Firm Growth and Stagnation in the United States: Key Trends and New Data Opportunities*

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Abstract

Using administrative data from the U.S. Census Bureau, we introduce a new public-use dataset ("BDS-HG") that captures the full distribution of firm growth in the United States between 1978 and 2021. BDS-HG enables researchers to analyze not only high-growth firms but also stagnant and shrinking firms, disaggregated by firm maturity, size, industry, region, and year. We begin by documenting two key trends: (1) a significant decline in the share of high-growth firms—especially among young and small firms; and (2) a marked rise in stagnant firms. To help illustrate the dataset's usefulness, we provide three empirical applications and highlight research opportunities across major areas of strategic management. In addition to supporting new analyses, BDS-HG can be used to benchmark research samples and assess their generalizability.

Keywords: Firm Growth, Entrepreneurship, Business Dynamism, Publicly Available Dataset

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1 Introduction

Since Penrose's (1959) seminal work on the growth of firms, extant literature in both management and economics has offered various theoretical accounts of firm growth and decline—ranging from external factors such as environmental conditions and competition (e.g., Carroll and Hannan 1989; Baum and Mezias 1993; Sterk et al. 2021; Sivadasan et al. 2024) to organizational traits including routines, managerial quality, and technological innovation (e.g., Lucas Jr 1978; Nelson and Winter 1982; Acs and Audretsch 1987; Eisenhardt and Schoonhoven 1990). Yet despite this longstanding interest, empirical progress has often been constrained by data limitations. Access to nationally representative datasets——such as restricted-access Census Bureau microdata——requires significant barriers to entry and remains unavailable to many researchers (Nagaraj and Tranchero 2023). Meanwhile, existing alternative datasets generally do not provide a comprehensive coverage of firms in the economy. As a result, broad-based insights into patterns of firm growth, particularly among young and small firms which are widely understood to be primary drivers of high-growth and job creation (Khaire 2010; Haltiwanger et al. 2016; Guzman and Stern 2020), remain limited.

In this paper, we introduce the Business Dynamics Statistics–High Growth (BDS-HG) dataset, a new experimental public-use data product under the Business Dynamics Statistics program. Leveraging restricted-access administrative data from the U.S. Census Bureau, the BDS-HG data provide the full distribution of firm growth in the U.S. across regions and industries over the past fifty years. Strategic management research is fundamentally concerned with heterogeneity——not just among high-performing outliers, but across the full spectrum of firm outcomes (e.g., Rumelt 1991; Helfat and Peteraf 2003). Recent work shows that analyzing the full distribution of firm growth rates offers valuable insights into the underlying drivers of organizational scaling and stagnation (Coad 2024; Sivadasan et al. 2024). To this end, the BDS-HG data can help researchers examine how this heterogeneity evolves, compresses, or shifts across firm types and over

time. BDS-HG's breakdowns by firm age and size provide a useful opportunity to study which types of firms contribute to high-growth dynamics versus stagnation or decline. Although the data are aggregated for confidentiality reasons, they allow for detailed analysis across time, state, detailed industry (up to 4-digit NAICS), and firm characteristics. While firms are often the preferred unit of analysis in strategy research, many influential studies have drawn important insights from data aggregated to the state, industry, or occupation level (e.g., Stuart and Sorenson 2003; Marx et al. 2009; Raj 2021; Felten et al. 2021).

To help demonstrate this use case, we discuss three specific areas for future research in strategic management: (1) entrepreneurship & scaling, (2) institutional environment, and (3) competition & industry structure. For each, we provide an in-depth example analysis by linking BDS-HG to other existing data. First, we examine how the growth prospects of incumbent firms in a given industry are associated with the performance outcomes of venture capital–backed startups, using data from PitchBook and Revelio Labs. Second, we assess how institutional change—in this case, Michigan's 1985 reversal of non-compete enforceability—shapes firm growth dynamics in affected regions as reflected by the prevalence of startups, high-growth firms, and shrinking firms. Third, we use firms drawn from Compustat to explore how the underlying competitive environment, which we measure using BDS-HG data at the state-by-industry level, is associated with firms' investment decisions.

In addition to serving as a standalone data source for empirical analysis, BDS-HG can function as a practical benchmarking tool. Researchers working with selected samples—such as single-industry datasets, surveys, or proprietary firm records—often face questions about external validity. The difficulty of assessing how well such samples reflect the broader context has contributed to longstanding debates about replication and generalizability in strategic management research (e.g., Bettis et al. 2016). By using BDS-HG to benchmark against the full distribution of firm growth across the U.S. economy, re-

searchers can quantitatively assess the representativeness of their sample and the generalizability of their findings.

To further motivate future research using BDS-HG, we highlight two important facts in the changing nature of firm growth in the U.S. First, the share of firms that are high-growth has steadily decreased from 3.8% to 2.0% between 1978 and 2021—most prominently driven by both declining number of new firms and languishing growth among young firms. This decline has occurred in all sectors, although a few sectors such as Information (e.g., software, computing infrastructure, and media streaming) have shown a robust rebound beginning in 2010. Second, the share of stagnant firms—which we define as those with virtually no annual change in employment—has significantly risen from 28% to 37% between 1978 and 2021. This increase is especially strong among small and young firms. Given startups' disproportionate contributions to job creation and economic growth (Haltiwanger et al. 2013; Coad 2024; Sivadasan et al. 2024), this raises the question of whether steady employment reflects increasing frictions to venture growth.

Our paper proceeds as follows. In Section 2, we detail the underlying microdata and our methodology for constructing the BDS-HG dataset. Section 3 presents key descriptive patterns from the data, highlighting how firm growth dynamics in the United States have evolved over the past four decades. In Section 4, we illustrate the potential of BDS-HG for future research by showcasing two example analyses and outlining three broader thematic areas in strategy where the dataset can support new empirical work. Section 5 concludes.

2 Data and Measurement

The BDS-HG tables are derived from the Longitudinal Business Database (LBD), an administrative dataset that tracks all non-farm private establishments and firms with at least one paid employee in the United States (Jarmin and Miranda, 2002; Chow et al.,

2021). The LBD provides establishment-level information such as employment, payroll, industry, age, and firm identifiers. An establishment refers to a single physical location where business is conducted or where services or industrial operations are performed. A firm is defined as a grouping of one or more establishments under common operational control, with information on operational control drawn from the Economic Censuses and the Company Organization Survey.[1] Employment captures both full and part-time employees who are on the establishment's payroll, including salaried officers and executives of corporations, during the pay period that includes March 12th.[2] This also includes employees on paid sick leave, holidays, and vacations, but excludes owners of sole proprietorships or partners of unincorporated firms.

The LBD—and by extension, the BDS-HG—covers all employer firms regardless of their legal form of organization, which, according to the Internal Revenue Service (IRS), consists of partnerships, sole proprietorships, C-corporations, and S-corporations.[3] The BDS-HG provides data starting in 1978 and is scheduled to be updated annually. It contains the number of firms, establishments, employees, as well as flow measures such as job creation, job destruction, establishment entry and exit and associated job flows, across the full distribution of firm growth bins (described in detail below). These data are

[1]The Business Dynamics Statistics tabulations provide counts of both establishments and firms. The distinction allows researchers to capture the number of national, multi-establishment businesses operating within a given industry or geography, in addition to the number of unique physical business locations in that same cell.

[2]The March 12th reference period also implies that much of the economic effects of the COVID-19 pandemic appear in the 2021 but not 2020 BDS tabulations. None of the states in the U.S. had a mandatory shelter-in-place order (i.e., lockdown) as of March 12, 2020. For additional information about the timing of Census Business data and the COVID-19 pandemic, see Beem et al. (2022).

[3]A Limited Liability Company (LLC), established under state law rather than federal law, is not recognized by the IRS as a distinct legal form like a sole proprietorship, partnership, or corporation. While LLCs offer limited liability protection at the state level, the IRS treats them as a corporation, partnership, or disregarded entity for federal tax purposes, depending on the number of owners and the tax election made.

available not only for the overall economy, but also disaggregated by firm size, age, state, four-digit NAICS industry, and selected two-way combinations of these dimensions, subject to confidentiality constraints.

We compute year-to-year growth of establishments and firms using a measure first developed by Törnqvist et al. (1985), which has become standard in the firm dynamics literature (Davis et al., 1996; Coad, 2024). This growth measure, henceforth TVV/DHS, divides the change in employment from $t-1$ to t by average employment. We discuss this measure in greater detail below. The TVV/DHS measure is a second-order approximation to the log difference while also naturally accommodating entry and exit. Since the denominator contains the average value over two years, this measure is also symmetric and alleviates regression-to-the-mean effects (Haltiwanger et al., 2013). Moreover, TVV/DHS growth has useful aggregation properties. It can be flexibly defined for aggregations of establishments either into firms or into cells defined by establishment or firm characteristics. Aggregating this growth measure to the firm-level results in a measure of "organic" firm growth that abstracts away from firm-level employment changes due to mergers and acquisitions (c.f., Sivadasan et al. 2024). By construction TVV/DHS growth is bounded between -2 (firms that transition from non-zero to zero employment i.e., exit) and 2 (firms that transition from non-zero to zero employment i.e., entry).

