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High-Growth Firms 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 database that tracks activities across firm growth distributions over time. With these new data, we uncover several key trends for 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 rates of entrepreneurship 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. We also find rich variation across states and sectors. To facilitate future research, we highlight how these data can be used to address various research questions.

JEL Codes: L11, L25, L26, O30, O40
Keywords: Organizational Growth, Entrepreneurship, High-Growth Firms, 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 where and how high-growth firms emerge—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). In spite of the different disciplinary roots, a common theme in this large body of research is that firm growth critically depends on the age of the organization (for review, see Khaire 2010 and Coad 2024). In particular, recent studies have shown that young firms exhibit both high dispersion and positive right skewness in growth rates (Decker et al., 2016; Haltiwanger et al., 2016; Guzman and Stern, 2020), highlighting the central role of entrepreneurship for economic dynamism and high-growth activity. At the same time, others document a decline in the pace of entrepreneurship and growth rates among young firms, as well as an increasingly dominant role of large incumbent firms (Autor et al., 2020; Haltiwanger, 2022). While the heterogeneous nature of firm growth is an increasingly active area of research, one barrier to studying high-growth firms—especially among young and small organizations—is the limited access to large-scale data.

Nationally representative administrative microdata, such as the Census Bureau's Longitudinal Business Database (LBD), have been valuable for advancing our understanding of organizations and how they grow (Nagaraj and Tranchero 2023; Sterk et al. 2021; Sivadasan et al. 2024). However, gaining access to such data can be difficult. In the case of confidential Census microdata, access is limited to approved projects via the Federal Statistical Research Data Centers (FSRDCs). Alternative data sources such as National Establishment Time Series (NETS) or Compustat introduce sample selection

and measurement challenges.[1] Meanwhile, the Organisation for Economic Co-operation and Development (OECD) has collected and made available aggregate data on firm dynamics—with an emphasis on high-growth firms given their relevance for policy—by partnering with national statistical agencies. To date, no such data are available for the U.S.

We address these gaps by introducing the Business Dynamics Statistics of high-growth firms (BDS-HG) tables, which offers a rich, public-use source of information on firm growth in the U.S. Although the BDS-HG tables provide category-level statistics, they are very granular. For example, the statistics by detailed industries provides more than 114 thousand observations of growth rate bin by 4-digit NAICS classification. These newly available public-use statistics open up new research opportunities by providing variation by state and industry. We describe some of the potential research avenues enabled by these data in greater detail below. Additionally, the BDS-HG tables allow researchers to validate analyses conducted using other datasets or measures. We regard the BDS-HG data as a complement rather than a substitute for comprehensive administrative microdata on firms such as the LBD. The latter remain important sources for firm-level analysis. However, the BDS-HG provides novel firm-based growth rate distribution statistics at a granular level in the public domain that can be used for a variety of research purposes.

In this paper, we describe the BDS-HG tabulations, which provide the annual 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 covering all non-farm employer businesses in the U.S. between 1977 and 2021. The BDS-HG tables provide tabulations by both within-year growth rate percentile groups and absolute growth rates. The BDS-HG data tabulates firms, establishments, and employment by firm growth at the national-level and by state, detailed

[1] We discuss some of these challenges in greater detail below.

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).[2] The BDS-HG data will be updated on annual basis. 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`. 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 the origins of high-growth firms.

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 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 firms with virtually zero employment change from 32% to 40% over the same 30-year period. Second, we explore 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 in high-growth activity 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 dispropor-

[2]The Fall 2024 release will include more granular statistics at the sector $\times$ state level, which would enable researchers to make use of sector- or state-specific shocks in a difference-in-differences analytic framework.

tionately contribute to high-growth firms even after accounting for their relatively large baseline share of all firms.

Our initial results highlight the rich potential of the BDS-HG data for future research. To further demonstrate this point, we discuss various domains for future research related to firm growth—such as diversification, labor market frictions, and innovation—and how the BDS-HG data can help in advancing each line of work. Our hope is that the BDS-HG data will help enable a host of new research questions underlying high-growth firms.

The paper proceeds as follows. Section 2 describes the input data and the methodology for computing firm growth rates 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. Sections 4 outlines specific use cases of the BDS-HG for relevant future research in strategic management and economics. Section 5 concludes.

