High-Growth Firms in the United States: Key Trends and New Data Opportunities

by

J. Daniel Kim
The Wharton School, University of Pennsylvania

Joonkyu Choi
Federal Reserve Board of Governors

Nathan Goldschlag
U.S. Census Bureau

John Haltiwanger
University of Maryland

CES 24-11 March 2024

Abstract

Using administrative data from the U.S. Census Bureau, we introduce a new public-use database that tracks activities across firm growth distributions over time and by firm and establishment characteristics. With these new data, we uncover several key trends on high-growth firms—critical engines of innovation and economic growth. First, the share of firms that are high-growth has steadily decreased over the past four decades, driven not only by falling firm entry rates but also languishing growth among existing firms. Second, this decline is particularly pronounced among young and small firms, while the share of high-growth firms has been relatively stable among large and old firms. Third, the decline in high-growth firms is found in all sectors, but the information sector has shown a modest rebound beginning in 2010. Fourth, there is significant variation in high-growth firm activity across states, with California, Texas, and Florida having high shares of high-growth firms. We highlight several areas for future research enabled by these new data.

Keyword*:* Firm Growth, Business Dynamism, Entrepreneurship, Business Dynamics Statistics

JEL Classification: L11, L25, L26, O30, O40

[*] All authors contributed equally. Any opinions and conclusions expressed herein are those of the author and do not represent the views of the U.S. Census Bureau, the Federal Reserve Board of Governors or its staff. The Census Bureau has ensured appropriate access and use of confidential data and has reviewed these results for disclosure avoidance protection. DRB Approval Number(s): CBDRB-FY24-0168. DMS Project Number 7083300. We thank Sean Wang, Cheryl Grim, and participants at the U.S. Census Bureau Center for Economic Studies seminar series for helpful comments and suggestions.

1 Introduction

> "There are important administrative restraints on the speed of the firm's growth. Human resources required for the management of change are tied to the individual firm and so are internally scarce. Expansion requires the recruitment of more such resources... The growth process is, therefore, dynamically constrained" (Penrose 1959).

High-growth firms play a central role in creating jobs and fostering innovation and productivity growth (Penrose, 1959; Schreyer, 2000; Schumpeter, 1942; Foster et al., 2019; Gort and Klepper, 1982). As such, both management and economics researchers have sought to better understand the nature of firm growth and the sources of high-growth firms.[1] In particular, recent studies have shown that young firms exhibit both high dispersion and also positive right skewness in growth rates (Decker et al., 2014, 2016; Haltiwanger et al., 2016), highlighting the central role of entrepreneurship for economic dynamism and high-growth activity. At the same time, recent studies show a decline in the pace of entrepreneurship, a decline in high-growth young firm activity, and an increasingly dominant role of incumbent large firms (Autor et al., 2020; Haltiwanger, 2022). Understanding how these patterns are related is an active area of research.

Given the importance of these issues for both researchers and policymakers, the OECD (Organisation for Economic Co-operation and Develop) launched a partnership with several national statistical agencies to provide annual statistics on firm growth in each country. Unfortunately, there has been a lack of comparable efforts in the United States. We respond to this opportunity by generating public-use statistics that systematically capture the evolution of the firm growth rate distribution and the characteristics of high-growth firms over time in the U.S. In this paper, we introduce the Business Dynamics Statistics of high-growth firms tables (BDS-HG), which capture the stock and flow of firms, establishments, and employment across the firm growth rate distribution. These new public-use data tables leverage confidential administrative data from the U.S. Census Bureau on all non-farm employer businesses in the U.S. between 1977 and 2021. Firms are categorized on an annual basis into classes based on their rate of employment growth. To illustrate the potential use and promise of these new data, we begin by characterizing the changing nature of the firm employment growth distribution in the past few decades and examine where high-growth firms emerge from.

Several striking patterns emerge. First, while there generally has been an increase in the number of firms in the U.S. in the past four decades, the share of firms that

[1] For example, see Acs and Audretsch (1987); Coad et al. (2014); Acemoglu et al. (2018); Azoulay et al. (2022).

are high-growth has steadily decreased from 18% in 1985 to 12% in 2015. This decline is driven by both falling shares of new firms and languishing growth among existing firms. In tandem, the U.S. economy has witnessed a substantial rise in stagnant firms—that is, firms that experience little to no change in employment—from 32% to 40% in the same 30-year period. Second, we transition to the question around the evolving sources of high-growth firms. With respect to firm size and age, we find that the decline in the share of high-growth firms is particularly severe for young and small firms. In contrast, mature and large firms do not exhibit substantial changes over time. In terms of industry, we find that all sectors—especially construction and manufacturing—have shown a general decline in the share of high-growth firms. Interestingly, a few sectors such as Information (e.g., software, media streaming, computing infrastructure) have shown a modest rebound beginning in 2010. However, all sectors remain far below their shares of high-growth firms from earlier decades. We also find meaningful geographic variation in high-growth firm activity. Compared to the baseline share of all firms, 14 states and DC are "overrepresented" in their share of high-growth firms. Among them, Florida, California, and Texas disproportionately contribute to high-growth firms even after accounting for their relatively large baseline share of all firms.

Our initial results highlight the rich potential for future research using these data and we point to two broad themes to help motivate future work. First, one rich area for research is to explore the antecedents of high-growth firm activity. That is, what are the factors—ranging from labor market frictions to industry agglomeration—that enhance versus suppress the emergence of high-growth firms? Extending beyond this static view, how are the factors that impact high-growth firms evolving over time and how are they impacted by the arrival and diffusion of new technologies? Second, what are the consequences of high-growth firms for markets and individuals? For instance, the prevalence of high-growth firms in a region can have meaningful effects on the wages of high- versus low-skilled workers in the region. Our hope is that the BDS-HG data will help enable a host of new research questions underlying high-growth firms.

The BDS-HG data provide new annual, public-use statistics covering 1977 to 2021 on the distribution of firm growth at the national-level and by state, detailed industry (up to 4-digit NAICS), firm size, and firm age categories with several multi-way tables (e.g,. firm growth by firm age and firm size). Firms are classified into 9 growth rate bins including 7 bins for continuing firms. The BDS-HG tables also provide tabulations by within-year growth rate percentile groups, which allow data users to focus on firms in the top decile of the growth rate distribution. For each of these growth rate or percentile bins, the BDS-HG tables provide the full suite of BDS statistics including employment, firm and establishment counts, and job creation and destruction. The BDS-HG data will be updated on annual basis. The BDS-HG tables, with rich firm growth distribution statistics, offer rich variation to explore the nature and sources of firm growth dynamics. For example, the statistics by 4-digit NAICS industries provides more than 114 thousand observations based on growth rate bin by 4-digit NAICS classification. Access to these new data along with additional documentation can be found at `https://www.census.gov/programs-surveys/ces/data/public-use-data/experimental-bds/bds-high-growth.html`.

The novel distributional statistics provided by the BDS-HG tables complement the large literature on productivity dispersion documenting and studying the evolution of productivity differences across businesses (see, e.g. Syverson (2011)). Productivity differences are influenced by several factors including efficiency differences, demand shocks, frictions such as adjustment costs, and distortions such as markups (Blackwood et al., 2021). Productivity differences are also closely related to the growth rate distribution of businesses–high productivity businesses are more likely to grow and low productivity ones are more likely to contract and exit. The BDS-HG data provides a new perspective on the decline in indicators of business dynamism, which are closely connected to the evolution of productivity dispersion statistics (Decker et al., 2020). Relatedly, the BDS-HG data complement the productivity dispersion statistics released by a joint BLS-Census project (*DiSP*).[2]

The paper proceeds as follows. Section 2 describes the input data and the methodology for computing firm growth rates. We briefly describe the approach used by the OECD (Organisation for Economic Co-operation and Development) and outline the approach used for the BDS-HG tables along with some descriptive statistics about the properties of the firm growth rate distribution. Section 3 provides a preview of the BDS-HG data, describing the characteristics of high-growth firms. Section 4 concludes.

2 Data and Methodology

Understanding employment dynamics, productivity, and firm growth requires fine-grained microdata at the establishment and firm-level, which are typically administered by national statistical offices. Currently, there are no publicly available statistics on firm growth for the U.S. In contrast, the OECD has produced such statistics in partnership

[2]For the *DiSP* statistics see `https://www.bls.gov/productivity/articles-and-research/dispersion-statistics-on-productivity`. *DiSP* currently only covers manufacturing but there are plans for releases of productivity dispersion statistics for other sectors.

with national statistical offices for a number of countries. These efforts enable timely tracking of not only the emergence of high-growth firms in each country, but also the comparison of such trends across countries. We follow the OECD methodology as closely as possible to ensure maximal cross-country comparability. In this section we briefly describe the OECD's efforts and outline our approach, highlighting differences when they appear.

2.1 OECD Approach

Given confidentiality concerns and other administrative challenges, it is often difficult to make cross-country comparable statistics (Desnoyers-James et al., 2019). To meet this need, the OECD partners with national statistical offices to generate comparable statistics on business dynamism as part of the OECD DynEmp program. One dimension used in the DynEmp program is firm growth, which allows the OECD to measures the contribution of high-growth firms to business dynamism.

The OECD computes 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). 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 OECD's DynEmp program assigns firms to one of six growth bins based on the firm's position on the within-year employment growth rate distribution.[3] The share of firms with zero growth is often larger than any one of six bins, and to avoid zero growth firms all being assigned to a single group, the DynEmp procedure randomly perturbs the growth rate of zero-growth firms. The OECD uses two different weighting schemes to create these groupings. The first is firm-weighted. The second is weighted by average employment between t-1 and t (the denominator of the TVV/DHS growth measure). In the employment-weighted tabulations, for example, the first group (p1-p10) accounts for exactly 10% of the total employment in the economy.[4] A key benefit of employment-weighted bins is that they fix the amount of employment associated with each group. Even as the growth rate distribution changes over time (e.g., overall contraction during the great financial crisis), each bin represents a fixed portion

[3] Specifically, the six groups are the following based on percentile value: p1-10, p11-p25, p26-p50, p51-p75, p76-p90, and p91-p99.

[4] It is important to note that the unit of analysis (e.g., firm versus establishment) varies across countries; but when units are mixed in the underlying data, the OECD recommends analysis at the firm-level. For more, see Desnoyers-James et al. (2019) on the Stata command dynemp3, which generates these statistics on firm growth.

of total employment in a given year. The firm-weighted groupings use a similar logic for the share of all firms (e.g., p1-p10 accounts for 10% of firms in a given year). Finally, the DynEmp program computes the growth rate distribution used for the bins for two samples: all firms and continuers only.

2.2 BDS High-Growth Approach

The approach described below aims to provide comparable measures of high-growth firms, meeting as many requirements of the DynEmp program as possible, while integrating the measures into the existing Business Dynamics Statistics (BDS) infrastructure. Our data are derived from the Longitudinal Business Database (LBD), the frame of all non-farm employer businesses in the U.S. (Jarmin and Miranda, 2002; Chow et al., 2021). Currently, the LBD covers years 1976 to 2021. The LBD provides information at the establishment-level such as employment, payroll, industry, age, and firm ownership. 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 12$^{\text{th}}$. This also includes employees on paid sick leave, holidays, and vacations but excludes proprietors and partners of unincorporated businesses.[5]

Similar to the OECD, we compute the TVV/DHS firm employment growth rate by aggregating establishment-level employment growth rate to the firm level using establishment size as weights. The TVV/DHS measure shares useful properties with log differences, while it also accommodates entry and exit. Since the denominator contains the average value over two years, this measure is also symmetric and it 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 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. 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 ($g_{i,t}$) are defined as follows.