Specifically, establishment i's growth rate ($g_{i,t}$) is defined as

$$g_{i,t} = \frac{E_{i,t} - E_{i,t-1}}{X_{i,t}} \tag{1}$$

where $E_{i,t}$ is employment at establishment i at time t and $X_{i,t} = \frac{1}{2}(E_{i,t} + E_{i,t-1})$. Firm-level growth is then the sum of employment changes divided by the sum of average establishment employment, for all establishments i associated with firm f at time t, as follows:

$$g_{f,t} = \frac{\sum_{i \in f} E_{i,t} - E_{i,t-1}}{\sum_{i \in f} X_{i,t}} = \sum_{i \in f} \left(\left(\frac{X_{i,t}}{\sum_{i \in f} X_{i,t}} \right) \left(\frac{E_{i,t} - E_{i,t-1}}{X_{i,t}} \right) \right) \tag{2}$$

The sum of employment changes weighted by average employment is equivalent to the weighted average of establishment-level growth rates using the employment share, $(\frac{X_{i,t}}{\sum_{i \in f} X_{i,t}})$, as weights.[4]

There are several relationships between firm size, age, and growth that are important to note. First, the shape of the growth rate distribution by firm size depends critically on whether average (between $t-1$ and t) or initial ($t-1$) firm size is used to classify firms.[5] Average size will tend to allocate more growth and less contraction to large firm size bins compared to an initial size measure. This is because firm growth exhibits significant mean reversion—firms that grew from $t-2$ to $t-1$ are much more likely to contract from $t-1$ to t—due to transitory shocks. Second, in addition to transitory shocks, firms experience systematic and persistent growth patterns over the firm age life cycle (Decker et al., 2016). Online Appendix A provides additional details about the TVV/DHS measure and its relationship to size and age.

We categorize high-growth firms using two distinct but related methods of grouping firms based upon their employment growth rates. The first is percentile-based and uses the distribution of growth rates across firms and the second is based upon growth rate values. In both cases, our methodology attempts to maximize the comparability of the BDS-HG tabulations to the OECD's DynEmp program, which provides internationally comparable measures of business dynamism for a number of OECD countries.[6]

[4]Exiting establishments will be assigned a firm growth rate based upon their associated firm in $t-1$.

[5]Average and initial firm size groupings corresponds to fsize and ifsize, respectively, from the BDS tabulations.

[6]Notable differences between the BDS-HG and OECD DynEmp methodologies include: (1) we do not randomly perturb the growth rates of zero growth firms, (2) provide slightly less detail around the median of the within-year employment-weighted growth rate distribution, and (3) we do not provide firm weighted percentile bins.

For the first method, we classify firms based on their position in the within-year, average-employment-weighted growth rate distribution. Importantly, we locate each firm's position on the growth rate distribution within a given year, rather than pooling years. This approach ensures that comparisons are made among firms subject to the same set of contemporaneous macroeconomic conditions. To do this, we first compute each firm's growth rate between $t-1$ and t, as described in Equation 2. We then sort firms in ascending order by their growth rates, breaking ties randomly. We then compute each firm's share of the cumulative sum of average employment (`denom`). This procedure allows us to identify the set of firms that account for a chosen cumulative share of total average employment—for instance, 10 percent; these firms are assigned to the p1-p10 bin.

We classify firms into five percentile-based employment growth bins (`fempgr_grpct` in the BDS-HG tables): a) p1-p10; b) p11-p25; c) p26-p75; d) p76-p90; e) p91-p99. By construction, this method involves growth rate cut-offs that vary over time. As the firm growth rate distribution contracts over time, for example, the growth rate associated with the 90^{th} percentile of the employment-weighted growth rate distribution will change. To illustrate this point, Figure 1 shows the average growth rate associated with the 10^{th}, 50^{th}, and 90^{th} percentile of the employment-weighted growth rate distribution for groupings of years. Consistent with the findings of Decker et al. (2016), we find that the growth rate associated with the 90^{th} percentile of the growth rate distribution has fallen significantly over time from 0.35 to 0.23 from the late 1980s to the 2010s. Less dramatic, but still apparent, is the rise of the growth rate associated with the bottom, or 10^{th} percentile, which rose from -0.27 to -0.20 over the same period. Even the median, or 50^{th} percentile, has contracted slightly falling towards zero. These patterns over roughly forty years imply an increasing compression in the firm growth rates at both the top and bottom portions of the distribution, whereby the fastest growing firms in the economy are growing less and the firms contracting the most are contracting by less.

[Insert Figure 1 here]

Motivated by the time varying nature of the percentile-based method, our second and default approach classifies firms based upon their employment growth rate values. We classify firms into nine bins (`fempgr_gr` in the BDS-HG tables): a) -2; b) (-2 to -0.8]; c) (-0.8 to -0.2]; d) (-0.2 to -0.01]; e) (-0.01 to 0.01); f) [0.01 to 0.2); g) [0.2 to 0.8); h) [0.8 to 2); i) 2.[7] By defining fixed ranges of employment growth rates for each group, this time-invariant approach allows us to compare the absolute growth dynamics of firms over time. During economic downturns, for example, firms may be growing less and contracting more, in which case economic activity will shift across the growth rate bins.

In the analyses that follow, we focus on high-growth firms using the growth rate-based tabulations (`fempgr_gr`). This allows us to analyze the absolute growth performance of firms in the U.S. economy over time. We classify group "h) [0.8 to 2)" as high-growth firms—that is, existing firms whose growth rate is 0.8 or greater. It is worth noting that this definition excludes new firms, whose growth rate is, by construction, equal to 2. Under this definition, firms are considered high growth if their size increased by more than approximately 130% year-over-year.[8]

To motivate this threshold for high-growth firms, Figure 2 shows the count of firms across detailed firm growth rate bins in Panel A and the percent of firms Panel B.[9] In Panel A, the height of each dark circle shows the count of firms (with a log scale y-axis) at each point along the firm growth rate distribution on average between 1978 and 1982. The size of each bubble reflects the share of average employment accounted for by each growth rate bin in those years. The hollow circles show a similar statistic for the years

[7] In our empirical analyses (see Tables 1, 4, and 5), group a represents "failing firms", b "shrinking firms", e "stagnant firms", h "high-growth firms", and i "new firms."

[8] The TVV/DHS growth measure can be translated into percent differences using the implied relationship between the two. For a given x and y, the percent difference is given as $g_{pct} = \frac{x-y}{y}$ and the TVV/DHS difference is $g_{tvv/dhs} = \frac{x-y}{0.5(x+y)}$. This implies that $g_{pct} = \frac{2g_{tvv/dhs}}{2-g_{tvv/dhs}}$.

[9] These bins have more details than are available in the BDS-HG tabulations.

2016 to 2021. Panel B shows the share of firms across growth bins over time rather than firm counts. Several patterns stand out in Figure 2. First, there's a notably high concentration of firms with no change in employment (those in the -0.01 to 0.01 bin), along with fat tails on both sides—a pattern well documented in other settings such as manufacturing firms in France (Coad 2010), Italy (Bottazzi and Secchi 2006), and the U.S. (Caballero et al. 1997). Second, in Panel A and B we see that the majority of firms have growth rates between -0.2 and 0.2, which roughly corresponds to a 22% contraction or expansion.[10] In particular, almost 29% of firms in the late 1970's had nearly zero growth rates, which rose to 37% in late 2010's. There are also a large number of firms that exit (-2) or enter (2), but they account for much less employment than those within the -0.2 to 0.2 band. Since the number of firms has risen significantly over time, the absolute count of firms that enter or exit increases slightly (Panel A) but the share of firms that enter or exit has declined (Panel B). Third, the compression of the growth rate distribution shown in Figure 2 can be seen in the changes in the counts and shares of firms across the growth rate distribution. The number of firms that with little to zero change in employment rose the most between 1980 to 2018. The count of firms that experienced significant growth or contraction declined significantly.

[Insert Figure 2 here]

In the next section we provide a preview of these statistics, highlighting interesting patterns in the composition of high-growth firms over time in terms of firm size, age, industry, and geography.[11] All of the following figures can be generated using the new, publicly available BDS-HG tabulations.

[10]The "kink" in the distribution at (-1,0.8] and [0.8,1) is driven by "lumpiness" in the joint size and growth rate distribution. Firms with one or two employees are quite common among the population of firms. If a firm with one employee adds two additional employees its growth rate is 1, which is on the excluded edge of the [0.8,1) bin.

[11]For a complete list of values for the BDS-HG growth variables see Table B1 in the Online Appendix. For a complete list of BDS measures and their definitions, see the BDS Codebook and Glossary (`https:`

3 Anatomy of Firm Growth Over Time

Table 1 shows the count of firms and total job creation along with the relative contributions by each group in the distribution of firm growth. We track five groups based on firm growth rates as defined in Section 2—namely, new, high-growth, stagnant, shrinking, and failing firms. Despite being the smallest group at 2.7% of all firms, high-growth firms account for roughly 12% of all gross job creation. Similarly, new firms are 11% of all firms, but account for 19% of jobs created. Over time, both high-growth and new firms have experienced a significant decline in their representation by roughly 30%. Meanwhile, the total number of firms in the economy increased from 4 to 5.7 million in a given year. Overall, the fall in the share of high-growth firms and their reduced contribution to job creation—together with the patterns shown in Figure 1—are consistent with the findings of Decker et al. (2016).

[Insert Table 1 here]

Another important trend is the rising share of stagnant firms, which are defined as those with little to no change in their employment. The share of stagnant firms rose from roughly 28.4% to 37.1% as shown in Table 1.[12] Despite their rising prevalence, it is not

//www.census.gov/content/dam/Census/programs-surveys/business-dynamics-statistics/codebook-glossary.pdf).