2 Data and Methodology

The BDS-HG tables 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).[3] Currently, the LBD covers years 1976 to 2021. The LBD provides information at the establishment-level such as employment, payroll, industry, age, and firm

[3]Several alternative data sources are currently available, but they face some constraints. For instance, researchers commonly use data on venture capital-financed startups (e.g., VentureSource) and public companies (e.g., Compustat) to study high-growth firms. However, a key limitation is that these samples are highly selected on successful companies that manage to raise funding or reach an IPO. In contrast, establishment-level data from NETS provide a more comprehensive coverage. However, this dataset is known to be limited in its longitudinal coverage especially for startups; for example, Crane and Decker (2019) estimate that 90% of young firms' employment records are imputed. Similarly, state business registration records provide large-scale data on potential high-growth firms at birth (Guzman and Stern 2020), but longitudinal information (e.g., employment growth) is not available.

identifiers. 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. This also includes employees on paid sick leave, holidays, and vacations but excludes proprietors and partners of unincorporated businesses.[4]

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 shares useful properties with log differences and naturally accommodates 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 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

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

[4]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).

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.[5]

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.[6] 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

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

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

comparable measures of business dynamism for a number of OECD countries.[7]

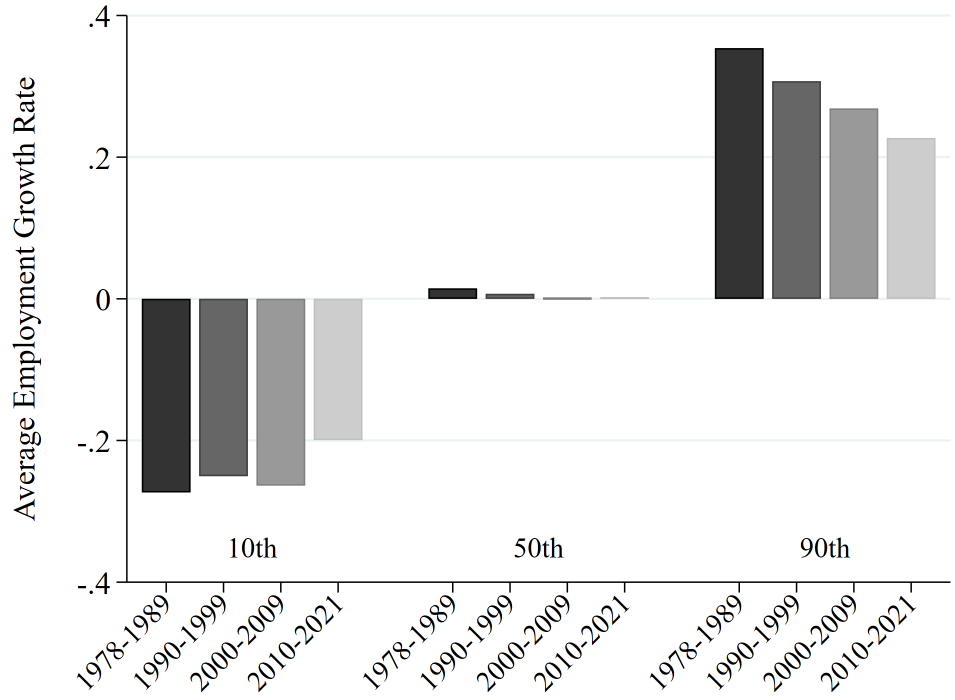
For the first method, we classify firms based on their position on the within-year average employment-weighted growth rate distribution. Employment weighting is done, after computing firm growth rates and the sum of average employment (`denom`) at the firm-level, sorting firms within a year in ascending 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 10 percent of total average employment are assigned to the p1 to 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, 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

[7]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.

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 9th and 11th (labeled 10th), 49th and 51th (labeled 50th), and the 89th and 91th (labeled 90th) 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, 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 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.