[5]The March 12$^{\text{th}}$ 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).

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

For employment values E and where $X_{i,t} = \frac{1}{2}(E_{i,t} + E_{i,t-1})$. Firm-level growth is then the sum of employment changes weighted by the sum of average establishment employment, for all establishments i associated with firm f at time t[6], as follows:

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

This "organic" firm growth measure, which aggregates from establishment-level changes in employment, naturally abstracts from changes in a firm's size due to mergers, acquisitions, and divestitures. 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.[7] Average size will tend to allocate more growth and less contraction to large firm size bins compared to an initial size measure. Second, firms in the LBD exhibit significant mean reversion—firms that grew from $t-2$ to $t-1$ are much more likely to contract from $t-1$ to t. Third, in addition to transitory shocks, firms experience systematic and persistent growth patterns over the firm age life cycle (Decker et al., 2014). 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 contrast to the OECD methodology, we do not randomly perturb the growth rates of zero growth firms.

For the first method, following the OECD's DynEmp methodology, we classify firms based on their position on the within-year average employment-weighted growth rate distribution. Employment weighting is done, after computing firm growth rates and the sum of average employment (`denom`) at the firm-level, sorting firms within a year in ascending order by their growth rate, breaking ties randomly, computing each firm's cumulative share of economy wide average employment, then summing this share across firms in the sorted file. Firms that account of a cumulative share of less than or equal to

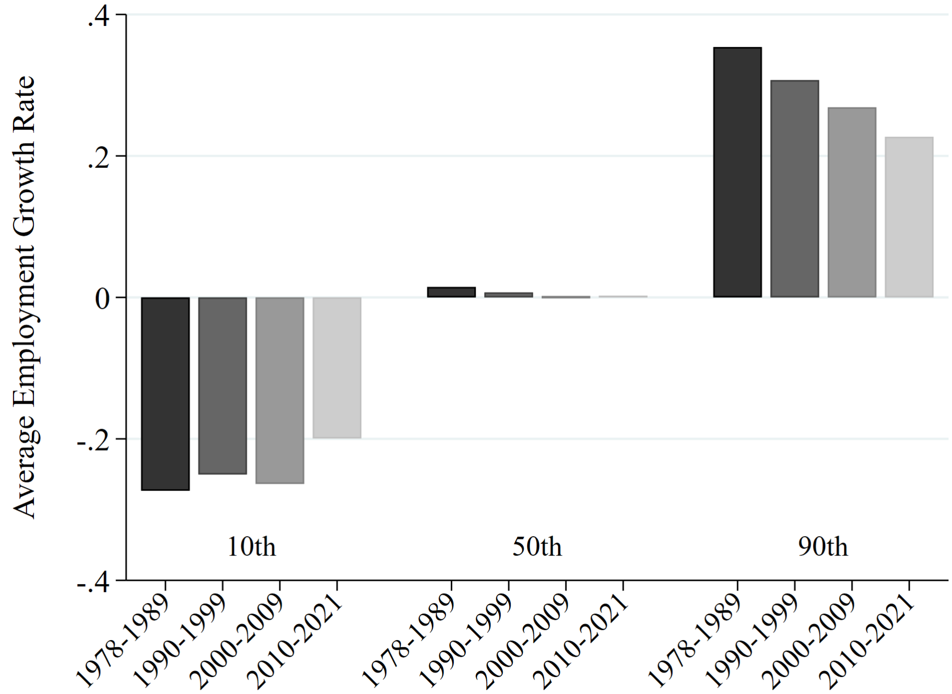
[6]Exiting establishments will be assigned a firm growth rate based upon their associated firm in $t-1$.

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

10 percent of total average employment are assigned to the p1 to p10 bin.

We use similar percentile-based growth rate bins as DynEmp but combine the middle bins into a single group. 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 contracts over time the growth rate associated with the 90th percentile of the employment-weighted growth rate distribution will change. To illustrate this point, Figure 1 shows the average growth rate associated with the 10th, 50th, and 90th 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 90th 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 10th percentile, which rose from -0.27 to -0.20 over the same period. Even the median, or 50th 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.

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.

Motivated by the time varying nature of the percentile-based method, our second 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. 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 and 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 define high-growth firms whose firm growth rate is 0.8 or greater. For comparison, for the percentile-based measures we define firms in the top 10 percentile of the within year growth rate distribution as high-growth. Continuing firms are considered high-growth, by this definition, if their size increased by more than approximately 130% year-over-year.[8] In addition to continuers, new and reactivating firms will also be considered high-growth since their growth rate is mechanically equal to 2.

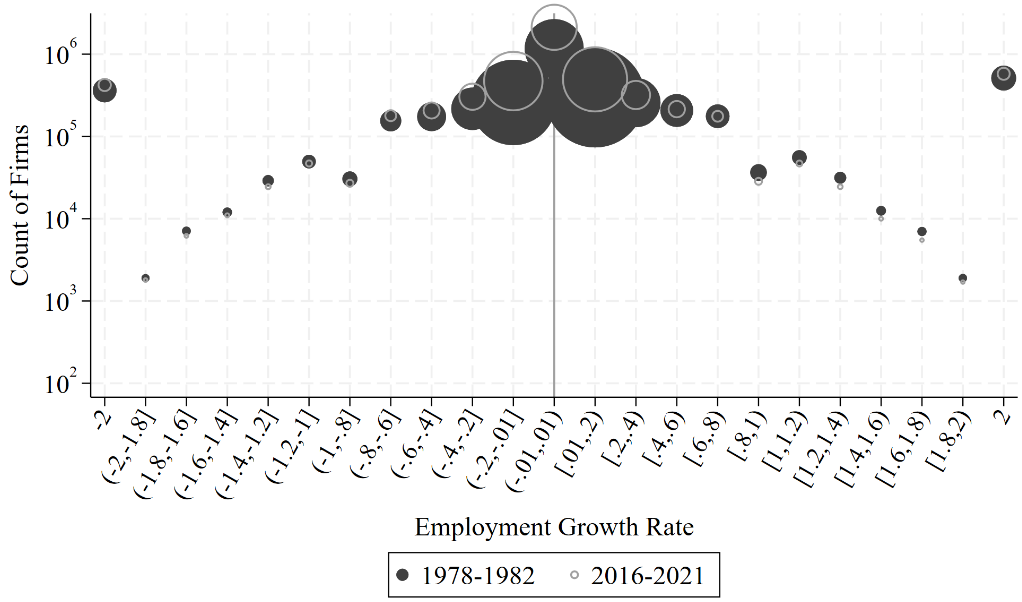
To motivate this threshold for high-growth firms, Figure 2 shows the count of firms across detailed firm growth rate bins in Panel A and the percent of firms Panel B.[9] In Panel A, the height of each dark circle shows the count of firms (with a log scale y-axis) at each point along the firm growth rate distribution on average between 1978 and 1982. The size of each bubble reflects the share of average employment among firms within each growth rate bin in those years. The hollow circles show a similar statistic for the years 2016 to 2021. Several patterns are notable in Figure 2. First, 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 1970s had nearly zero growth rates, which rose to 37% in late 2010s. 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). Second, 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 or no growth rose the most between 1980 to 2018. The count of firms that experienced significant growth or contraction declined significantly.

[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 with more details are available in the 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.

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



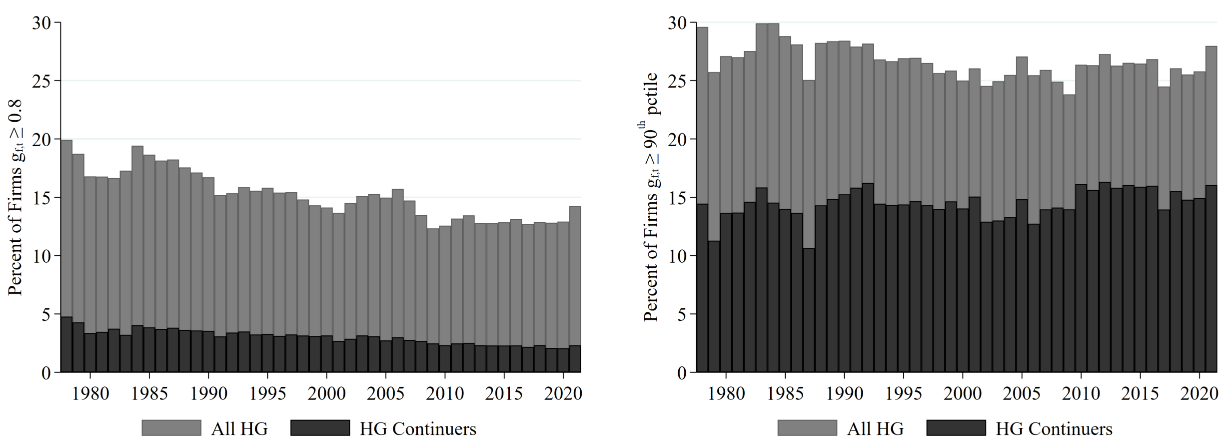
(a) Log Firm Counts

(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.

To further demonstrate the differences between the percentile-based and growth rate-based bins, Figure 3 shows the share of firms that are classified as high-growth by both measures. Panel A shows the percent of firms that are classified as high-growth using the growth rate-based measures, decomposed into all firms (light gray bars) and just continuers (dark gray bars). Panel B does the same but for the percentile-based measures. Panel A shows whereas roughly 17% of firms were high-growth in 1980, that share fell to 13% in 2020. In contrast, unsurprisingly, the percentile-based bins show a much flatter series for both all high-growth firms and continuer high-growth firms. As mentioned previously, this is driven by the fact that as the growth rate distribution contracts so too does the 90$^{\text{th}}$ percentile cutoff. The top percentile-based bin will always contain the 10% of average employment with the highest growth rates even as the growth rates of those firms declines. Variation in the share of firms covered by that bin, then, reflect differences in the size composition of the fastest growing firms. The percentile-based method also casts a wider net with many more firms classified as high-growth than the 0.8 cutoff we use for the growth rate-based method.

Figure 3: High-Growth Firm Shares



(a) Growth Rate-based Method (b) Percentile-based Method

Source: BDS-HG 2021.
Notes: Panel (A) shows the percent of firms classified as high-growth using the growth rate-based method (≥ 0.8 TVV/DHS) and Panel (B) shows the percent using the percentile-based method ($> 90^{th}$ percentile). All high-growth firms as a percent of all firms is shown in light gray and only continuer high-growth firms in dark gray.