[12]The Business Employment Dynamics (BED) data published by the Bureau of Labor Statistics (BLS) provides comparable measures of zero change businesses. The BED publishes the count of establishments with zero employment change from the prior quarter. Both series exhibit a trend increase in stagnant businesses. The BED stagnant establishment share rises from 46% to 54% from 1993 to 2021 and the BDS-HG firm share rises from 34% to 38% over the same period. These measures are not directly comparable because (1) the BED measures are establishment-level while the BDS-HG are firm-level, (2) the BED measures are changes from the prior quarter while the BDS-HG captures year-over-year changes, and (3) the BDS-HG reflects near-zero changes (-0.01 to 0.01) while the BED measures exact zero change establishments.

clear how to interpret firms with steady employment. One benign view is that firms—especially large, incumbent firms—are more easily able to reach their optimal size and thus keep their employment relatively stable. In contrast, it may be that firms—in particular, startups and small firms—face increasing frictions to growth in spite of a desire for greater scope and scale (e.g., Alvarez and Barney 2017; Lee and Kim 2024), consistent with the declining responsiveness to shocks documented in Decker et al. (2020). To explore these perspectives, we break down the prevalence of stagnant firms by their size and age.

Figure 3 shows the change in the percent of stagnant firms by firm size (Panel A) and firm age (Panel B). By firm size, the largest increase in stagnant firms was among the smallest firms—those with 1 to 19 employees. Panel A shows that the percent of stagnant firms among those with 1 to 19 employees rose 12 p.p. from 33% to 45% from 1978 to 2020. Among large firms, the share of stagnant firms is much lower at around 7% in 1978, but also rose to 13% in 2020. Perhaps most surprising, Panel B shows that even the youngest firm age group saw a significant increase in the percent of stagnant firms. Among startups with ages 1 to 5, the share of stagnant firms fell from 38% to 35% between 1983 and 1990, but then rose to 45% by 2020—meaning nearly half of young startups saw no year-to-year change in employment in 2020. Mature startups (i.e., ages 6-10) and established firms (i.e., ages 11 and above) saw 8 and 7 percentage points increase in the percent of stagnant firms, respectively. Analysis taking size and age together provides an even richer portrait of the evolution of stagnant firm shares. Table B2 in the Online Appendix shows the evolution of stagnant firms within firm size and firm age bins, which suggest, consistent with Figure 3, that the largest increases of stagnant firm shares within an age group is among the smallest firms.

[Insert Figure 3 here]

Next, we decompose net job creation, or contributions to net employment growth in the economy, across the growth rate distribution. Figure 4 shows the count of jobs

created or destroyed, on net, by firms in each growth rate bin. On average, each year, new firms account for about 3 million jobs per year, high-growth firms ([0.8 to 2)) account for about 1.8 million, moderately growing firms ([0.2 to 0.8)) about 4.2 million and the slower growth firms ([0.1 to 0.2)) about 2.7 million. Consistent with the compression of the growth rate distribution and the declining share of activity among high-growth firms, the amount of net job creation from the high-growth firms declines over time. Much of the variation in the levels of net job creation across the firm growth rate bins reflects differences in total employment. The net job creation rate, for example, of the high-growth firms is roughly 118% and the moderately growing bin ([0.2 to 0.8)) has a net job creation rate of about 37%. The net job creation of the negative firm growth rate bins, not surprisingly, are uniformly negative. The most prominent COVID-19 effects, which appears for the first time in 2021 due to the fact that employment measurement is taken on March 12th of each year, are most severe for the moderately contracting ((-0.8 to -0.2]) and the significantly contracting firms ((-2, -0.8]).

[Insert Figure 4 here]

Sources of high-growth firms

Given the outsized role of high-growth firms in terms of job creation and firm performance, we use the BDS-HG tabulations to examine their origins. The composition of activity in the U.S. economy has changed dramatically since the 1980s. There has been a secular decline in entry (Decker et al., 2016), a rising share of activity among large firms (Autor et al., 2020), and significant sectoral changes, in particular a decline in manufacturing (Fort et al., 2018). In light of these changes, we examine where high-growth firms originate from (e.g. firm age, firm size, sector, and state) and how that has changed over time. To do this, we focus on the share of firms and employment in a group that are associated with high-growth firms ("high-growth intensity"). This allows us to abstract

away from the changing composition of economic activity and see how different groupings of firms and establishments have contributed more or less, relative to their size, to high-growth activity over time.[13]

By firm maturity. We begin with firm maturity, categorizing firms as young startups (i.e., ages 1-5), mature startups (i.e., ages, 6-10), and established firms (i.e., ages 11 and above).[14] Figure 5 presents the intensity of high-growth firm activity by firm maturity. Panel A shows the share of high-growth firms and Panel B shows the share of employment among high-growth firms. The key takeaway from this figure is that a smaller share of young startups grow quickly after entry than in the past. In Panel A, 7.4% of young startups in 1985 were high-growth, but this share fell to less than 4.5% before the COVID-19 pandemic. We see a similar pattern in employment shares (Panel B). The share of employment among young startups associated with high-growth firms fell from 8.8% in 1985 to 4.9% in 2020. The share of high-growth mature startups, on the other hand, has fallen on both a firm-weighted basis and an employment-weighted basis. The share of mature startups that were high-growth fell from 3.1% in 1990 to 1.9% 2020. The share of mature startup employment that was high-growth fell from 2.7% in 1990 to 1.5% in 2020. Established firms saw a relatively flatter trend in the share of high growth firms and employment, with the share of firms falling about 0.8 percentage points and the share of employment falling by about 0.4 percentage points from the 1990 to 2020.

[Insert Figure 5 here]

The effects of the COVID-19 pandemic can be seen in the 2021 spike in the share of high-growth firms for all age groups. Taken together, the patterns across firm age

[13] A related but distinct analysis could focus on the distribution of high-growth firms and employment across different age, size, industry, and geography cells. While meaningful, this alternative approach is subject to compositional changes of firms such that if a specific group (e.g., young firms) experiences a decline in the number of firms over time.

[14] In the LBD, firm birth is recorded as the year during which the firm is observed with the first paid employee. Birth year is coded as firm age of zero. In this analysis, we exclude new firms (i.e., age zero).

groups suggest that the intensity of high-growth firm activity reflects not only a decline in entry but also slower post-entry growth.

By firm size. Next, we describe how high-growth firm activity varies with firm size. We classify firms based on their employment size into the following groups: small if between 1 and 19 employees, medium if between 20 and 499 employees, and large if 500 employees or more.[15] Similar to the firm age figures, Panel A of Figure 6 shows the share of firms that are high-growth by firm size groups and Panel B shows the share of employment associated with high-growth firms by firm size groups. We find that the decline in high-growth firms between 1980 and 2020 is particularly severe for small (from 3.4% to 2.2%) and medium firms (from 2.8% to 1.3%), while their larger counterparts experienced a smaller decline (from 1.1% to 0.8%). We find roughly similar trends in the share of employment from high-growth firms for each of the three groups except for a slightly flatter trend for the largest firms. The growth rate-based bins allow us to provide additional intuition for the magnitude of the changes across size bins. For example, a growth rate of 0.8 is equivalent to a 130% change in employment from $t-1$ to t. For the 1 to 19 size group, this means adding between 2 to 26 employees. Interestingly, about 1% of firms with 500+ employees added at least 667 employees. In sum, we find that while the shares of firms and employment from high-growth have declined for small- and medium-sized firms, similar declines are not observed for large firms.

[Insert Figure 6 here]

By firm maturity and size. We now examine how growth rates vary with both firm age and size. Figure 7 shows the share of high-growth employment within firm age and firm size bins. The darker shaded bars capture younger firm age groups with the bars grouped by firm size. Holding size constant, a much larger share of employment among

[15] We use the average size measure from the BDS (fsize), which captures the average size of the firm in t and $t-1$.

younger firms is associated with high-growth firms. Holding age constant, there is less of a systematic relationship. For very young firms, the largest size classes has the highest share. For firms 6-10 (still young), the highest share is the small firms but medium and large firms have similar shares. For mature firms, there is decline in the share of high-growth employment moving from the small to large groups. The strong relationship between firm age and high-growth incidence in our data aligns with prior research showing that younger firms are more likely to scale rapidly and that age, more than size, explains systematic variation in growth dynamics (Coad et al. 2014; Haltiwanger et al. 2016; Sivadasan et al. 2024).

[Insert Figure 7 here]

By industry. There have been significant changes over the past four decades in the composition of economic activity across broad sectors of the economy (Fort et al., 2018). In this section we examine what industries contribute relatively more or less to high-growth activity. We classify industries based on two-digit 2017 North American Industry Classification System (NAICS) codes, which represent the broadest categorization scheme and are commonly referred to as sectors. Panel A of Figure 8 shows the percent of high-growth firms for a subset of sectors. All six sectors shown exhibit a general decline in the share of high-growth firms. Construction has the largest decline from 8.4% in 1978 to 3% in 2021. Manufacturing and professional services saw similar declines falling from 4.8% to 2% in manufacturing and from 5.1% to 2.4% in professional services. Interestingly, a few sectors began to flatten out beginning in 2010 including Information and Education & Health. Nonetheless, the share of high-growth firms in 2020 remains well below the levels in 1978 for all sectors.

[Insert Figure 8 here]

The construction sector has the highest share of high-growth firm activity, which may seem surprising given its meager productivity growth (Goolsbee and Syverson,

2021). However, this is a reminder that a high share of high-growth firms reflects volatility. In construction, this volatility arises from firms expanding and contracting as large, temporary projects begin and end—creating jobs at the outset and shedding them upon completion. Panel B of Figure 8, which displays the distribution of each sector's employment across the growth rate bins, supports this interpretation. While the construction has a high share of employment in the high-growth bin, it generally has longer tails at both ends, including firm entry and exit.