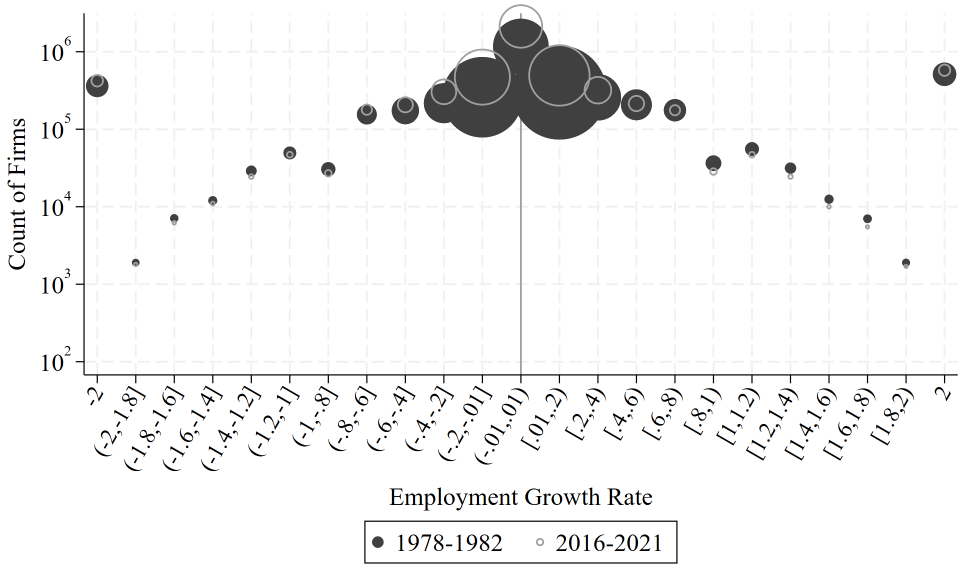
To motivate this threshold for high-growth firms, Figure 2 shows the count of firms across detailed firm growth rate bins in Panel A and the percent of firms Panel B.[9] In Panel A, the height of each dark circle shows the count of firms (with a log scale y-axis) at each point along the firm growth rate distribution on average between 1978 and 1982. The size of each bubble reflects the share of average employment accounted for by each growth rate bin in those years. The hollow circles show a similar statistic for the years 2016 to 2021. Panel B shows the percent of firms across the growth bins over time rather than firm counts. 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

[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 $g_{pct} = \frac{2g_{tvv/dhs}}{2-g_{tvv/dhs}}$.

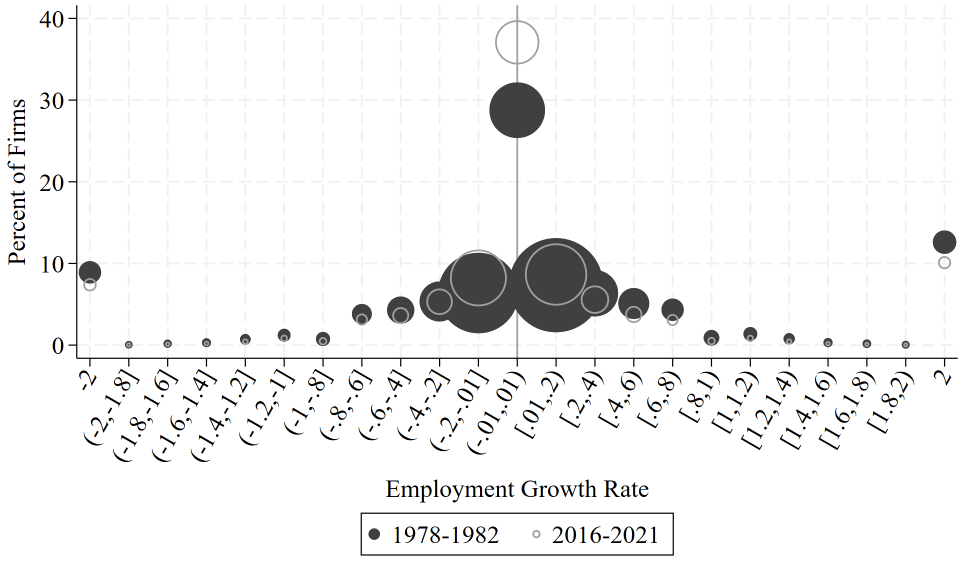
[9]These bins have more details than are available in the BDS-HG tabulations.