The methodology used to produce the BDS-HG tabulations follows that of the OECD's

DynEmp program closely. We provide slightly less detail for the employment-weighted growth rate distribution-based percentile bins (collapsing the 25th to 75th bins) and for the initial release of the BDS-HG tabulations we produce only employment-weighted rather than firm-weighted percentile-based bins. We build upon the OECD's method by also producing growth rate-based bins that allow us to observe the shifting firm growth rate distribution over time. After categorizing firms into growth bins, we compute standard BDS measures of the stock and flow of establishments, firms, and employment. We provide statistics across the firm growth rate distribution by establishment and firm characteristics such as age, size, industry, and geography. 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. All of the following figures can be generated using the new, publicly available BDS-HG tabulations.

3 Trends in High-Growth Firm Activity

Anatomy of firm growth over time

Table 1 shows the count of firms, job creation, and total employment associated with all firms and the share of each accounted for by high-growth continuing firms, and high-growth entrants over time. All of the analyses in this section utilize the growth rate-based high growth classification. The total number of non-farm employer firms rises from about 3.6 million in the late 1970s to roughly 5.3 million by 2020. Over the same period, the share of high-growth firms fell from approximately 18.4% to 13.1%. The share of high-growth continuers declined by half and high-growth entrants fell by approximately a quarter over the period. In terms of employment, high-growth firms account for a much smaller share, falling from about 4% of total employment in the late 1970s to about 2.2% by the end of the period. In contrast, high-growth firms account for a large but falling share of job creation, from approximately 40.3% in the late 1970s to 32.2% in the 2010s.

One important trend that these new tabulations highlight is the rising share of stagnant or zero growth firms. Figure 4 shows the percent of firms with growth rates between -.01 and .01 (`fempgr_gr` bin **e)**). The share of stagnant firms rose from roughly 30% in 1980 to 40% in 2020. Interestingly, this trend has reversed in 2021, during which COVID-19 likely shifted many stagnant firms toward contraction or exit. Stagnant firms tend to be relatively small. Despite being 40% of firms in 2020, they only account for

Table 1: Summary Statistics of High-Growth Firms in the U.S.

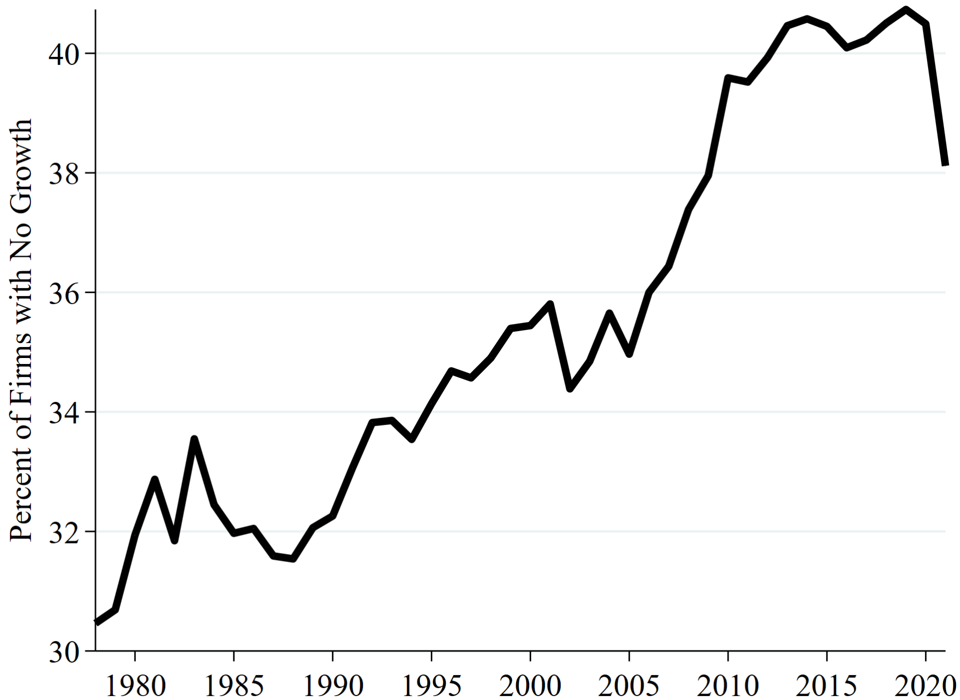
Decade	Firms			Employment			Job Creation		
	All	high-growth (%)		All	high-growth (%)		All	high-growth Firms (%)	
		Cont.	Entrants		Continuers	Entrants		Continuers	Entrants
1978-1980	3,663	4.1	14.3	71,603	2.2	1.8	11,120	16.5	23.8
1981-1985	3,883	3.7	14.1	76,301	2.1	2	10,776	17.9	27.8
1986-1990	4,303	3.7	13.9	87,498	2.1	2	13,002	16.8	26.9
1991-1995	4,514	3.3	12.3	93,615	1.7	1.6	12,571	14.9	23.7
1996-2000	4,827	3.2	11.7	105,511	1.7	1.5	15,150	14.2	20.3
2001-2005	5,018	2.9	11.8	113,433	1.5	1.5	14,944	13.9	22.2
2006-2010	5,178	2.7	11.1	117,188	1.3	1.3	13,731	13.1	21.9
2011-2015	5,072	2.4	10.6	116,651	1.1	1.2	13,434	11.2	20
2016-2021	5,302	2.2	10.9	128,764	1	1.1	13,603	11	21.2

Source: BDS-HG 2021

Notes: Table reports the average count of firms within groupings of years. Employment is average employment (denom). High growth firms are those with growth rates of 0.8 or higher. Counts reported in 1,000s.

about 15.3% of employment.

Figure 4: Rise of stagnant firms over time

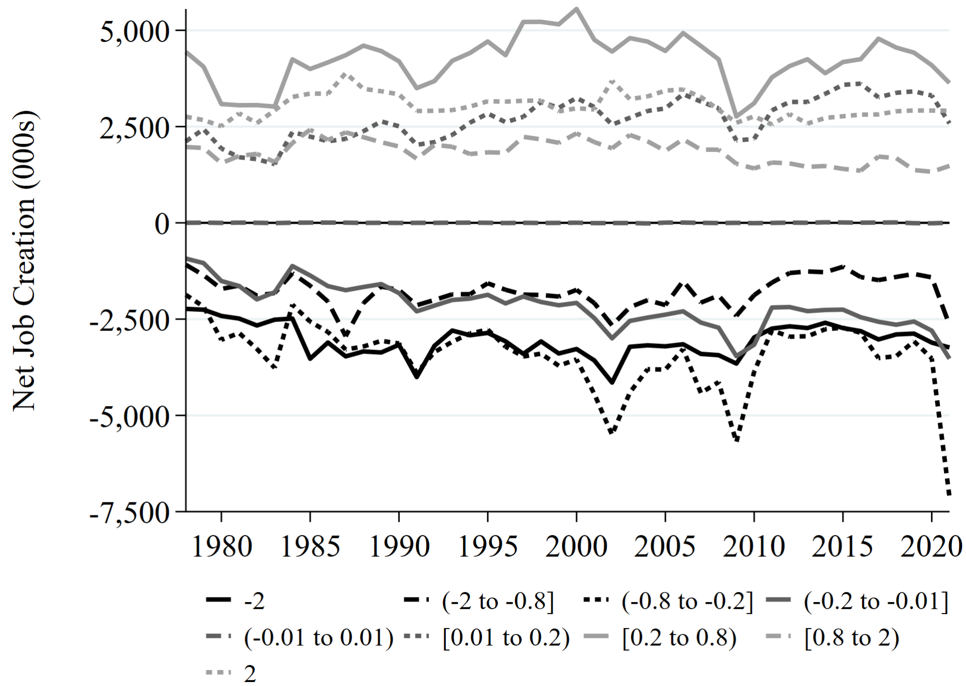


Source: BDS-HG 2021.
Notes: Figure shows the percent of firms with firm growth between -0.01 and 0.01.

Next, we decompose net job creation, or contributions to net employment growth in the economy, across the growth rate distribution. Figure 5 shows the count of jobs created or destroyed, on net, by firms in each growth rate bin. On average, each year, entrants account for about 3 million jobs per year, high-growth continuers ([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 continuers 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 continuers 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]).

Figure 5: 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.

What are the characteristics of high-growth firms?

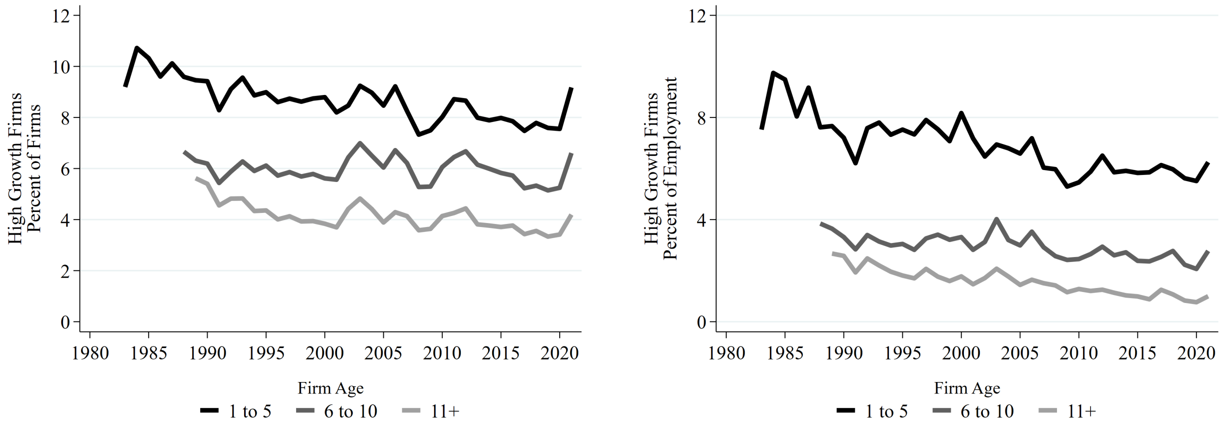
In this section, we use the BDS-HG tabulations to examine where high-growth firms come from. The composition of activity in the U.S. economy has changed dramatically since the 1980s. There has been a secular decline in entry (Decker et al., 2014), a rising share of activity among large firms (Autor et 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 associated with high-growth firms (those growing at a rate of 0.8 or higher), or "high-growth intensity", by firm and establishment characteristics. 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.[11]

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).[12] Much of the decline in the economy-wide share of high-growth firms is due to a decline in entry (Figure 3, Panel A), but an interesting question is how much high-growth activity declined among different firm age groups. For instance, are firms less likely to grow quickly post-entry? Figure 6 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, 10% of young startups in 1985 were high-growth, but this share fell to less than 8% 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 just under 10% in 1985 to below 6% in 2020. The share of high-growth mature startups, on the other hand, have remained more stable on a firm-weighted basis but declined on an employment-weighted basis. The share of mature startups that were high-growth remained around 6% while their share of employment fell from just below 4% in 1988 to about 2% in 2020. This suggests that high-growth mature startups are becoming smaller over time. Established firms also saw a decline in the share of firms and the share of employment associated with high-growth firms.

[11] 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.

[12] 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) because they are by definition high-growth.