The BDS-HG tables allow us to explore patterns at a more detailed industry level. For illustration, Table 2 lists the top five four-digit NAICS industries by decade, ranked by the share of high growth firms. Consistent with the large share of high growth firms and the volatility documented in Figure 8, industries within the construction sector consistently appear among the top five across all decades. Industries with notable right tail activity reflecting more than volatiliy include the Scientific R&D industry in the 2000s and Home Health Care Services in the 1990s. Relatedly, computer and IT equipment manufacturing industries comprise the majority of the top five in the 1980s, indicating that elevated high growth activity in these industries preceded the broader IT boom of the 1990s.

[Insert Table 2 here]

By geography. An important dimension of these data for local and regional policy makers is the geographic distribution of high-growth activity. With these new BDS tabulations we can ask the question: where are high-growth firms located? High-tech employment, for instance, is highly concentrated in a relatively small number of metro areas (Chow and Goldschlag, 2023). To do this we analyze state-level data with the growth rate distribution for all 50 states and the District of Columbia. First, we assess the share of all high-growth firms in the U.S. economy residing in each state. Because larger states are more likely to account for more high-growth firms, we normalize this measure by differencing each state's share of high-growth firms from its share of all

firms in the economy. This measure indicates a region's contribution to high-growth firms relative to its overall share of firms. Positive values indicate "more" high-growth firms than we would have expected given the state's size.

The results are shown in Figure 9, with the difference (in percentage points) between a state's share of high-growth firms and its share of all firms on average between 2010 and 2019 captured by the height of each bubble and the size of the bubble reflecting total employment of each state. A handful of states have significantly more high-growth firms that one would expect just based on their size. In particular, California and Texas are distinctly positioned with the highest premium in high-growth firm share along with a large base. California, for example, accounts for 12.2% of all firms but 13.4% of high-growth firms, which yields the 1.2 percentage points difference shown in the figure. Texas, similarly, accounts for 7.4% of all firms and 7.9% of high-growth firms, a gap of about 0.5 percentage points. Washington, Nevada, and Utah also have more high-growth firms than we would expected given their share of all firms. In contrast, states such as New York, Pennsylvania, Illinois and Ohio exhibit a lower share of high-growth firms than their share of all firms. Given the long time series available in the BDS-HG tabulations, we also examine the dynamic changes across the firm growth rate distribution in each state over time (see Figure B1 in the Online Appendix).

[Insert Figure 9 here]

4 Potential Research Applications of the BDS-HG Dataset

In this section, we discuss how researchers can leverage the BDS-HG dataset's key advantages—namely, its detailed growth rate distributions, long time series since 1978, and broad coverage across firm types, industries, and geographies—to address important questions in various research domains such as corporate strategy, firm dynamics, and entrepreneurship. Because strategic management is fundamentally concerned with

heterogeneity in firm performance (e.g., Rumelt 1991; Helfat and Peteraf 2003)——not just among the superstars, but across the full spectrum of firm outcomes—BDS-HG's ability to capture variation across the entire growth rate distribution offers unique opportunities to study patterns of growth, stagnation, and decline.

One practical use of BDS-HG is to help researchers assess the generalizability of their empirical setting. Much of empirical research in strategy and management relies on selected samples—such as single-industry datasets, surveys, or proprietary firm records—which often raises concerns about the external validity of reported findings. A key challenge is that researchers typically lack access to a comprehensive benchmark against which to compare their sample. As a result, discussions around replicability and external validity have remained prominent in management research (e.g., Bettis et al. 2016). By offering broad coverage of all employer firms in the U.S. over five decades, BDS-HG provides a comparison tool for researchers to quantitatively evaluate the representativeness of their study sample.

In addition to serving as a benchmarking tool, BDS-HG can also be directly incorporated into future research as a complementary source of data. Although BDS-HG is aggregated above the firm level due limitations in data disclosure, we follow the example of Felten et al. (2021), who demonstrate how aggregated occupational-level data on AI exposure can enable meaningful insights for management research. We follow this approach by first comparing BDS-HG with existing alternative datasets. Next, we highlight three thematic areas for future research aided by the use of the BDS-HG dataset. To illustrate, we accompany each thematic area with an example analysis by integrating BDS-HG with other data sources.

4.1 Comparison between BDS-HG and existing alternatives

Nationally representative administrative microdata—such as the Census Bureau's Longitudinal Business Database (LBD)—have been among the most valuable resources for

advancing our understanding of organizations and their growth (Nagaraj and Tranchero 2023; Sterk et al. 2021; Sivadasan et al. 2024).[16] However, conducting research with such data can be costly in certain respects. In particular, access to confidential Census microdata is restricted to approved projects through the Federal Statistical Research Data Centers (FSRDCs), and the disclosure of research outputs is subject to limitations—such as restrictions on the number and granularity of estimates. As such, enabling public access to detailed information derived from the LBD—as granular as possible—would benefit scholars studying firm growth, including those in economics, finance, and strategic management.

An alternative dataset that aims to be nationally representative is the National Establishment Time Series (NETS), an establishment-level dataset intended to cover all private-sector firms in the U.S. NETS is more readily accessible to researchers compared to administrative data such as the LBD, though the monetary cost of access is typically high. An important disadvantage of NETS relative to the LBD is measurement error: recent studies indicate that a substantial share of employment and sales data in NETS is imputed and, as a result, NETS performs poorly in capturing firm growth dynamics, particularly for young and small firms (Crane and Decker, 2019). Such limitation makes it difficult to analyze detailed growth and shrinkage outcomes with NETS. Other commonly used datasets—such as those covering venture capital–financed startups (e.g., VentureSource) or publicly traded firms (e.g., Compustat)—provide detailed firm-level information but are limited to highly selected samples of companies that have already secured VC funding or reached an IPO.

BDS-HG fills these gaps by providing public access to detailed information on the full distribution of growth rates—not just the average, but also the number of firms

[16]Other useful Census datasets, such as the Census of Manufacturers (CM), Annual Survey of Manufacturers (ASM), or the Annual Business Survey (ABS), can be linked to the LBD to provide additional information on establishments and firms. While informative, these datasets are more limited in scope; for example, CM and ASM cover only manufacturing, while ABS is available only from 2018 onward.

and employment in various percentiles and growth rates—at a highly granular level. This level of granularity distinguishes BDS-HG from existing similar public-use datasets, including the base BDS, Quarterly Census of Employment and Wages (QCEW), and Business Employment Dynamics (BED) of the BLS. The dataset also spans a long time period, allowing researchers to analyze distant historical episodes. It also includes all industries and geographies, making it possible to conduct analysis across a wide range of sectors and regions.

4.2 Thematic areas for future research

With these relative advantages in mind, we discuss future research that can be aided by BDS-HG. To organize our discussion, we identify three thematic areas for future research in strategic management. To help demonstrate the use case of BDS-HG in each area, we complement this discussion by providing in-depth empirical analysis by integrating BDS-HG with other data sources. Together, these empirical examples demonstrate how BDS-HG can be used in applied research and motivate a wide range of strategy-relevant research questions.

4.2.1 Entrepreneurship and scaling

A growing body of research has documented a decline in U.S. business dynamism, marked by fewer high-growth startups and increasing stagnation among startups (Decker et al. 2016). Consistent with these trends, our analysis of the BDS-HG dataset reveals a notable rise in firms exhibiting virtually zero employment growth. One possible explanation is that more firms are being founded without meaningful growth aspirations (Hurst and Pugsley 2011). Another is the rising frictions to post-entry scaling in spite of growth ambitions (Alvarez and Barney 2017; Lee and Kim 2024). This raises important open questions in strategy about the post-entry growth trajectories of entrepreneurial firms and the conditions that shape their outcomes.

One particularly salient question concerns the competitive interplay between startups and mature firms. Do high-performing incumbent firms crowd out startup growth by intensifying competition and raising barriers to scale (e.g., Chen and Hambrick 1995; Huyghebaert and Van de Gucht 2004)? Or do they enable startup success by providing demand-side opportunities as customers, partners, or acquirers (e.g., Myles Shaver and Flyer 2000; Gans et al. 2002; Singh and Mitchell 2005)? The BDS-HG dataset offers a useful way to explore this question by capturing the annual growth dynamics of incumbent firms across sectors and regions. To illustrate this, we integrate BDS-HG with two complementary data sources: a large-scale sample of venture capital-financed startups from PitchBook and firm-level employment data from Revelio Labs based on LinkedIn profiles. We identify U.S. startups that received Series A funding between 2005 and 2020 and link them to sector-year-level incumbent growth measures derived from BDS-HG, focusing on firms older than ten years.[17] We then examine a suite of startup outcomes——employment growth, survival, total funding raised, and liquidity event (IPO or acquisition)——in one- and five-year windows following initial funding.

[Insert Table 3 here]

Table 3 presents the results from our firm-level regressions. Panel A reports outcomes measured five years after the startup's Series A financing. We find that an increase in the number of high-growth incumbents operating in the startup's industry is associated with significantly lower employment growth ($p < .01$), based on LinkedIn employment data. This negative relationship also holds for the total amount of VC funding raised in the five-year window ($p = .038$). Interestingly, a higher rate of firm failure among mature incumbents correlates with increased VC funding for startups ($p = .014$), suggesting that competitive shakeouts may benefit new entrants. In contrast, we find no systematic relationship between incumbent dynamics and the likelihood of startup survival,

[17] High-Growth, New, Stagnant, Shrinking, and Failing Firms are defined by BDS-HG growth bins [0.8,2), 2, (-0.01,0.01), (-2,-0.8], -2, respectively.

acquisition, or IPO. However, conditional on being acquired, startups in sectors with more high-growth incumbents are acquired more quickly ($p = .072$), while those facing higher incumbent failure rates experience longer durations to acquisition ($p < .01$). Panel B shows directly similar patterns using a one-year window, though estimated effects are smaller and less precise, indicating that the influence of incumbent dynamics may take time to materialize. Overall, these results support the competitive crowding-out perspective: startups tend to grow less and raise less capital when surrounded by thriving incumbents, but perform better when established firms fail——consistent with the logic of creative destruction.