[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

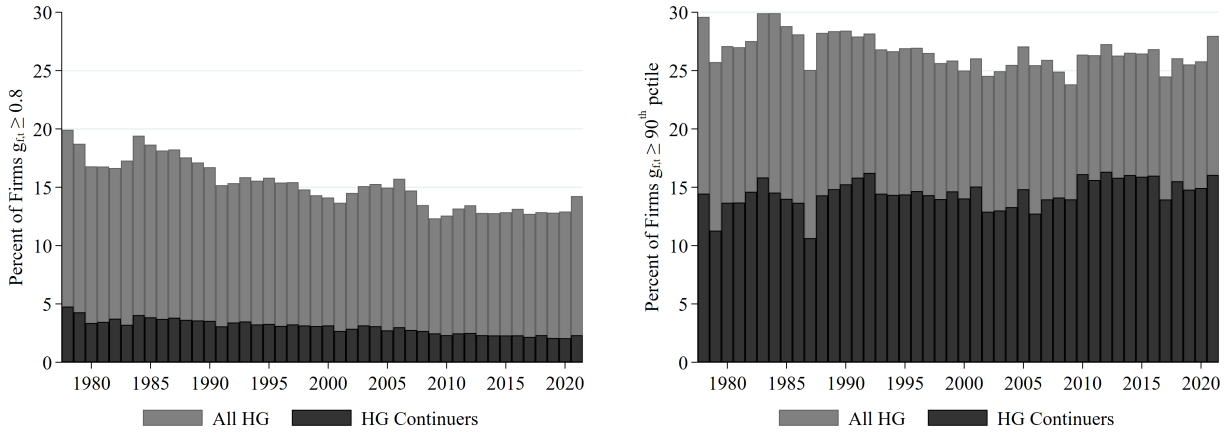
Source: LBDv202100.
Notes: Panel A shows average count of firms (log scale y-axis) across groupings of years by detailed growth rate bins. Note that these bins are more disaggregate than those provided in the BDS-HG tabulations. Solid circles represent average counts for the earlier period (1978-1982)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

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 to zero change in employment rose the most between 1980 to 2018. The count of firms that experienced significant growth or contraction declined significantly.

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 that 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^{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.

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.

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 ($\geq$ 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.

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.[11]

[11]Entrants account for the bulk of high growth firms as can be seen from Table 1. Therefore, with the recent surge in new business applications (Haltiwanger, 2022; Decker and Haltiwanger, 2023), the share of high growth firms is likely to have risen somewhat after the pandemic.

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

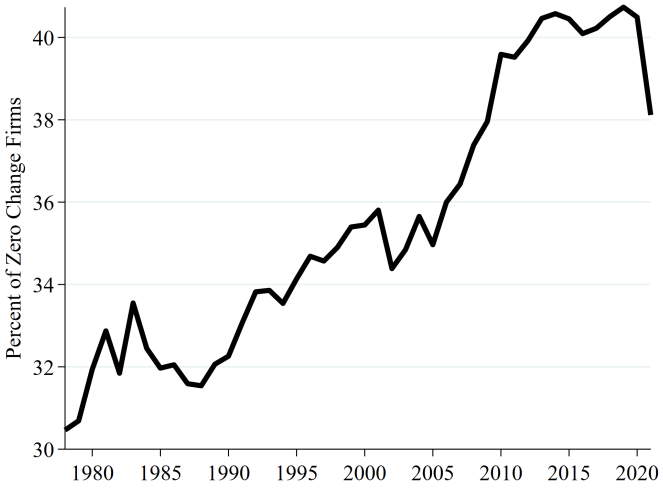
Decade	Firms			Employment			Job Creation		
	All	high-growth (%)		All	high-growth (%)		All	high-growth Firms (%)	
		Cont.	Entrants		Continuers	Entrants		Continuers	Entrants
1978-1980	3,663	4.1	14.3	71,603	2.2	1.8	11,120	16.5	23.8
1981-1985	3,883	3.7	14.1	76,301	2.1	2	10,776	17.9	27.8
1986-1990	4,303	3.7	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.