Figure 6: 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, Because we cannot observe firm birth occurring before 1976, which is when our data coverage begins, it is possible that firm age is not accurately measured in the earlier years. Therefore, we begin our analysis for each group in the year in which left truncation is no longer present—that is, 1983 for young startups and 1988 for mature startups and 1989 for established firms.

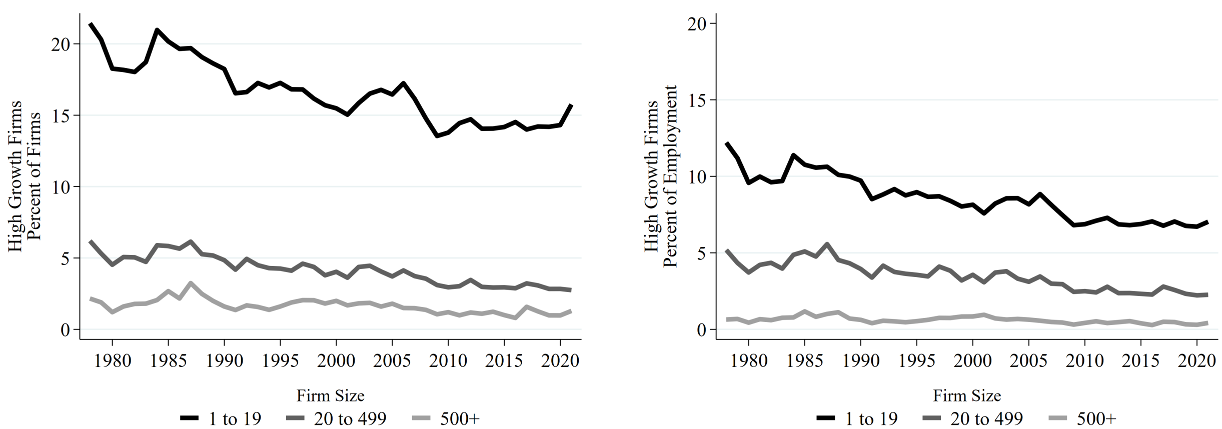
The effects of the COVID-19 pandemic can be seen in the 2021 spike in the share of high-growth firms for all age groups and a more modest increase in the share of employment in high-growth firms. This is consistent with recent evidence finding that the post-COVID surge in entry is concentrated among smaller firms (Dinlersoz et al., 2021). Taken together, the patterns across firm age 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.[13] Similar to the firm age figures, Panel A of Figure 7 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

[13] We use the current size measure from the BDS – the average size of the firm in t and $t-1$.

18% to 14%) and medium firms (from 4.5% to 2.8%), while their larger counterparts did not experience as significant changes (from 1.2% to 1%). We find similar trends in the share of employment from high-growth firms for each of the three groups. 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.

Figure 7: Intensity of High-Growth Firms by Small, Medium, and Large Firms

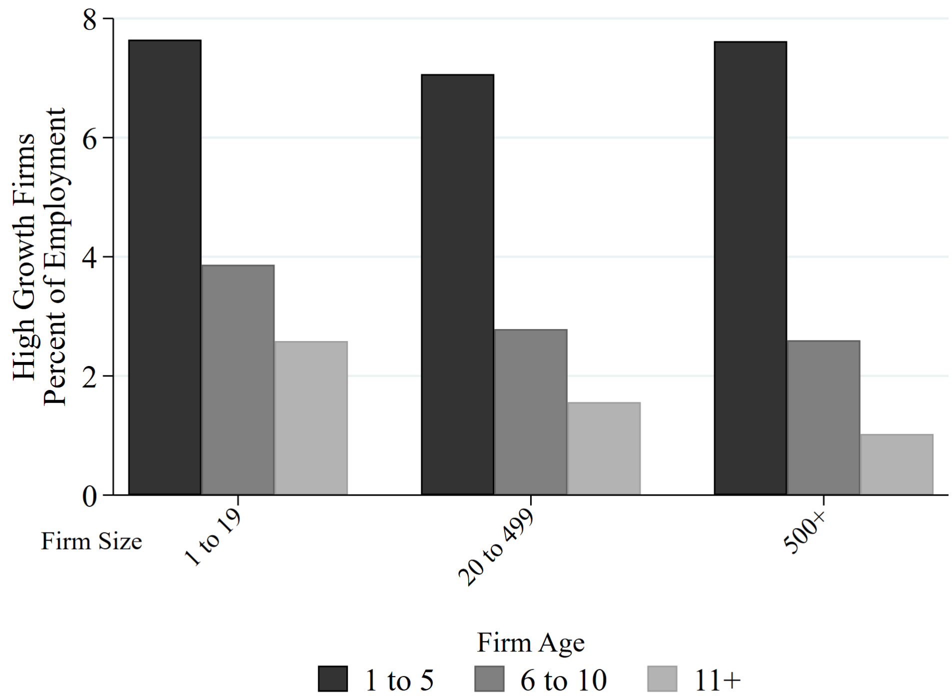


(a) Share of Firms (b) Share of Employment

Source: BDS-HG Tabulations.

By firm maturity and size. Analyzing the joint size and age distribution often yields rich insights into firm characteristics and dynamics (Haltiwanger et al., 2013). Figure 8 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 younger firms is associated with high-growth firms. This is consistent with young firms being more dynamic and innovative (Akcigit and Kerr, 2018). Holding age constant, there is less of a systematic relationship. For very young firms, the smallest and largest size classes have the highest shares. For firms 6-10 (still young), the highest share is the small firms but medium and large firms have about the same shares. For mature firms, there is decline in the share of high-growth employment moving from the small to large groups.

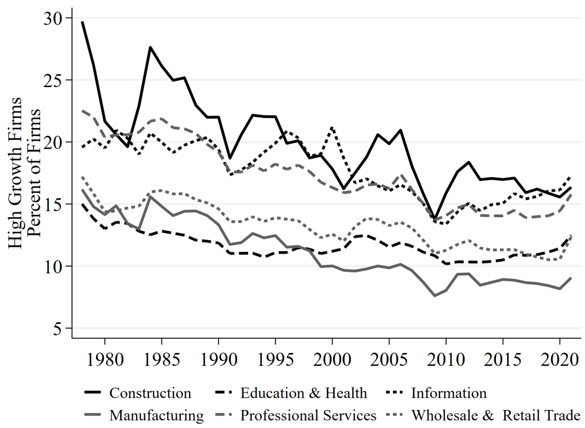
Figure 8: Share of Employment from High-Growth Firms by Size and Age



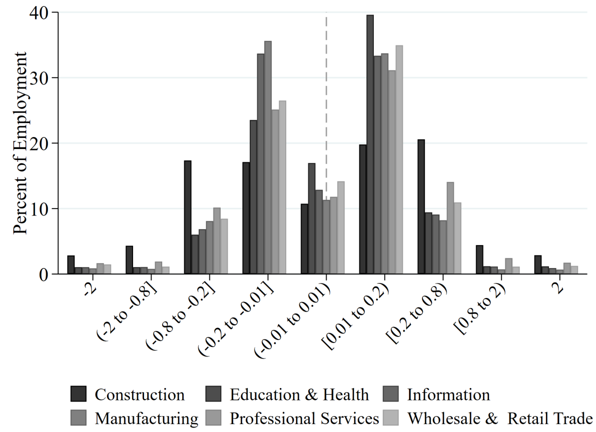
Source: BDS-HG 2021.

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 9 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 and manufacturing have the largest declines from 30% and 16% in 1978 to 16% and 8% in 2021, respectively. Interestingly, a few sectors have shown increases beginning in 2010—most notably Information, though others such as Education & Health with a more modest rebound. Nonetheless, the share of high-growth firms in all sectors in 2020 remains well below the levels in 1978.

Figure 9: 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.

The construction sector has the highest share of high-growth firms activity, which might at first glance seem perhaps surprising given evidence of stagnant productivity growth in that sector (Goolsbee and Syverson, 2021). However, this is a reminder a high growth share of a sector is a sign of volatility. In construction, this volatility stems from construction firms expanding and contracting as large, temporary projects start and are completed. As a new project begins many jobs are created in a specific location and once complete those jobs are destroyed. Panel B of Figure 9 provides evidence consistent with these patterns. Panel B shows the distribution of each sector's employment across the growth rate bins. While the construction sector has a particularly high share of employment from high-growth firms (i.e., growth rate between 0.8 and 2), it generally has longer tails at both ends including firm death and entry. These patterns highligh that the onstruction sector exhibits higher rates of both creation and destruction.

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.

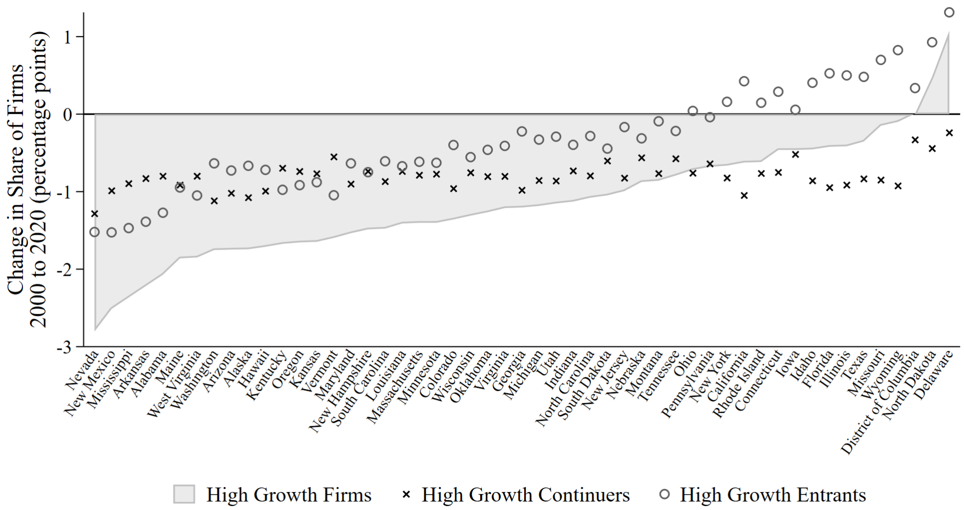
The results are shown in Figure 10, with the difference (in percentage points) between a state's share of high-growth firms and its share of all firms on average between 2010 and 2019 captured by the height of each bubble and the size of the bubble reflecting total employment of each state. A handful of states have significantly more high-growth firms that one would expect just based on their size. In particular, Florida, California, and Texas are distinctly positioned with the highest premium in high-growth firm share along with a large base. Florida, for example, accounts for 7% of all firms but 8.7% of high-growth firms, which yields the 1.7 percentage points difference shown in the figure. California, similarly, accounts for 11.8% of all firms and 13.5% of high-growth firms, a gap of about 1.7 percentage points. New York, Colorado, and Washington also have more high-growth firms than we would expected given their share of all firms. In contrast, states such as Pennsylvania and Ohio exhibit a substantially lower share of high-growth firms than their share of all firms.

Figure 10: 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.