This analysis highlights how BDS-HG enables strategy scholars to investigate the scaling trajectories of startups in the context of broader market dynamics. More broadly, the BDS-HG dataset allows researchers to analyze the full distribution of growth outcomes among startups, track post-entry dynamics by firm age and size, and assess how regional growth dynamics may be tied to startups' growth outcomes. Moreover, BDS-HG can allow for comparative analyses of geographic and temporal variation in startup growth, and enables benchmarking of U.S. firm dynamics against OECD economies (Calvino et al. 2020).

Moreover, we use BDS-HG as a benchmarking tool to assess the external validity of this analytic sample. Using the same category of firm growth, we find that this sample is substantially over-represented in terms of high-growth firms compared to all young firms in this time period from BDS-HG (27.4% versus 3.0%). In tandem, this sample has a much lower share of stagnant firms compared to BDS-HG (7.4% versus 32.1%). This exercise demonstrates that this sample of venture capital-financed startups reflects a specific type of entrepreneurship that is highly selected on growth-oriented startups. As such, the results should be interpreted with this context.

4.2.2 Institutional environment and firm growth dynamics

Research in strategy and entrepreneurship increasingly investigates how legal and regulatory environments shape firm growth. Prior work shows that policy changes such as non-compete enforceability and trade secret protections (e.g., Castellaneta et al. 2017; Starr et al. 2018) can influence both firm entry and growth. The BDS-HG dataset enables researchers to study these institutional impacts through a long panel of firm growth rate distributions across state and industry. This can help researchers to design natural experiment studies examining how policy shocks shape firm dynamics by age, size, and sector.

To illustrate, we build on a seminal paper by Marx et al. (2009), who document that an increase in the enforceability of covenants not to compete ("non-competes") leads to reduced mobility among inventors. We assess how non-competes can influence firm performance by examining the number of firms in different parts of the growth distribution. Following the empirical setup in Marx et al. (2009), we employ a difference-in-differences framework exploiting the 1985 reversal of non-competes law in Michigan. To assess both the medium- and long-term effects, we separately estimate outcomes using five- and ten-year windows.

[Insert Table 4 here]

Regression results are presented in Table 4. In Panel A, which uses a five-year window, we find that stronger enforceability of non-compete agreements is associated with a significantly lower number of de-novo startups ($p < .01$), consistent with prior evidence (Starr et al. 2018; Marx 2022). In addition, we observe negative estimates on the number of high-growth, shrinking, and failing firms ($p < .01$). When we extend the analysis to a ten-year window in Panel B, the effects of non-competes appear more muted. The estimate for high-growth firms remains negative but is substantially attenuated ($p = .05$), while the effects for other firm types are statistically indistinguishable

from zero ($p > .25$).

Taken together, these results suggest that non-competes can suppress economic dynamism in affected regions——not only by reducing entrepreneurship, but also by limiting both expansion and reallocation through high-growth, shrinking, and failing firms. However, these effects appear to dissipate over the longer run. Our finding that non-competes reduce the number of both high-growth and under-performing firms suggests that enforceability can contribute to a more static competitive landscape. This opens up opportunities for future research on how legal constraints shape the intensity of competition and patterns of firm growth, decline, and turnover—core concerns in the organizational ecology tradition as long emphasized in organizational ecology (e.g., Hannan and Freeman 1989).

4.2.3 Competition and industry structure

A long-standing literature has examined how competition and industry structure interact with the firm's strategy in explaining growth outcomes. Classic work highlights diversification as a response to risk and rivalry (Rumelt 1982; Montgomery 1985), while others emphasize the importance of radical innovation and technological disruption (Tushman and Anderson 1986; Tripsas 1997; Benner 2010). Changes in market concentration——such as the rise of "superstar firms" (Autor et al. 2020)——may alter the strategic response for both incumbents and entrants. The BDS-HG dataset provides granular growth rate distributions by firm size, age, and industry, enabling researchers to examine how industry-level dynamics can influence firm-level strategic decisions.

For instance, Dixit and Pindyck (1994) provide a real options framework that explains how firms time and scale investments based on industry volatility and uncertainty, a concept widely applied in strategic management as discussed in Trigeorgis and Reuer (2017). By linking BDS-HG growth metrics to firm-level capital expenditure from Compustat, we showcase the dataset's potential to address some of these questions about

resource allocation and competitive positioning in dynamic industries. Table 5 presents results from regressions where the dependent variable is firm-level investment-to-capital ratio and the explanatory variables are the shares of firms in each growth bin—namely, high-growth, new, stagnant, shrinking, and failing firms—within each four-digit NAICS industry and year. We use one-year lagged values for explanatory variables to partially capture delays in firms' response. We also control for industry and year fixed effects and cluster the standard errors at the industry level.

[Insert Table 5 here]

The regression analysis shows significant associations between industry growth measures and firm investment in physical capital. Industries with higher shares of high-growth and new firms are significantly correlated with increased investment ($p < .01$), suggesting firms expand capital in response to growth opportunities. Conversely, a higher proportion of significantly contracting firms correlates with reduced investment ($p < .01$), indicating strategic retrenchment in declining industries. This example shows how BDS-HG can be incorporated in firm-level analysis to examine how the evolving competitive landscape may be associated with the firms' strategic behavior.

5 Conclusion

In this paper, we present a newly available dataset of firm growth rates in the United States. By offering public access to granular data on the full distribution of firm growth outcomes——spanning nearly five decades and broken down by firm maturity, size, industry, and geography——BDS-HG helps enable new empirical inquiries that were previously constrained by data availability. Despite being aggregated above the firm level, we showcase how BDS-HG can be combined with other datasets to conduct analyses even at the firm-level. This feature expands the dataset's relevance far beyond descriptive

statistics. Moreover, BDS-HG can be used as a direct resource for research but also as a point of comparison and benchmarking to firm-level datasets that have selection issues.

BDS-HG opens new avenues for empirical research across a wide spectrum of topics in strategic management. The examples we presented——on entrepreneurship and scaling, the influence of institutional and legal environments, and firms' investment responses to the evolving of competitive environment——are aimed to illustrate the kinds of questions BDS-HG can help address. By capturing the full distribution of firm growth outcomes at a granular level, BDS-HG provides a useful complement to firm-level data sources, allowing researchers to design sharper empirical strategies. The dataset, along with detailed information, can be accessed through the U.S. Census Bureau's Public-Use Data program which we plan to update on an annual basis.[18]

[18]Data can be accessed here: https://www.census.gov/programs-surveys/ces/data/public-use-data/experimental-bds/bds-high-growth.html

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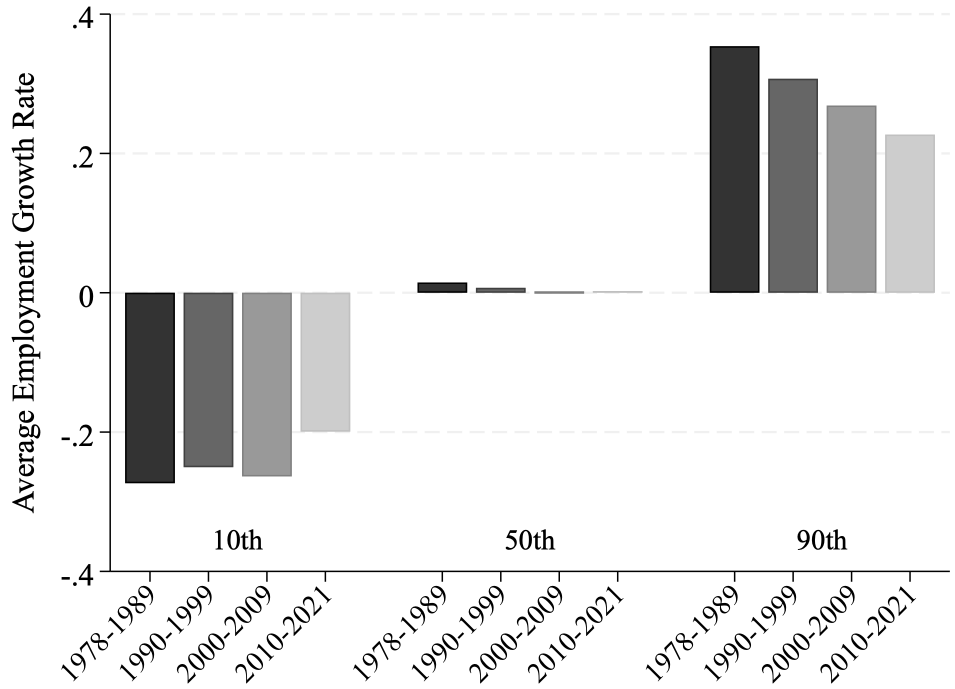
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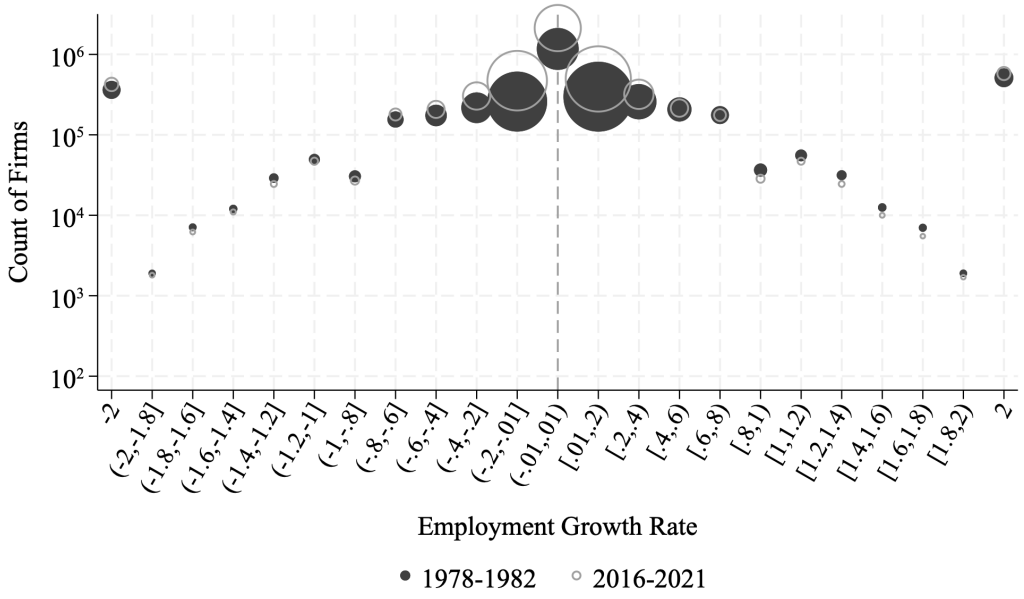
Figures