One important trend that these new tabulations highlight is the rising share of firms with little to zero change in their employment. Figure 4 shows the percent of firms with growth rates between -.01 and .01 (`fempgr_gr` bin **e)**). The share of zero-change 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 zero-change firms toward contraction or exit. Zero-change firms tend to be relatively small. Despite being 40% of firms in 2020, they only account for about 15.3% of employment.[12]

FIGURE 4: RISE OF FIRMS WITH NO CHANGE IN EMPLOYMENT



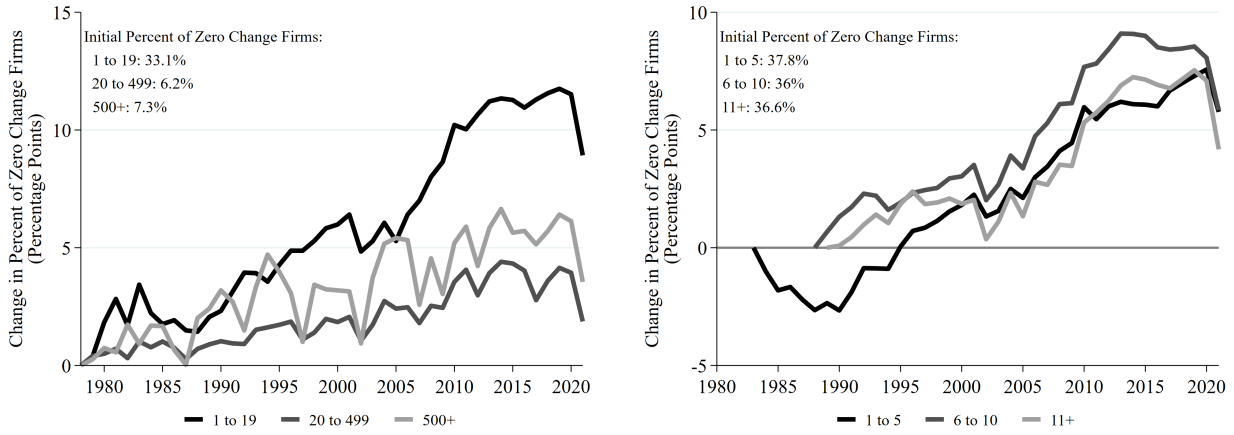
Source: BDS-HG 2021.
Notes: Figure shows the percent of firms with firm growth between -0.01 and 0.01.

[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 zero change businesses. The BED zero change 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.

Despite their rising prevalence, it is not 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. To explore these perspectives, we break down the prevalence of zero-change firms by their size and age.

Figure 5 shows the change in the percent of zero change firms by firm size (Panel A) and firm age (Panel B). By firm size, the largest increase in zero change firms was among the smallest firms—those with 1 to 19 employees. Panel A shows that the percent of zero change 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 zero change firms is much lower, about 7% in 1978, but also rose by about 6 p.p. 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 zero growth firms. Among firms ages 1 to 5, from 1983 to 1990 the share of zero growth firms fell from 38% to 35% but then rose to 45% by 2020. Nearly half (45%) of firms age 1 to 5 years saw zero 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 p.p. increase in the percent of zero growth firms, respectively. Analysis taking size and age together provides an even richer portrait of the evolution of zero change firm shares. Table A1 in the Online Appendix shows the evolution of zero change firms within firm size and firm age bins, which suggest, consistent with Figure 5, that the largest increases of zero change firm shares within an age group is among the smallest firms.