Given the long time series available in the BDS-HG tabulations, we are able to ask a related question: how has the high-growth firm intensity of each state changed over time? To do this, we start with the percent of firms in each state that are high-growth in 2000 and 2020 and difference the two. This is shown as the shaded line in Figure 11. It is also important to consider the heterogeneity across states in the changes in high-growth entrants (growth rate of 2) and high-growth continuers (growth rate in [0.8,2)). Some states saw a much steeper decline in entry than others, which drives their declining share of high-growth firms. The change in the high-growth entrant share and high-growth continuer shares are shown as the gray circles and black "X"s respectively. Nevada, for instance, saw a decline in the share of high-growth firms within the state of about 2.8 percentage points (18.6% to 15.8%), with its share of high-growth entrants falling my 1.5 percentage points (14.8% to 13.3%) and its share of high-growth continuers falling 1.3 percentage points (3.8% to 2.5%). Unlike Figure 10, these statistics are not normalized by the region's overall share of firms.

Figure 11: Change in High-Growth Firm Share by State in 2000 versus 2020



Source: BDS-HG 2021.
Notes: States are ordered by the overall change in within state high-growth firm shares, in percentage points, captured by the shaded region. The change in high-growth continuers is shown in the "X"s and the change in high-growth entry is shown circles. The change in high-growth continuers and entry can be aggregated to get the total for a given state.

Several striking patterns emerge in Figure 11. First, all but three states—Delaware, North Dakota, and the District of Columbia—have experienced a decline in their share of high-growth firms in this twenty-year period. Second, the change in the high-growth continuer share varies much less across states than the change in the high-growth entrants. Most states saw a decline in the share of high-growth continuers of about one percentage point. In contrast, some states like Nevada, New Mexico and Mississippi saw a decline in the share of entrants of about 1.5 percentage points while Florida, Missouri, Wyoming, North Dakota, and Delaware all saw an increase in their share of entrants of more than 0.5 percentage points. This implies that differences in the overall high-growth intensity across regions is primarily driven by differences in the decline of entry.

4 Conclusion

In this paper, we present a newly available dataset on the sources and contributions of high-growth firms in the United States. This dataset allows us to compute national statistics around high-growth firms that are comparable to those generated by the OECD. Using this dataset spanning 1978 to 2021, we find several striking patterns. First, high-growth firms contribute disproportionately to economic vibrancy; while they make up roughly 15% of all firms in a given year, and typically less than 2% of employment, they account for 45% of job creation. Second, the firm growth distribution has become less dispersed and less skewed over time, resulting in a decline in the share of high-growth firms coupled with a rise in the share of stagnant firms demonstrating little to no growth. Third, while the share of high-growth firms has fallen for all types of firms, this decline is particularly severe for young as well as small firms. Fourth, in terms of industries, information sector has shown a considerable rise in the share of high-growth firms since 2010, though all industries have generally exhibited a downward trend throughout our sample period. Fifth, Florida, California, and Texas exhibit the greatest intensity of high-growth firms as measured by the difference between high-growth firm share and overall firm share. However, all regions have shown a decline in their high-growth activity between 2000 and 2020.

Our hope is that this new, publicly available dataset can enable fruitful avenues for future research. We conclude by discussing a few of these opportunities. For instance, researchers can examine whether and how high-growth firms in a region can impact local income inequality. While these firms can generate economic opportunities and boost wages and employment levels more generally, the effects may be highly heterogeneous and thus contribute to greater levels of inequality. Second, future research can explore the impact of worker mobility, and its underlying frictions such as the enforceability of non-compete agreements, on the high-growth prospects of firms in the region.

References

Acemoglu, Daron, Ufuk Akcigit, Harun Alp, Nicholas Bloom, and William Kerr (2018) "Innovation, reallocation, and growth," *American Economic Review*, 108 (11), 3450–3491.

Acs, Zoltan J and David B Audretsch (1987) "An empirical examination of small firm growth," *Economics Letters*, 25 (4), 363–366.

Akcigit, Ufuk and William R Kerr (2018) "Growth through heterogeneous innovations," *Journal of Political Economy*, 126 (4), 1374–1443.

Autor, David, David Dorn, Lawrence F Katz, Christina Patterson, and John Van Reenen (2020) "The fall of the labor share and the rise of superstar firms," *The Quarterly Journal of Economics*, 135 (2), 645–709.

Azoulay, Pierre, Benjamin F Jones, J Daniel Kim, and Javier Miranda (2022) "Immigration and entrepreneurship in the United States," *American Economic Review: Insights*, 4 (1), 71–88.

Beem, Richard, Christopher Goetz, Martha Stinson, Sean Wang et al. (2022) "Business Dynamics Statistics for Single-Unit Firms,"Technical report.

Blackwood, G. Jacob, Lucia S. Foster, Cheryl A. Grim, John Haltiwanger, and Zoltan Wolf (2021) "Macro and Micro Dynamics of Productivity: From Devilish Details to Insights.," *American Economic Journal: Macroeconomics*, 13 (3), 142–172.

Chow, Melissa C, Teresa C Fort, Christopher Goetz, Nathan Goldschlag, James Lawrence, Elisabeth Ruth Perlman, Martha Stinson, and T Kirk White (2021) "Redesigning the longitudinal business database," Working Paper 28839, National Bureau of Economic Research, `https://www.nber.org/papers/w28839`.

Chow, Melissa and Nathan Goldschlag (2023) "Where in the United States Are the High-Tech Jobs?"Technical report, U.S. Census Bureau.

Coad, Alex, Sven-Olov Daunfeldt, Werner Hölzl, Dan Johansson, and Paul Nightingale (2014) "High-growth firms: introduction to the special section," *Industrial and corporate change*, 23 (1), 91–112.

Davis, Steven J, John Haltiwanger, and Scott Schuh (1996) *Job Creation and Destruction*: MIT press.

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

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

——— (2020) "Changing Business Dynamism and Productivity: Shocks vs. Responsiveness.," *American Economic Review*, 11 (12), 3952–3990.

Desnoyers-James, Isabelle, Sara Calligaris, and Flavio Calvino (2019) "DynEmp and MultiProd: Metadata."

Dinlersoz, Emin, Timothy Dunne, John Haltiwanger, and Veronika Penciakova (2021) "Business formation: A tale of two recessions," in *AEA Papers and Proceedings*, 111, 253–257, American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203.

Fort, Teresa C, Justin R Pierce, and Peter K Schott (2018) "New perspectives on the decline of US manufacturing employment," *Journal of Economic Perspectives*, 32 (2), 47–72.

Foster, Lucia, Cheryl Grim, John Haltiwanger, and Zoltan Wolf (2019) "Innovation, productivity dispersion, and productivity growth," in *Measuring and Accounting for Innovation in the 21st Century*: University of Chicago Press.

Goolsbee, Austan and Chad Syverson (2021) "The Strange and Awful Path of Productivity in the US Construction Sector," Working Paper 30845, National Bureau of Economic Research, `https://www.nber.org/papers/w30845`.

Gort, Michael and Steven Klepper (1982) "Time paths in the diffusion of product innovations," *The economic journal*, 92 (367), 630–653.

Haltiwanger, John (2022) "Entrepreneurship in the twenty-first century," *Small Business Economics*, 1–14.

Haltiwanger, John, Ron S Jarmin, Robert Kulick, and Javier Miranda (2016) "High growth young firms: contribution to job, output, and productivity growth," in *Measuring entrepreneurial businesses: current knowledge and challenges*, 11–62: University of Chicago Press.

Haltiwanger, John, Ron S Jarmin, and Javier Miranda (2013) "Who creates jobs? Small versus large versus young," *Review of Economics and Statistics*, 95 (2), 347–361.

Jarmin, Ron S and Javier Miranda (2002) "The longitudinal business database," *Available at SSRN 2128793*.

Penrose, Edith Tilton (1959) *The Theory of the Growth of the Firm*: Oxford university press.

Schreyer, Paul (2000) "High-growth firms and employment," Working Paper No. 2000/03, OECD Publishing, Paris, `https://doi.org/https://doi.org/10.1787/861275538813`.

Schumpeter, Joseph A (1942) *Capitalism, socialism and democracy*: Harper & Brothers.

Syverson, Chad (2011) "What Determines Productivity?," *Journal of Economic Literature*, 49 (2), 326–365.

Törnqvist, Leo, Pentti Vartia, and Yrjö O Vartia (1985) "How should relative changes be measured?" *The American Statistician*, 39 (1), 43–46.

Online Appendix for

High-Growth Firms in the United States: Key Trends and New Data Opportunities[*]

J. Daniel Kim[†] Joonkyu Choi[‡] Nathan Goldschlag[§]
John Haltiwanger[¶]

March 15, 2024

[*]All authors contributed equally. Any opinions and conclusions expressed herein are those of the author and do not represent the views of the U.S. Census Bureau, the Federal Reserve Board of Governors or its staff. The Census Bureau has ensured appropriate access and use of confidential data and has reviewed these results for disclosure avoidance protection. DRB Approval Number(s): CBDRB-FY24-0168. DMS Project Number 7083300. We thank Sean Wang, Cheryl Grim, and participants at the U.S. Census Bureau Center for Economic Studies seminar series for helpful comments and suggestions.

[†]The Wharton School, University of Pennsylvania
[‡]Federal Reserve Board of Governors
[§]U.S. Census Bureau
[¶]University of Maryland

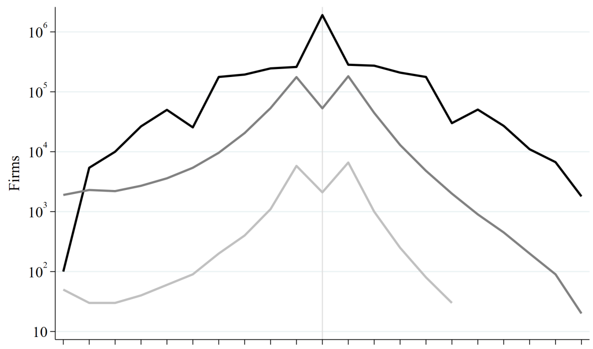
A TVV/DHS Growth Rates and Log Differences

The TVV/DHS measure of growth, which has become common in studies of firm dynamics, has a number of desirable properties (Törnqvist et al., 1985; Davis et al., 1996). First, it approximates log differences for growth rates near zero, which is the most common type of employment change in annual universe business microdata. Second, it readily accommodates different levels of aggregation. Growth rates can be easily aggregated from the establishment to the firm-level by summing positive and negative changes along with the sum of average employment. Third, the TVV/DHS measure naturally accommodates entry and exit, which comprise a significant share of establishment and firm-weighted activity. Fourth, the measure is symmetric in positive and negative employment changes. For example, a firm or establishment with 10 employees in $t-1$ that expands to 15 employees in t will have a growth rate of 0.4 (50% increase) and a firm that has 15 employees in $t-1$ that contracts to 10 employees in t will have a growth rate of -0.4 (-33% decrease).

