407***
	(0.035)	(0.032)	(0.044)	(0.105)
R^2	0.503	0.798	0.627	0.846
Observations	3006	3006	3006	3006
B. Pandemic-inclusive (2004:Q3 through 2022:Q4)				
PBF4Q PC	0.700***	0.419***	0.775***	0.284***
	(0.034)	(0.031)	(0.045)	(0.102)
R^2	0.456	0.669	0.652	0.844
Observations	3618	3618	3618	3618
Controls	None	State	Time	State,Time

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: All variables expressed in per capita terms. State-by-quarter regressions of log establishment births per capita on log 4-quarter predicted firm births per capita (PBF4Q). Column 1 uses no controls, column 2 uses state effects, column 3 uses time effects (year-by-quarter), and column 4 uses state and time effects time. Variables winsorized at 99% and 1%.

Source: Author calculations from BFS and BED.

Table D6: Pre-pandemic elasticity of establishment births per capita with respect to lagging average of PBF4Q per capita, state/quarterly

	(1) Estab Births	(2) Estab Births	(3) Estab Births	(4) Estab Births
A. Pre-pandemic (2005:Q2 through 2019:Q4)				
Avg PBF4Q PC (t,t-3)	0.656***	0.221***	0.805***	0.483***
	(0.037)	(0.034)	(0.045)	(0.120)
R^2	0.491	0.793	0.628	0.847
Observations	2853	2853	2853	2853
B. Pandemic-inclusive (2005:Q2 through 2022:Q4)				
Avg PBF4Q PC (t,t-3)	0.708***	0.409***	0.783***	0.319**
	(0.036)	(0.037)	(0.047)	(0.123)
R^2	0.443	0.654	0.657	0.844
Observations	3465	3465	3465	3465
Controls	None	State	Time	State,Time

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: All variables expressed in per capita terms. State-by-quarter regressions of log establishment births per capita on average of log 4-quarter predicted firm births per capita (PBF4Q) over the current and prior 3 quarters. Column 1 uses no controls, column 2 uses state effects, column 3 uses time effects (year-by-quarter), and column 4 uses state and time effects. Variables winsorized at 99% and 1%.

Source: Author calculations from BFS and BED.

Table D7: Applications, population density, establishment density and changes in working from home

	Dependent variable: Application growth
ln(population density)	-0.736***
	(0.158)
$ln(\text{population density})^2$	0.111***
	(0.024)
$ln(\text{population density})^3$	-0.005***
	(0.001)
R-squared	0.55
ln(establishment density)	-0.102***
	(0.020)
$ln(\text{establishment density})^2$	0.039***
	(0.006)
$ln(\text{establishment density})^3$	-0.004***
	(0.001)
R-squared	0.53
$Growth$(WFH)	-1.00***
	(0.293)
$Growth(\text{WFH})^2$	1.05***
	(0.286)
$Growth(\text{WFH})^3$	-0.302***
	(0.086)
R-squared	0.53

Note: Three separate regressions reported. All have dependent variable of county-level regression of change in (log) applications per capita, 2020-2022 versus 2010-2019 (see equation 1) on population density. CBSAs with 2019 population at least one million. Includes CBSA fixed effects. First panel uses cubic in Log population density measured in 2019. Second panel uses cubic in log establishment density measured in 2019. Third panel uses cubic in growth in fraction of workers working from home between 2019 and 2021 from the ACS. Robust standard errors in parentheses. ***denotes statistical significance with $p < 0.01$. Source: Author calculations from BFS and Census Bureau population estimates.

Table D8: Applications, population density, establishment density, and working from home; own and adjacent counties

	Dependent variable: Application growth		
	Own county	Adjacent county	Indirect Impact
ln(population density)	-1.075**	-0.847***	-0.526***
	(0.480)	(0.217)	(0.134)
ln(population density)^2	0.247***	0.318***	0.197***
	(0.069)	(0.063)	(0.039)
ln(population density)^3	-0.013***	-0.021***	-0.013***
	(0.003)	(0.004)	(0.003)
ln(establishment density)	-0.306***	-0.397	-0.247
	(0.089)	(0.270)	(0.167)
ln(establishment density)^2	-0.052	-0.119**	-0.074**
	(0.025)	(0.058)	(0.036)
ln(establishment density)^3	0.007	0.019***	0.012***
	(0.002)	(0.005)	(0.003)
$Growth$(WFH)	-0.818***	-1.251**	-0.777**
	(0.227)	(0.633)	(0.393)
$Growth$(WFH)^2	0.851***	1.056*	0.656*
	(0.221)	(0.615)	(0.382)
$Growth$(WFH)^3	-0.264***	-0.303	-0.188
	(0.067)	(0.186)	(0.115)
Observations	282		
Pseudo R-squared	0.77		