Figure 5: Firms with no change in employment, size and age



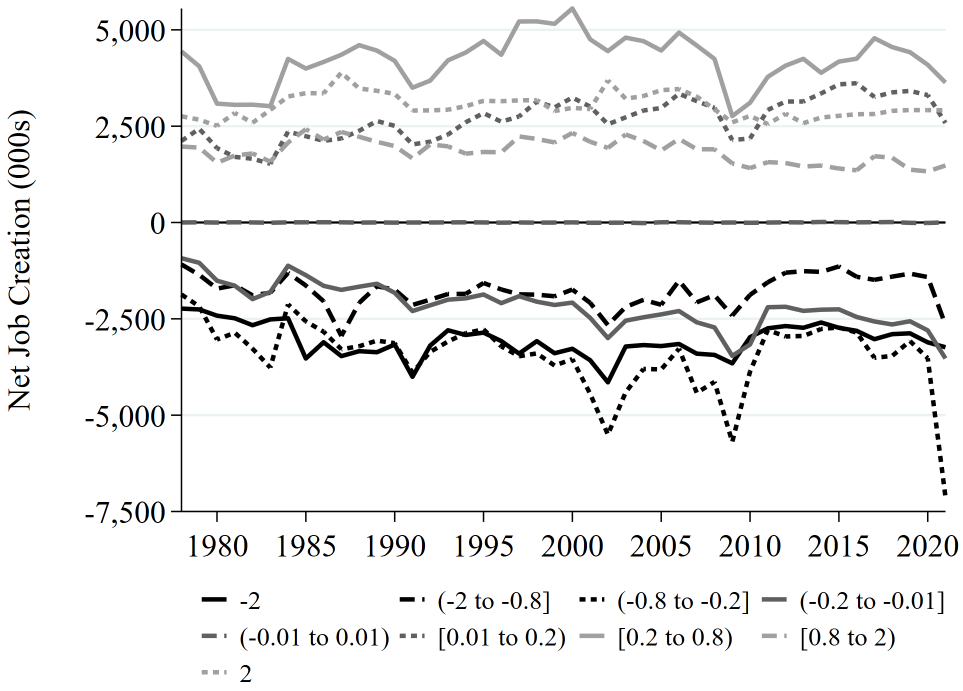
(a) Firm Size (b) Firm Age

Source: BDS-HG 2021.
Notes: Panel (A) shows the percent of firms with firm growth between -0.01 and 0.01 by firm size bins. Panel (B) shows the same by firm age bins.

Next, we decompose net job creation, or contributions to net employment growth in the economy, across the growth rate distribution. Figure 6 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 6: 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., 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 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.[13]

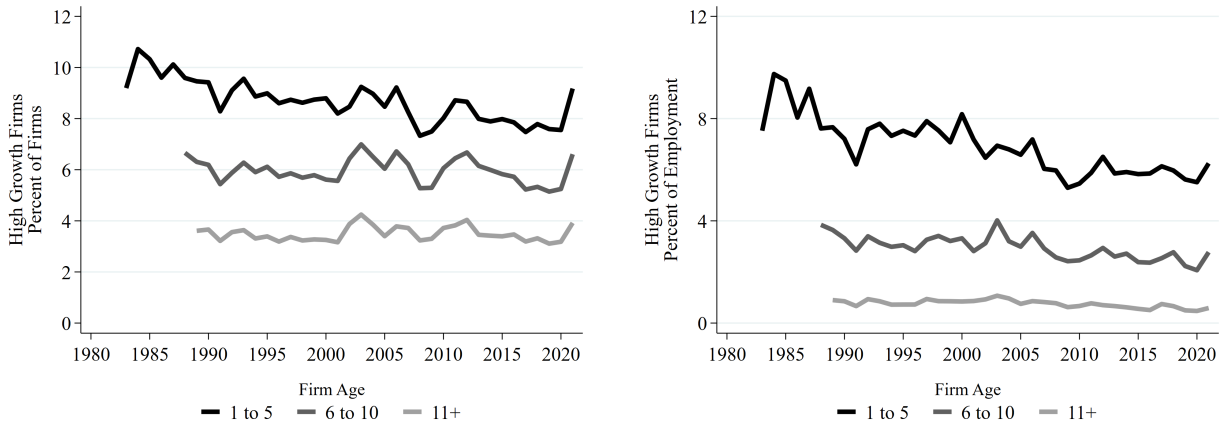
By firm maturity. We begin with firm maturity, categorizing firms as young startups (i.e., ages 1-5), mature startups (i.e., ages, 6-10), and established firms (i.e., ages 11 and above).[14] Much of the decline in the economy-wide share of high-growth firms is due to a decline in entry (Figure 3, Panel 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 7 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

[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) because they are by definition high-growth.

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 saw a relatively flat trend in the share of high growth firms and the high growth share of employment fell by a quarter, 0.2 p.p., from .8 to .6, from the early 1990s to 2020.