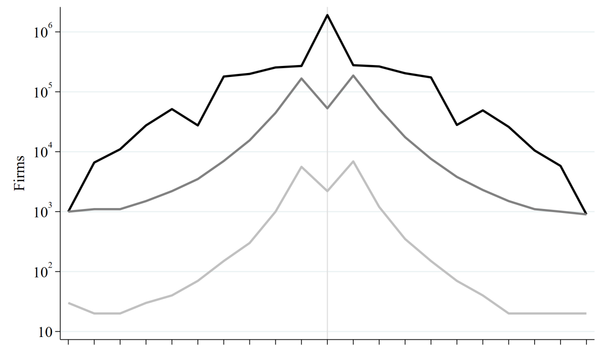
An alternative growth measure used to study firm growth rate distributions is log differences, or the natural log of the ratio of employment in t to employment in $t-1$ (Stanley et al., 1996). These measures can only be used for continuing establishments or firms since they are not defined for entrants or exits. Among continuing units, prior studies using log changes have found asymmetry in the growth rate distribution with positive growth volatility declining in size (Bottazzi et al., 2002; Perline et al., 2006). These patterns are notably absent from Figure 2 Panel A, which shows the log count of firms across bins of the TVV/DHS growth rate distribution. The counts in Figure 2 appear symmetric between positive and negative growth. There are several notable differences, however, between Panel A of Figure 2 and the findings of Perline et al. (2006) (henceforth PAT), who use similar data on the universe of non-farm employer businesses in the U.S. but find asymmetry in the growth rate distribution. First, asymmetries appear to increase in size and since Figure 2 displays firm counts it is dominated by small firms, which are for more numerous than large firms. Second, PAT focus on establishment rather than firm growth rates. Finally, the choice of initial size to classify size bins also affects the shape of the growth rate distribution.

Figure A1 demonstrates the role of size classifications on the structure of the growth rate distribution. Figure A1 shows the count of firms by both TVV/DHS and log growth for small, medium, and large firms classified by both initial size and average size with counts within annual growth rate bins averaged over 2000 to 2021. Initial size corresponds to "ifsize" or "iesize" in the BDS tabulations while average size corresponds to "fsize" and "esize". Cells with 15 or fewer firms are censored. Comparing the two initial size plots (A and C), both the TVV/DHS and log growth rates exhibit significant asymmetry among medium and large firms when employment in $t-1$ is used to classify firms. The role of size classifications becomes clear when we compare the initial and average size graphs for a given growth measure (Panel A to B and C to D). The asymmetric shape of the growth rate distribution is no longer visible using either TVV/DHS or log growth when the average size is used to classify firms. It is also worth noting the similarity between TVV/DHS growth rates and log growth rates especially for growth rates near zero.

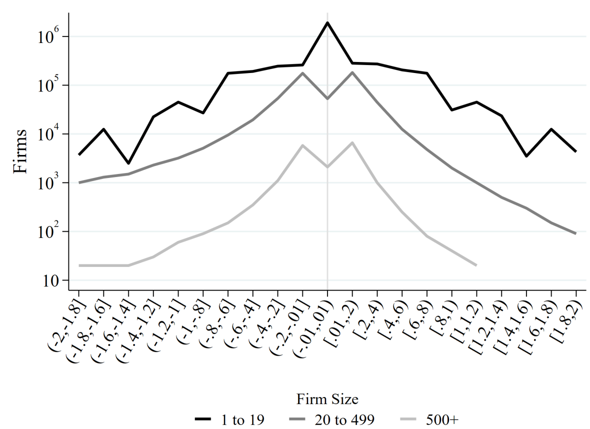
Figure A1: TVV/DHS, Log Differences, and Firm Size



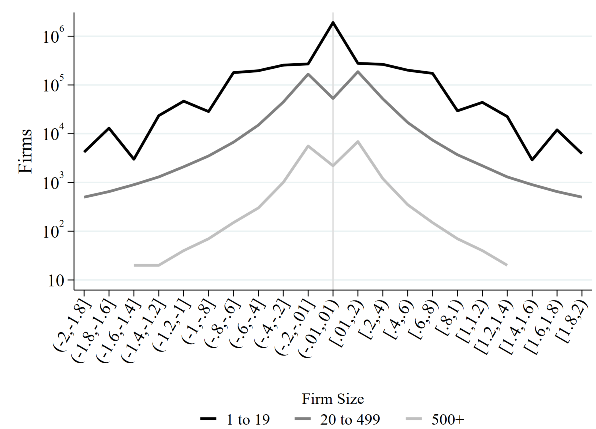
(a) Initial Size, TVV/DHS Growth



(b) Average Size, TVV/DHS Growth



(c) Initial Size, Log Growth

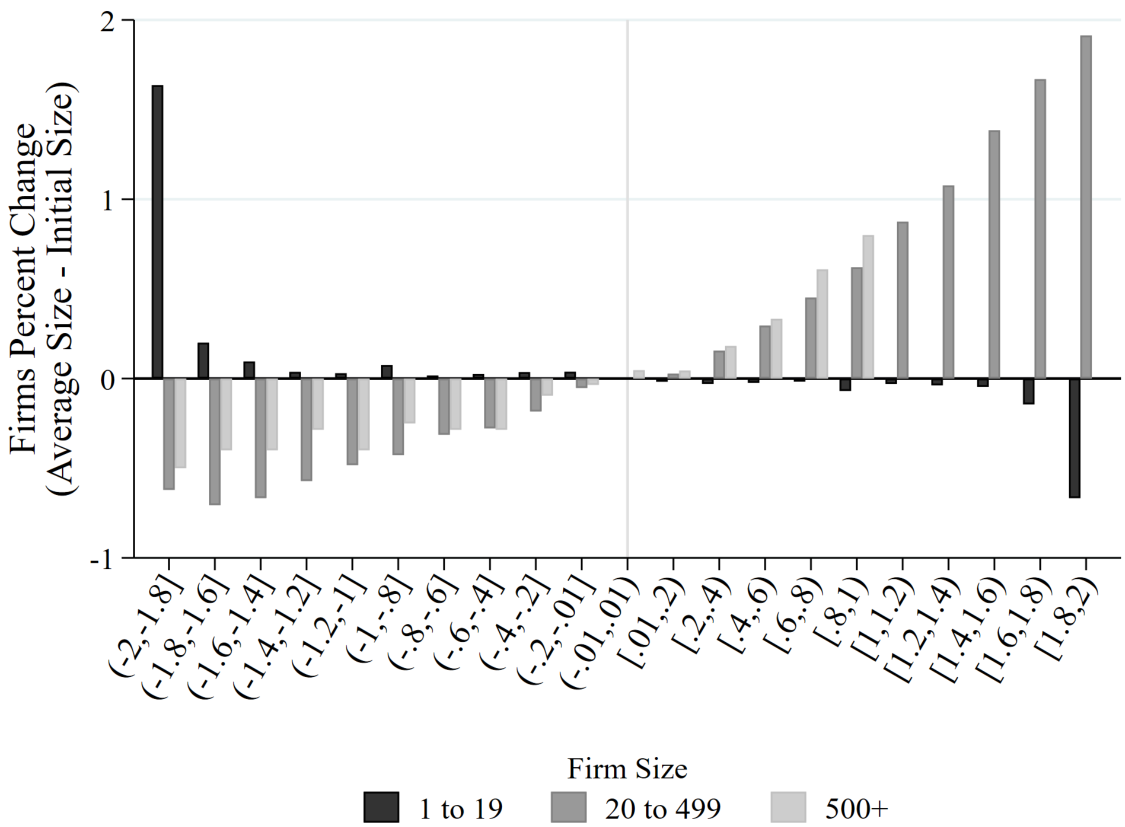


(d) Average Size, Log Growth

Source: LBDv202100.
Notes: Each panel shows the count of firms, with log scale y-axis, by firm size groups and firm growth bins, where firm size groups are either initial size (Panel A, C) or average size (Panel B, D) and firm growth rates are either TVV/DHS (Panel A, B) or log differences (Panel C, D). Cells with firm counts of 15 or fewer have been censored for disclosure avoidance purposes.

The log scale of Figure A1 masks changes to the small size group when comparing initial size and average size. To make these changes more visible, Figure A2 shows the percent change in firm counts within growth rate bins (TVV/DHS) and size groups between the average and initial size classification. Again, note that cells with 15 or fewer firms have been censored for disclosure purposes. As was clear in Figure A1, average size pushes up counts on the positive side of the growth rate distribution for medium and large firms. Moreover, the percentage increase in firm counts rises in growth rates. Using average size rather than initial size adds more than 1.5% to the count of firms in the highest growth rate bins. The count of firms within each growth rate bin is identical between the initial and average size charts for a given growth rate measure. That is, the changes firm counts are zero-sum across the size bins. This can be seen in the decreasing count of firms in the smallest firm bins on the positive side of the growth rate distribution. Similar but inverse patterns can be seen on the negative side of the growth rate distribution in Figure A2. Intuitively, by using the firm's size in $t-1$ to classify, the initial size grouping allocates more growth to small firms. Similarly, the initial size classification allocates more employment declines to larger firms than does the average size groupings.

Figure A2: Firm Growth and Change in Firm Counts, Average Size Minus Initial Size

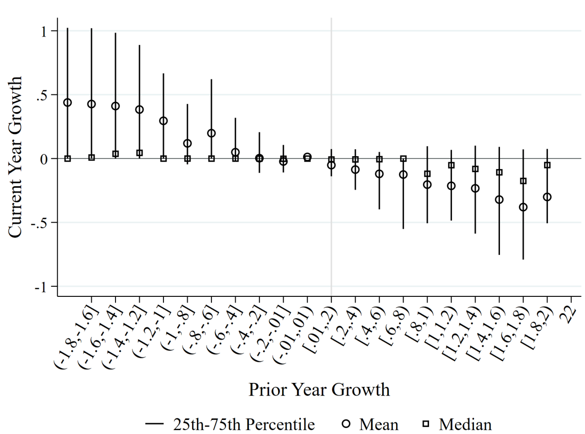


Source: LBDv202100.
Notes: Figure shows the change in firm counts within a given TVV/DHS growth bin in percentage points between the average size and initial size groupings. Cells with firm counts of 15 or fewer have been censored for disclosure avoidance purposes.

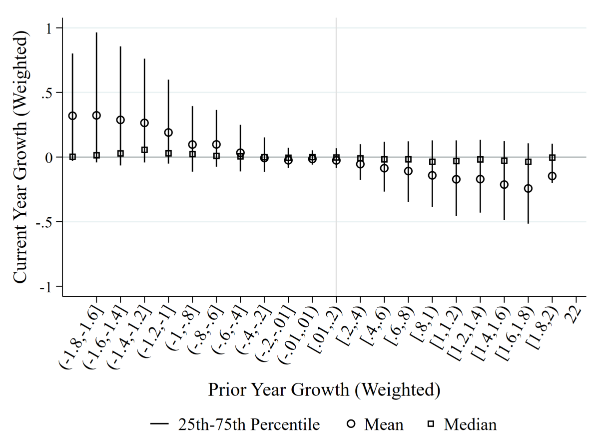
The use of initial versus average size to classify firms is related to temporary shocks and mean reversion in the data. Firms may experience temporary, i.i.d. shocks to their size from year-to-year. Firms classified as small based upon initial size ($t-1$ employment) are more likely to have experienced a negative shock while firms classified as large by initial size are more likely to have experienced a positive shock. This is consistent with initial size allocating more growth to small firms in Figure A2. Average size, on the other hand, dampens the impact of mean reversion.