Figure 1: Firm growth rates by percentile over time

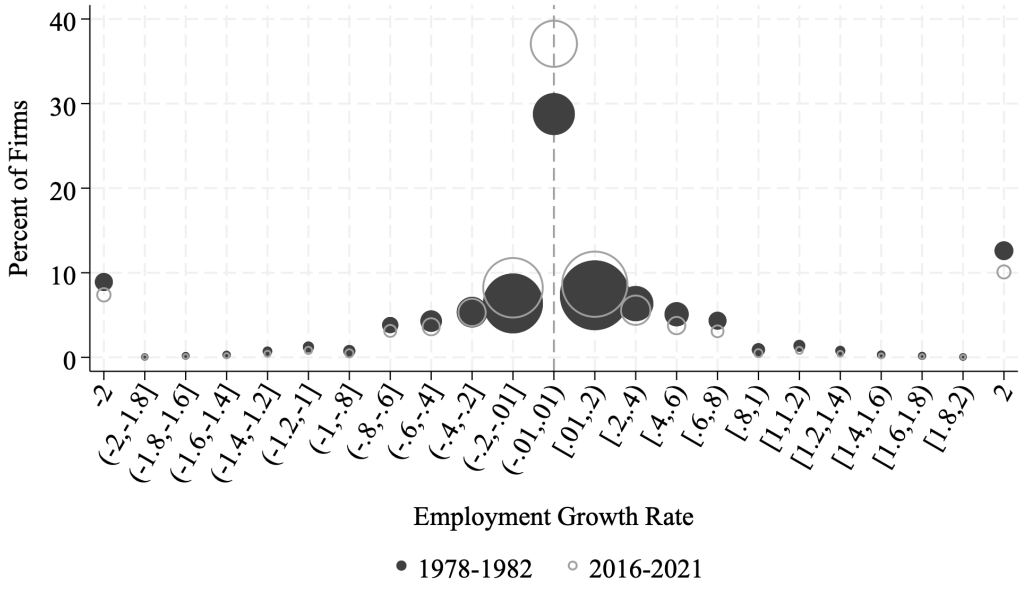


Source: LBDv202100.
Notes: Figure shows the average firm-employment growth rates by decades among firms classified between the 9^{th} and 11^{th} (labeled 10^{th}), 49^{th} and 51^{th} (labeled 50^{th}), and the 89^{th} and 91^{th} (labeled 90^{th}) percentiles of the employment weigthed growth rate distribution.

Figure 2: Detailed Distribution of Firm Growth Rates, 1980 vs. 2018



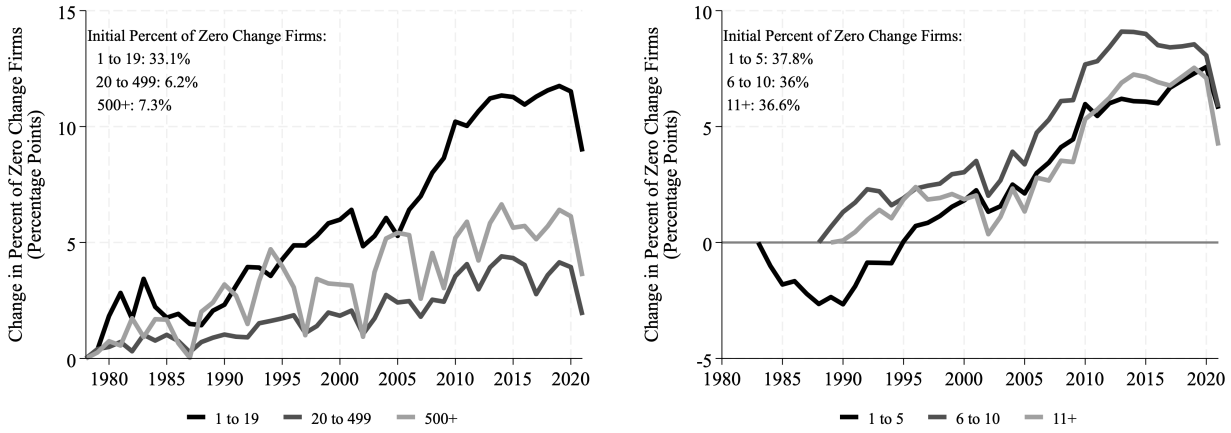
(a) Log Firm Counts



(b) Percent of Firms

Source: LBDv202100.
Notes: Panel A shows average count of firms (log scale y-axis) across groupings of years by detailed growth rate bins. Note that these bins are more disaggregate than those provided in the BDS-HG tabulations. Solid circles represent average counts for the earlier period (1978-1982) and hollow circles show average counts for the later period (2016-2021). Panel B shows ther percent of firms accounted for by each bin.

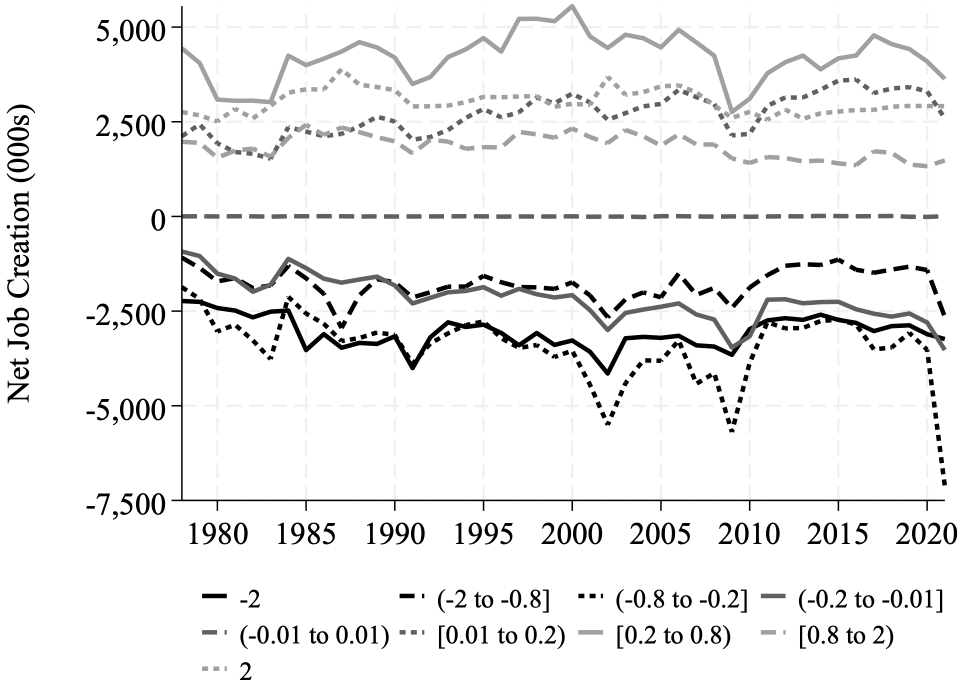
Figure 3: Stagnant Firms by Size and Age



(a) Firm Size (b) Firm Age

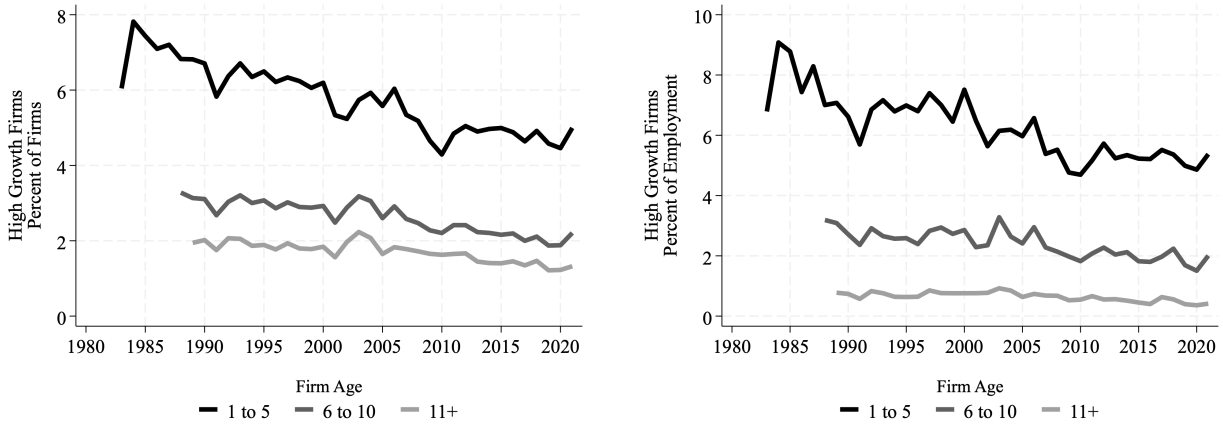
Source: BDS-HG 2021.
Notes: Panel (A) shows the change in the share of stagnant firms, which are defined as those with firm growth between -0.01 and 0.01, by firm size bins. To show relative changes, shares are benchmarked to the initial year. Panel (B) shows the same by firm age bins.