Note: Single county-level regression of change in (log) applications per capita, 2020-2022 versus 2010-2019 (see equation 1) on population density, establishment density, and change in fraction of workers working from home 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. Change in working from home from the ACS from 2019 to 2021. 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, ACS and Census Bureau population estimates.

Table D9: Three-digit NAICS 2012 codes and titles (part I)

Code	Title
111	Crop Production
113	Forestry and Logging
114	Fishing, Hunting and Trapping
115	Support Activities for Agriculture and Forestry
211	Oil and Gas Extraction
212	Mining (except Oil and Gas)
213	Support Activities for Mining
221	Utilities
236	Construction of Buildings
237	Heavy and Civil Engineering Construction
238	Specialty Trade Contractors
311	Food Manufacturing
312	Beverage and Tobacco Product Manufacturing
313	Textile Mills
314	Textile Product Mills
315	Apparel Manufacturing
316	Leather and Allied Product Manufacturing
321	Wood Product Manufacturing
322	Paper Manufacturing
323	Printing and Related Support Activities
324	Petroleum and Coal Products Manufacturing
325	Chemical Manufacturing
326	Plastics and Rubber Products Manufacturing
327	Nonmetallic Mineral Product Manufacturing
331	Primary Metal Manufacturing
332	Fabricated Metal Product Manufacturing
333	Machinery Manufacturing
334	Computer and Electronic Product Manufacturing
335	Electrical Equipment, Appliance, and Component Manufacturing
336	Transportation Equipment Manufacturing
337	Furniture and Related Product Manufacturing
339	Miscellaneous Manufacturing
423	Merchant Wholesalers, Durable Goods
424	Merchant Wholesalers, Nondurable Goods
425	Wholesale Electronic Markets and Agents and Brokers
441	Motor Vehicle and Parts Dealers
442	Furniture and Home Furnishings Stores
443	Electronics and Appliance Stores
444	Building Material and Garden Equipment and Supplies Dealers
445	Food and Beverage Stores
446	Health and Personal Care Stores
447	Gasoline Stations
448	Clothing and Clothing Accessories Stores
451	Sporting Goods, Hobby, Musical Instrument, and Book Stores
452	General Merchandise Stores
453	Miscellaneous Store Retailers
454	Nonstore Retailers

Table D10: Three-digit NAICS 2012 codes and titles (part II)

Code	Title
481	Air Transportation
482	Rail Transportation
483	Water Transportation
484	Truck Transportation
485	Transit and Ground Passenger Transportation
486	Pipeline Transportation
487	Scenic and Sightseeing Transportation
488	Support Activities for Transportation
491	Postal Service
492	Couriers and Messengers
493	Warehousing and Storage
511	Publishing Industries (except Internet)
512	Motion Picture and Sound Recording Industries
515	Broadcasting (except Internet)
517	Telecommunications
518	Data Processing, Hosting, and Related Services
519	Other Information Services
521	Monetary Authorities-Central Bank
522	Credit Intermediation and Related Activities
523	Securities, Commodity Contracts, and Other Financial Investments and Related Activities
524	Insurance Carriers and Related Activities
525	Funds, Trusts, and Other Financial Vehicles
531	Real Estate
532	Rental and Leasing Services
533	Lessors of Nonfinancial Intangible Assets (except Copyrighted Works)
541	Professional, Scientific, and Technical Services
551	Management of Companies and Enterprises
561	Administrative and Support Services
562	Waste Management and Remediation Services
611	Educational Services
621	Ambulatory Health Care Services
622	Hospitals
623	Nursing and Residential Care Facilities
624	Social Assistance
711	Performing Arts, Spectator Sports, and Related Industries
712	Museums, Historical Sites, and Similar Institutions
713	Amusement, Gambling, and Recreation Industries
721	Accommodation
722	Food Services and Drinking Places
811	Repair and Maintenance
812	Personal and Laundry Services
813	Religious, Grantmaking, Civic, Professional, and Similar Organizations
814	Private Households