To demonstrate the role of mean reversion in firm growth rates, Figure A3 plots the average growth rate of establishments between $t-1$ and t (current year) by their position on the $t-2$ to $t-1$ (prior year) growth rate distribution. Panel A shows establishment-weighted statistics and Panel B presents employment-weighted statistics. We focus on establishment growth rates for this exercise because longitudinal linkages are more robust at the establishment-level than the firm-level. Again, we average these measures between 2001 to 2021. Note also that Figure A3 includes only continuing establishments; we exclude establishments that enter or exit from $t-2$ to $t-1$ and establishments that enter or exit in t. From Panel A we see that among continuing establishments, those in higher prior year growth rate bins experience lower and indeed often negative current year growth. Conversely, establishments that contracted in the prior year were more likely to experience positive current year growth. On the tails of the prior year growth rate distribution, the current year growth rates are highly skewed. The median current year growth rate for establishments that contracted by was roughly zero while the mean at the tail was over 0.4. On the positive side of the prior year growth rate distribution the median becomes negative. More than half of establishments that grew more than 0.8 in the prior year lost employees.

Figure A3: Establishment Growth and Mean Reversion



(a) Establishment Weighted



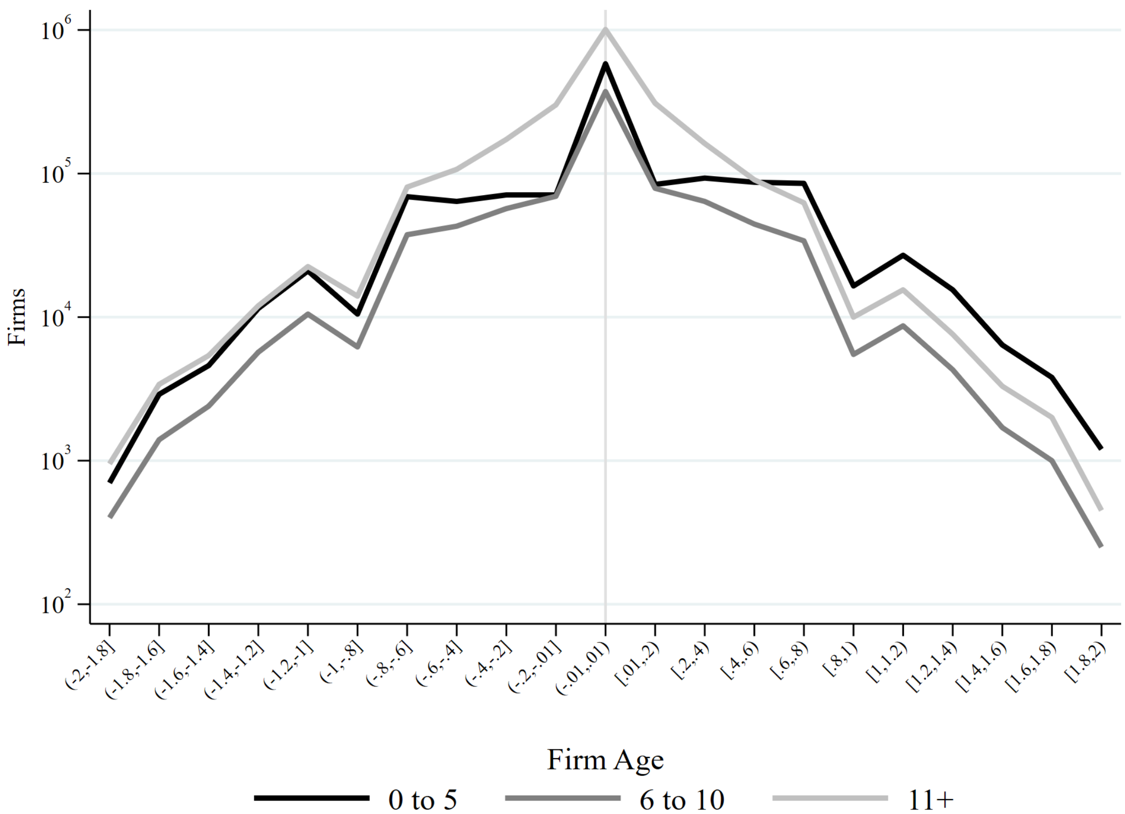
(b) Employment-Weighted

Source: LBDv202100.
Notes: Panel A presents establishment-weighted statistics and Panel B shows employment-weighted statistics. Figures shows the 75th, 50th, 25th and mean current year TVV/DHS growth rate ($t-1$ to t) by the prior year growth rate distribution ($t-2$ to $t-1$), averaged between 2000 and 2021. The 25th is the mean of the 24th and 26th, the 50th is the mean of the 49th and 51th, and the 75th is the mean of the 74th and 76th.

The patterns in Panel A of Figure A3, since it is establishment weighted, could be driven by relatively small establishments adding relatively few employees, which result in large TVV/DHS growth rates. To address this, Panel B shows an employment-weighted version of the same figure. The patterns in Panel B are quite similar to those in Panel A. The employment-weighted median current year growth rate is closer to zero across the prior year growth rate distribution. Some of the skewness in the tails of the prior year growth rate distribution are dampened with the 75th percentile growth rates falling closer to 0.75 for some of the largest contractions and above -0.5 for the largest expansions. Finally, both on an establishment and employment-weighted basis there appears asymmetry in the skewness of the current year expansion among prior year contractors as compared to the skewness of current year contraction among establishments expanding employment in the prior year. On an establishment weighted basis (Panel A) the 75th percentile of the growth rate distribution is above 0.5 for most of the prior year contracting bins, reaching as high as 1 in the tail. Conversely, among establishments that grew in prior year, the 75th percentile is more often above -0.5. This asymmetry is despite the TVV/DHS measure being symmetric in expansions and contractions. For example, an establishment that expands from 1 to 3 employees has a TVV/DHS of 1 while an establishment contracting from 3 to 1 employee has a TVV/DHS of -1. This asymmetry is likely driven by selection on survival. Establishments that experience significant prior year contraction that survive are more likely to have better growth outcomes in the future. Overall, the patterns in Figure A3 are consistent with many establishments that exist on the tails of growth rate distribution experiencing temporary idiosyncratic shocks that are quickly reversed from year-to-year.

An important limitation of Figure A1 is that it focuses only on size. For the reasons noted above, classifying firms by initial versus average size has significant impacts on the presence of asymmetry between positive and negative changes in employment. Firm age may also play an important role in shaping the growth rate distribution. As shown in Figure A3, temporary shocks and mean reversion affect the shape of the growth rate distribution of establishments. We expect that some shocks, however, may be more permanent. Consistent with canonical models of firm dynamics (Jovanovic, 1982), we might expect that as young firms learn about their own efficiency they may experience persistent shocks and grow quickly and consistently. Figure A4 shows the count of firms across the growth rate distribution by firm age groups. Interestingly, asymmetry, with fewer firms among the high growth groups, appears for middle aged (6 to 10) and older firms (11+). Young firms, in contrast, exhibit positive-growth skewness.

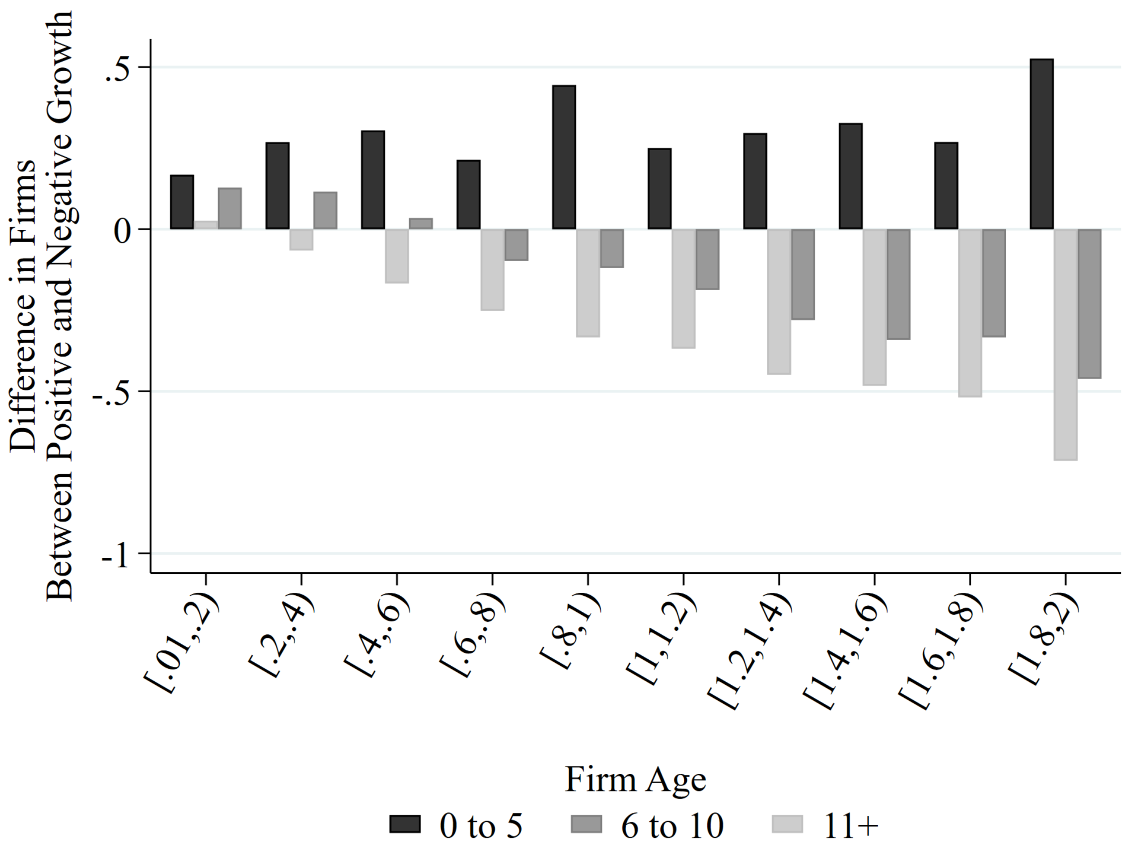
Figure A4: Firm Growth Distribution and Firm Age



Source: LBDv202100.
Notes: Figure shows the count of firms, with log scale y-axis, by firm age groups and firm growth bins.

To aid the comparison of the positive and negative sides of the growth rate distribution of Figure A4, Figure A5 shows the difference between symmetric positive and negative growth bins (e.g. between (-.4,-.2] and [.2,.4)). This figure "folds" Figure A4 on itself, directly comparing positive and negative sides of the growth rate distribution. For all growth bins, young firms have more firms on the positive growth side of the growth rate distribution. Older firms, in contrast, have fewer firms on the positive side of the growth rate distribution with the exception of the slowest growth bin ([0.01,.2)). Interestingly, middle aged firms show positive-side asymmetry through up to a 0.6 growth rate and then again have more firms among the corresponding negative growth rate bins. Taken together, Figure A4 and A5 show that firm age plays an important role in shaping the growth rate distribution and generating asymmetry between the positive and negative sides of the growth rate distribution.