Figure 4: Net Job Creation by Firm Growth Bins



Source: BDS-HG 2021.
Notes: Figure shows net job creation counts in 1,000s by firm growth rate bins.

Figure 5: Intensity of High-Growth Firms by Firm Maturity

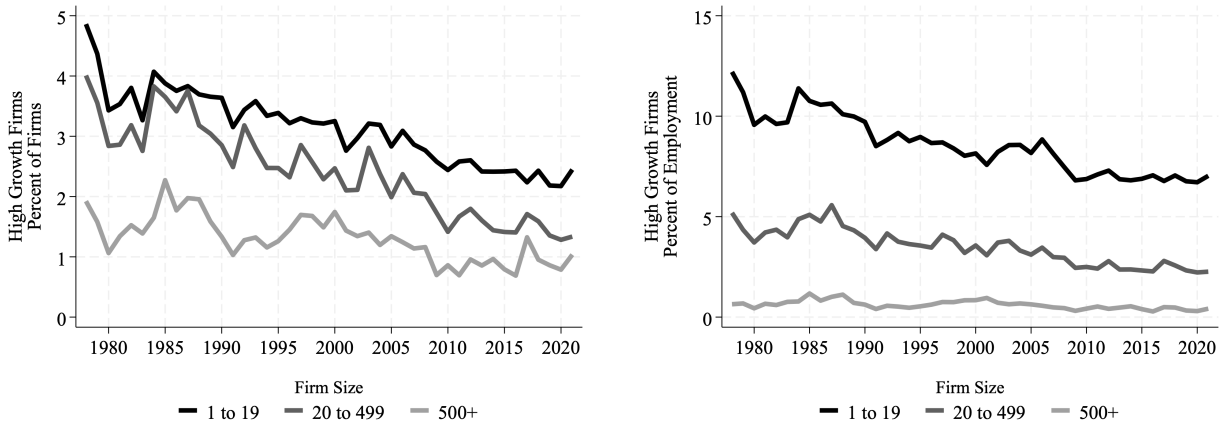


(a) Share of Firms

(b) Share of Employment

Source: BDS-HG Tabulations.
Notes: The first year observed in the LBD is 1976. Firms first observed in 1976 are classified as "Left Censored" in the BDS. To avoid mechanical increases as more ages are represented within a group, we begin our analysis in 1983 for young startups and 1988 for mature startups. The "11+" group includes "Left Censored" firms, all of which would be at least 11 years old in 1989, where we begin the "11+" series.

Figure 6: Intensity of High-Growth Firms by Small, Medium, and Large Firms

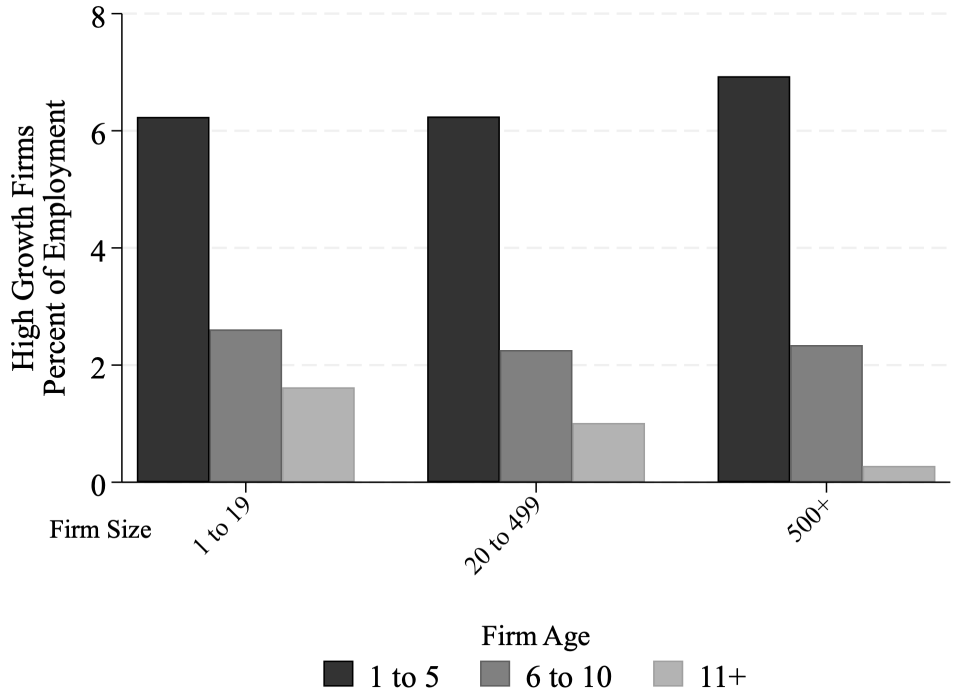


(a) Share of Firms

(b) Share of Employment

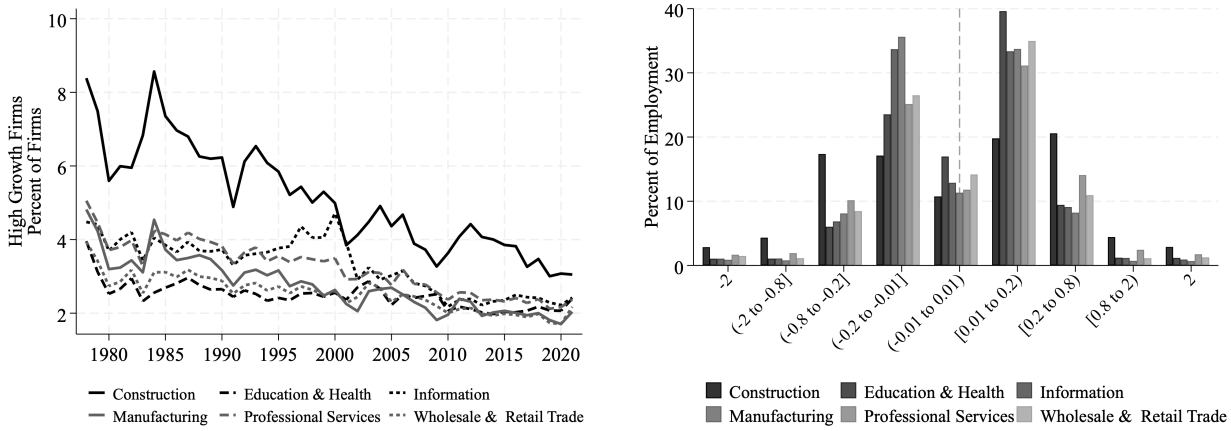
Source: BDS-HG Tabulations.
Notes: Firms classified by average employment in $t-1$ and t.

Figure 7: Share of Employment from High-Growth Firms by Size and Age



Source: BDS-HG 2021.
Notes: Firms classified by average employment in $t-1$ and t. Firms first observed in 1976 are classified as "Left Censored" in the BDS. The "11+" group includes "Left Censored" firms, all of which would be at least 11 years old in 1989, where we begin the "11+" series.

Figure 8: Intensity of High-Growth Firms by Industry



(a) Share of Firms

(b) Distribution of Employment

Source: BDS-HG Tabulations.
Notes: Panel A shows the share of high-growth firms within a subset of sectors over time. Panel B shows the distribution of employment on average, within sectors, by growth rate bins.

Figure 9: State's Share of High-Growth Firms versus Share of All Firms



Source: BDS-HG 2021.
Notes: States are ordered by the difference between a state's share of all firms and the state's share of all high-growth firms. Positive values indicate a state's share of high-growth firms is greater than its share of all firms. Bubble sizes capture the states size in terms of employment. All measures are averaged between 2010 and 2019.

Tables

Table 1: Summary Statistics of Firm Growth in the U.S.

Panel A: Firms

Years	Total Firms	Share (%) of Firms by Growth Type				
	(annual mean, in millions)	New	High-Growth	Stagnant	Shrinking	Failing
1978-1980	4.00	13.1	3.8	28.4	3.0	8.5
1981-1985	4.27	12.8	3.3	29.6	3.1	9.1
1986-1990	4.73	12.6	3.3	29.0	2.9	9.0
1991-1995	4.92	11.2	3.0	30.9	3.1	8.3
1996-2000	5.24	10.7	2.9	32.2	2.6	7.9
2001-2005	5.44	10.9	2.7	32.4	2.9	7.7
2006-2010	5.65	10.2	2.4	34.3	2.9	8.4
2011-2015	5.46	9.9	2.2	37.3	2.1	7.2
2016-2021	5.73	10.1	2.0	37.1	2.0	7.4
Overall		**11.1**	**2.7**	**32.9**	**2.7**	**8.1**

Panel B: Job Creation

Years	Total Job Creation	Share (%) of Firms by Growth Type				
	(annual mean, in millions)	New	High-Growth	Stagnant	Shrinking	Failing
1978-1980	13.24	20.0	13.8	2.2	0.1	0.0
1981-1985	13.22	22.7	14.6	2.8	0.1	0.0
1986-1990	15.90	22.0	13.7	2.3	0.1	0.0
1991-1995	15.00	19.9	12.4	2.4	0.1	0.0
1996-2000	17.66	17.4	12.2	2.4	0.1	0.0
2001-2005	17.66	18.8	11.8	2.6	0.1	0.0
2006-2010	16.16	18.6	11.1	2.9	0.1	0.0
2011-2015	15.58	17.3	9.6	3.2	0.1	0.0
2016-2021	15.90	18.1	9.4	2.8	0.1	0.0
Overall		**19.2**	**11.9**	**2.6**	**0.1**	**0.0**

Source: BDS-HG Tables (2021).
Notes: This table reports summary statistics of firm growth activity in each time period. The second column in Panel A (Panel B) shows the average number of total firms (gross job creation) during the time period; these counts are reported in millions. The next five columns show the percent share of firms belonging to the specific firm growth bin—specifically, (1) *New* firms as growth rate equal to 2, (2) *High-Growth* firms as growth rates between 0.8 and 2, (3) *Stagnant* firms as growth rates between -.01 and .01, (4) *Shrinking* firms as growth rates between -.8 and -2, and (5) *Failing* firms with growth rate equal to -2.