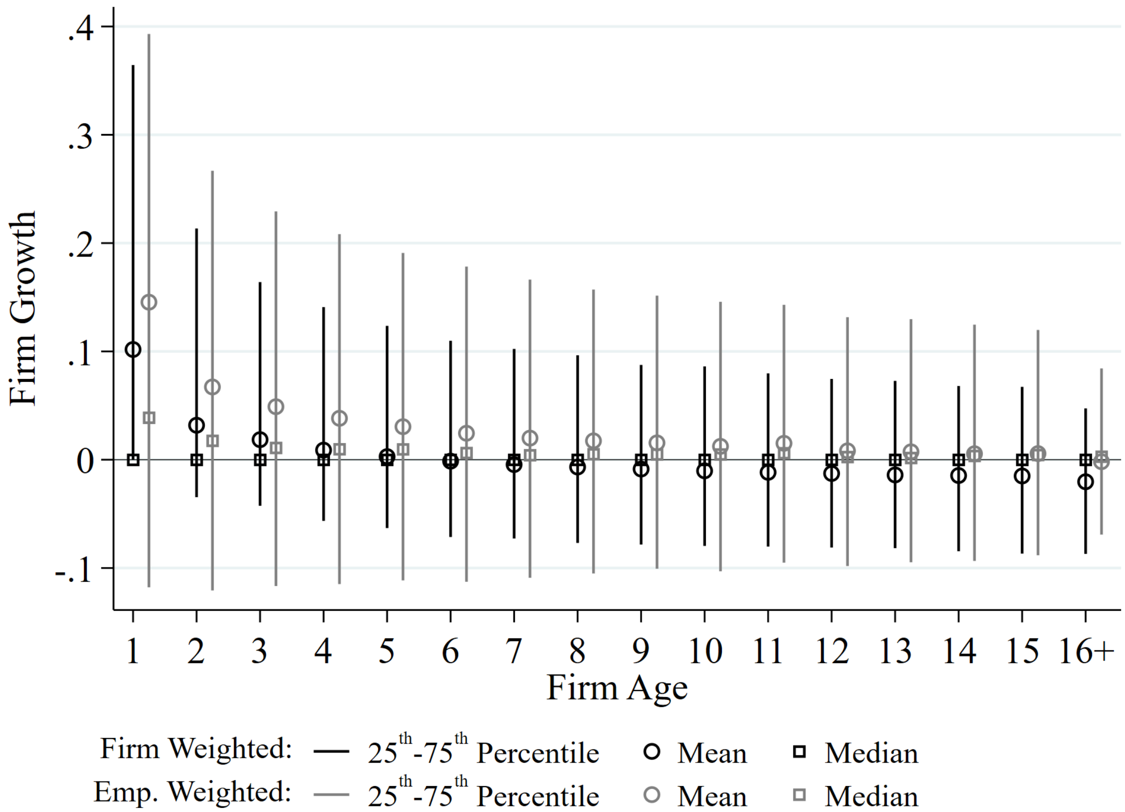
Figure A5: Asymmetry of Firm Growth Distribution and Firm Age



Source: LBDv202100.
Notes: Figure shows the difference between the count of firms for a given firm age group between corresponding positive and negative growth rate bins. Differences are computed as $\frac{pos_i - neg_i}{0.5*(pos_i + neg_i)}$, where pos_i is the count of firms in a given positive bin i and neg_i is the count of firms in the corresspondіng negative bin (e.g. (-.2,-.01] and [.01,.2)).

The patterns by firm age help account for the differences in the growth rate distributions by initial size and average size. Young firms tend to be small (most less than 500+) and some young firms exhibit high post-entry growth. Young high-growth firms will contribute relative more to high positive growth for initial size than for average size for firms less than 500+. To demonstrate the dynamics of firm growth over the firm's life cycle, Figure A6 shows the growth rate distribution by firm age among continuing establishments. This figure is very similar to Figure 2 of Decker et al. (2014), which shows the 90$^{\text{th}}$ percentile, 10$^{\text{th}}$ percentile, mean, and median of the net employment growth rates by firm age. Figure A6 shows the interquartile range (75$^{\text{th}}$ and 25$^{\text{th}}$ percentiles), mean, and median both firm and employment-weighted by firm age for continuing firms. Consistent with Decker et al. (2014), we see that young firms have much greater positive skewness in their growth rates than older firms, as captured by the gap between the mean and median growth rate. This skewness is more pronounced on an employment-weighted basis than on a firm-weighted basis. Moreover, the employment-weighted distribution is shows greater variation with higher 75th percentiles and lower 25th percentiles.

Figure A6: Firm Growth and Firm Age, Continuers



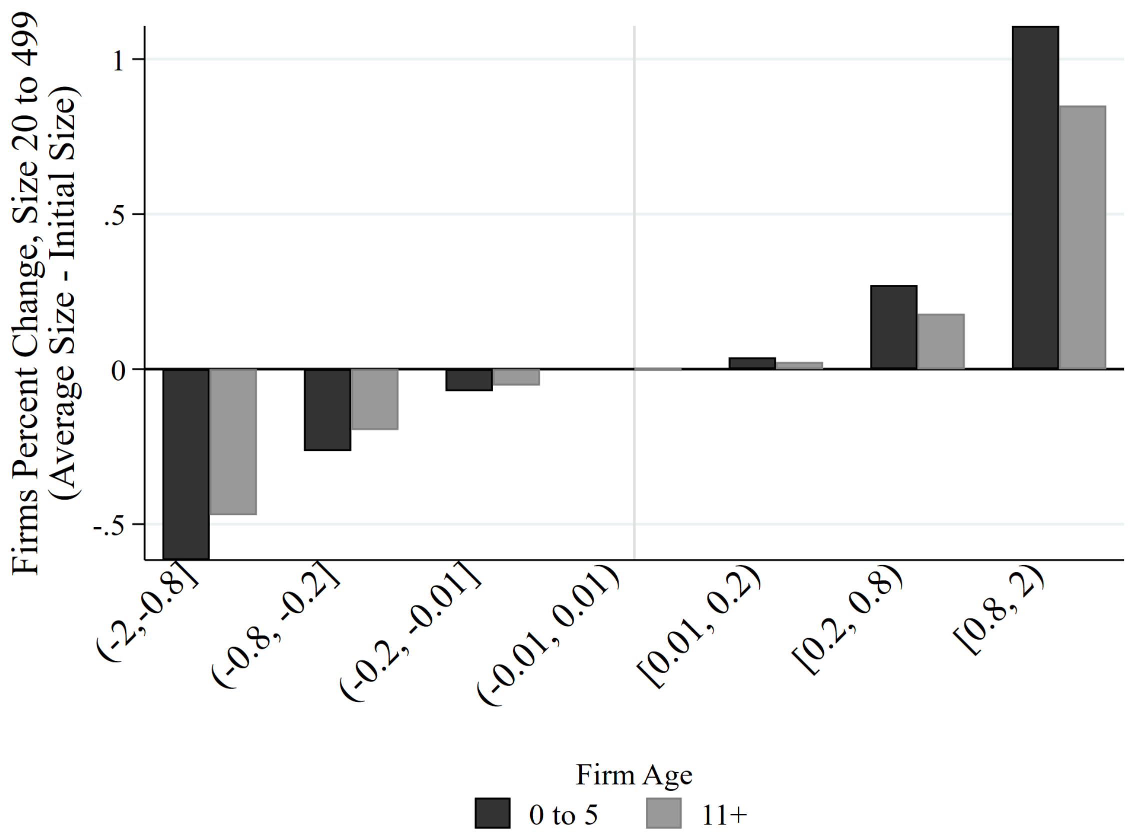
Source: LBDv202100.
Notes: Figure shows the 75th (average of 74th and 76th), 50th (average of 49th and 5th), 25th (average of 24th and 26th), and mean firm growth rates by firm age, both firm-weighted and employment-weighted.

The analyses thus far demonstrates that the firm growth rate distribution is shaped by how firm size is computed, mean reversion and temporary shocks, and by firm age and firm life cycle dynamics. It is difficult to draw inferences based on variation by firm size categories alone.[1] Figure A7 illustrates how size and age jointly affect the distribution of firms by initial and average size bins. The figure shows the change in firm counts when moving from initial to average size classifications for the 20 to 499 size group for both young (0 to 5) and mature (11+) firms. The upward shift on the right tail and negative

[1]The Bureau of Labor Statistics Business Employment Dynamics statistics uses a method to mitigate these alternative influences on the relationship between firm growth and size. They use a dynamic sizing method where the job creation or destruction is allocated based on the change within size classes. Decker et al. (2014) and Okolie (2004) find that the dynamic sizing and average size methods yield very similar patterns.

shift on the left tail of the growth rate distribution is more pronounced for younger firms than older firms, consistent with the skewness of the growth rate distribution for young firms.

FIGURE A7: FIRM GROWTH, FIRM AGE, AND CHANGE IN FIRM COUNTS, AVERAGE SIZE MINUS INITIAL SIZE



Source: LBDv202100.
Notes: Figure shows differences between firm counts using average and initial size bins for the 20 to 499 size group among young and mature firms. Differences are computed as $\frac{avg_i - init_i}{0.5*(avg_i + init_i)}$, where avg_i is the count of firms using the average size bin and $init_i$ is the count of firms using initial size bins.

To conclude, the BDS-HG tabulations utilize the TVV/DHS growth rate for a number of reasons including but not limited to: it being standard in the firm dynamics literature, its use by the OECD and the ability to maintain international comparability, ease of aggregation, and the inclusion of entry and exit. Despite these advantages, in this appendix we evaluate the relationship between the TVV/DHS growth rate and log differences, another growth metric used in the literature. One striking pattern found in analyses of the distribution of log differences is the asymmetry of the growth rate distribution especially for larger firms. We show that this asymmetry is in part driven by initial size categories, which in turn relates to temporary shocks and mean reversion.

Firm age also plays an important role in shaping the firm growth rate distribution, with young firms having greater skewness in growth rates.

References

Bottazzi, Giulio, Elena Cefis, and Giovanni Dosi (2002) "Corporate growth and industrial structures: some evidence from the Italian manufacturing industry," *Industrial and Corporate Change*, 11 (4), 705–723.

Davis, Steven J, John Haltiwanger, and Scott Schuh (1996) *Job Creation and Destruction*: MIT press.

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

Jovanovic, Boyan (1982) "Selection and the Evolution of Industry," *Econometrica: Journal of the econometric society*, 649–670.

Okolie, Cordelia (2004) "Why size class methodology matters in analyses of net and gross job flows," *Monthly Lab. Rev.*, 127, 3.

Perline, Rich, Robert Axtell, and Daniel Teitelbaum (2006) "Volatility and asymmetry of small firm growth rates over increasing time frames,"Technical report.

Stanley, Michael HR, Luis AN Amaral, Sergey V Buldyrev, Shlomo Havlin, Heiko Leschhorn, Philipp Maass, Michael A Salinger, and H Eugene Stanley (1996) "Scaling behaviour in the growth of companies," *Nature*, 379 (6568), 804–806.

Törnqvist, Leo, Pentti Vartia, and Yrjö O Vartia (1985) "How should relative changes be measured?" *The American Statistician*, 39 (1), 43–46.