Table 2: Top Industries of High-Growth Firms by Decade

NAICS Code	Industry Description	Share of High Growth Firms
1980s		
3341	Computer and Peripheral Equipment Manufacturing	20.19
3342	Communications Equipment Manufacturing	19.45
3261	Plastics Product Manufacturing	19.24
3344	Semiconductor and Other Electronic Component Manufacturing	19.09
2371	Utility System Construction	18.58
1990s		
2371	Utility System Construction	19.47
2362	Nonresidential Building Construction	18.39
2382	Building Equipment Contractors	18.21
6216	Home Health Care Services	17.84
2381	Foundation, Structure, and Building Exterior Contractors	17.84
2000s		
2371	Utility System Construction	17.62
2362	Nonresidential Building Construction	17.11
2382	Building Equipment Contractors	16.42
2381	Foundation, Structure, and Building Exterior Contractors	16.27
5417	Scientific Research and Development Services	15.76
2010s		
2371	Utility System Construction	17.32
2389	Other Specialty Trade Contractors	16.66
2362	Nonresidential Building Construction	16.52
2381	Foundation, Structure, and Building Exterior Contractors	16.26
2382	Building Equipment Contractors	16.18

Source: BDS-HG 2021.
Notes: The table reports the top five four-digit NAICS industries by decade, ranked by the share of high-growth firms—defined as firms with employment growth rates between 0.8 and 2 (excluding entrants). To avoid undue influence from small, volatile industries, we exclude the bottom 25% of industries by employment when constructing the rankings. The list is presented through 2019 to maintain a balanced sample across decades.

Table 3: Incumbent Growth Dynamics and Startup Outcomes

Panel A: 5-Year Window

Dependent Variable	Log Emp. Size	Log Total VC Funding	1(Survive)	1(Acquired)	1(IPO)	Time to Acq.	Time to IPO
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
High-Growth Incumbents	-0.504	-0.294	-0.037	0.036	0.005	-1.161	-2.190
	(0.126)	(0.142)	(0.033)	(0.028)	(0.013)	(0.646)	(1.599)
Stagnant Incumbents	0.397	0.128	0.046	0.010	-0.073	-0.420	2.480
	(0.278)	(0.311)	(0.072)	(0.061)	(0.028)	(1.075)	(2.207)
Shrinking Incumbents	-0.224	-0.423	-0.027	0.004	-0.010	-1.388	-2.356
	(0.149)	(0.167)	(0.038)	(0.033)	(0.015)	(0.719)	(1.648)
Failing Incumbents	0.113	0.684	0.052	-0.034	0.013	3.052	1.106
	(0.249)	(0.280)	(0.064)	(0.055)	(0.025)	(1.066)	(2.464)
Observations (firms)	14,696	14,696	14,696	14,696	14,696	4,127	852
R-squared	0.386	0.092	0.280	0.023	0.043	0.209	0.436
Year FE	YES	YES	YES	YES	YES	YES	YES
State FE	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES

Panel B: 1-Year Window

Dependent Variable	Log Emp. Size	Log Total VC Funding	1(Survive)	1(Acquired)	1(IPO)
	(1)	(2)	(3)	(4)	(5)
High-Growth Incumbents	-0.060	-0.134	0.021	0.006	-0.001
	(0.097)	(0.079)	(0.034)	(0.007)	(0.004)
Stagnant Incumbents	0.214	-0.388	0.094	0.015	0.004
	(0.212)	(0.174)	(0.074)	(0.015)	(0.009)
Shrinking Incumbents	0.284	-0.223	0.077	0.005	-0.019
	(0.114)	(0.093)	(0.040)	(0.008)	(0.005)
Failing Incumbents	-0.329	0.400	-0.088	-0.016	0.005
	(0.191)	(0.157)	(0.067)	(0.014)	(0.008)
Observations (firms)	14,696	14,696	14,696	14,696	14,696
R-squared	0.130	0.030	0.273	0.008	0.008
Year FE	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes

Source: BDS-HG 2021, PitchBook, Revelio Labs

Notes: This table presents linear regressions at the firm-level. Panel A (B) shows the startup's performance outcomes as measured in one (five) year after the year of first venture capital financing. In Model 1, *Log Emp. Size* is the logged number of individuals employed at the based on LinkedIn records. In Model 2, *Log VC Total Funding* is the logged total amount of venture capital funding raised subsequent to the focal initial round. In Models 3–5, the dependent variable is a binary variable equaling 1 if the startup survives, is acquired, or experiences an initial public offering, respectively. In Models 6–7, the dependent variable is the number of months until acquisition or IPO, respectively, for firms that experience such liquidity event. Explanatory variables are the logged number of incumbent (i.e., older than ten years old) firms in four growth bins—(1) *High-Growth* firms as growth rates between 0.8 and 2, (2) *Stagnant* firms as growth rates between -.01 and .01, (3) *Shrinking* firms as growth rates between -.8 and -2, and (4) *Failing* firms with growth rate equal to -2—measured at the sector $\times$ year level. Robust standard errors are shown in parentheses.

Table 4: Non-Competes and Firm Growth Outcomes

	Dependent Variable: Ln(Number of Firms)				
Firm Type	High-Growth	New	Stagnant	Shrinking	Failing
	(1)	(2)	(3)	(4)	(5)
	Panel A: 5-Year Window				
Treated × Post	-1.990	-1.593	-0.280	-1.121	-1.748
	(0.217)	(0.237)	(0.278)	(0.270)	(0.281)
Treated	1.989	1.879	1.559	1.874	2.033
	(0.466)	(0.444)	(0.473)	(0.416)	(0.464)
Post	1.071	0.745	1.087	0.216	0.802
	(0.544)	(0.725)	(0.667)	(0.768)	(0.702)
Observations (state-year)	110	110	110	110	110
R-squared	0.153	0.144	0.154	0.167	0.155
Year FE	Yes	Yes	Yes	Yes	Yes
	Panel B: 10-Year Window				
Treated × Post	-0.424	-0.123	0.180	-0.038	-0.273
	(0.191)	(0.175)	(0.239)	(0.221)	(0.223)
Treated	1.536	1.385	1.308	1.451	1.560
	(0.487)	(0.436)	(0.457)	(0.435)	(0.458)
Post	-0.009	0.241	0.619	0.785	0.853
	(0.820)	(0.709)	(0.455)	(0.548)	(0.828)
Observations (state-year)	220	220	220	220	220
R-squared	0.107	0.118	0.181	0.143	0.124
Year FE	Yes	Yes	Yes	Yes	Yes

Source: BDS-HG 2021

Notes: This table presents results from linear regressions at the state-year level. Following Marx et al. 2009, we define *Post* as a binary variable equaling 1 for years on or after 1985, and 0 otherwise. Similarly, *Treated* equals 1 if the state is Michigan, and 0 if the state is Alaska, California, Connecticut, Minnesota, Montana, North Dakota, Nevada, Oklahoma, Washington, or West Virginia. Panel A covers five years around 1985 while Panel B covers 10 years. Dependent variables are the logged number of firms each of the five growth bins—specifically, (1) *High-Growth* firms as growth rates between 0.8 and 2, (2) *New* firms as growth rate equal to 2, (3) *Stagnant* firms as growth rates between -.01 and .01, (4) *Shrinking* firms as growth rates between -.8 and -2, and (5) *Failing* firms with growth rate equal to -2—measured at the state × year level. Standard errors, clustered at the state level, are reported in parentheses.

Table 5: Industry Growth Environment and Firm Investment

	(1) Investment	(2) Investment	(3) Investment	(4) Investment	(5) Investment
High-Growth Firms	1.254				
	(0.213)				
New Firms		0.291			
		(0.046)			
Stagnant Firms			-0.144		
			(0.056)		
Shrinking Firms				-0.803	
				(0.266)	
Failing Firms					-0.094
					(0.078)
Observations (firms)	197032	197983	197992	197086	197878
R-squared	0.10	0.10	0.09	0.09	0.09
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes

Source: BDS-HG 2021, Compustat

Notes: This table presents results from firm-level linear regressions. In all models, the dependent variable is the investment-to-capital ratio, measured as capital expenditures divided by gross property, plant, and equipment. Following Crouzet et al. (2022), we trim ratio values below zero or above one. The explanatory variables are the one-year lagged shares of firms in each of the five growth bins—specifically, (1) *High-Growth* firms as growth rates between 0.8 and 2, (2) *New* firms as growth rate equal to 2, (3) *Stagnant* firms as growth rates between -.01 and .01, (4) *Shrinking* firms as growth rates between -.8 and -2, and (5) *Failing* firms with growth rate equal to -2—measured at the four-digit NAICS $\times$ year level. Standard errors, clustered at the four-digit NAICS level, are reported in parentheses.