Figure 7: Intensity of High-Growth Firms by Firm Maturity



(a) Share of Firms

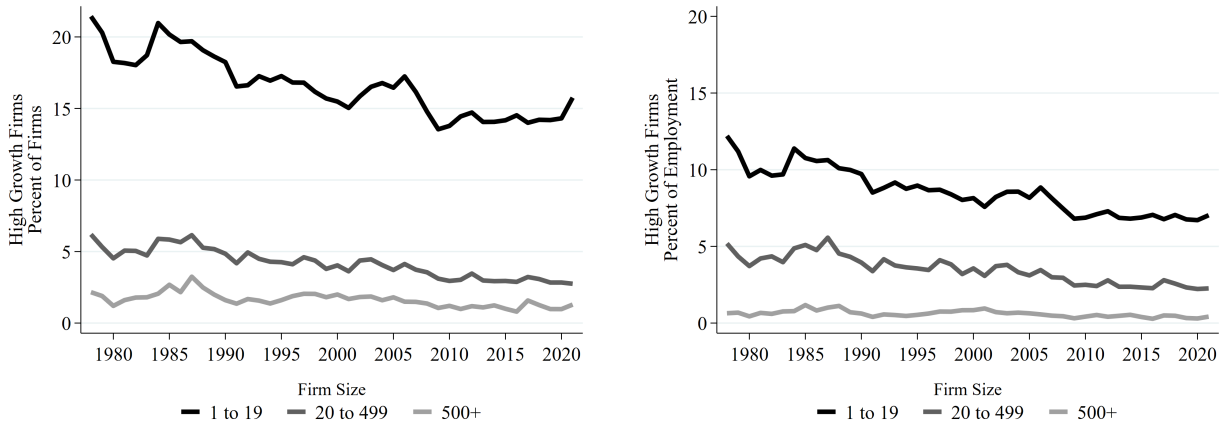
(b) Share of Employment

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.[15] Similar to the firm age figures, Panel A of Figure 8 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 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

FIGURE 8: INTENSITY OF HIGH-GROWTH FIRMS BY SMALL, MEDIUM, AND LARGE FIRMS



(A) SHARE OF FIRMS (B) SHARE OF EMPLOYMENT

Source: BDS-HG Tabulations.

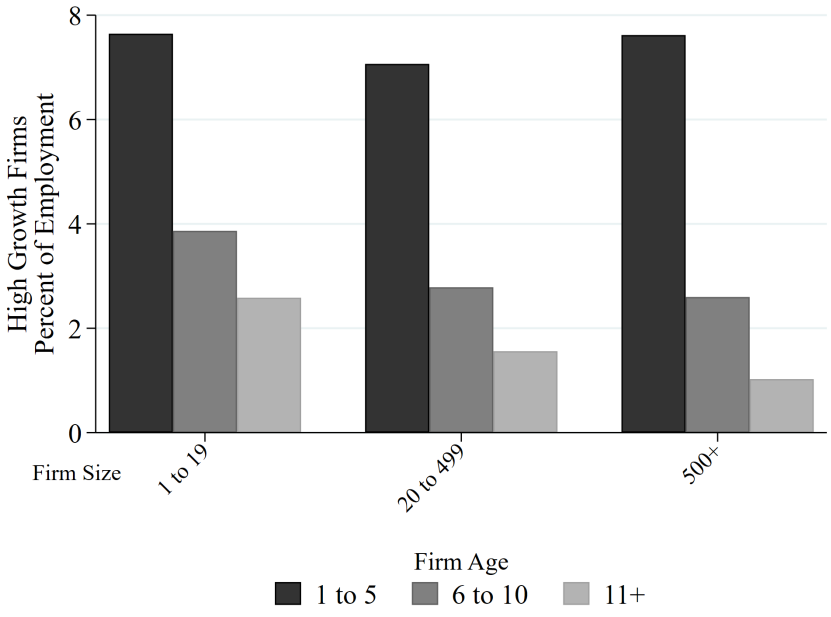
share of employment from high-growth firms for each of the three groups. The growth rate-based bins allow us to provide additional intuition for the magnitude of the changes across size bins. For example, a growth rate of 0.8 is equivalent to a 130% change in

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

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.

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; Sivadasan et al., 2024). Figure 9 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,

FIGURE 9: SHARE OF EMPLOYMENT FROM HIGH-GROWTH FIRMS BY SIZE AND AGE



Source: BDS-HG 2021.

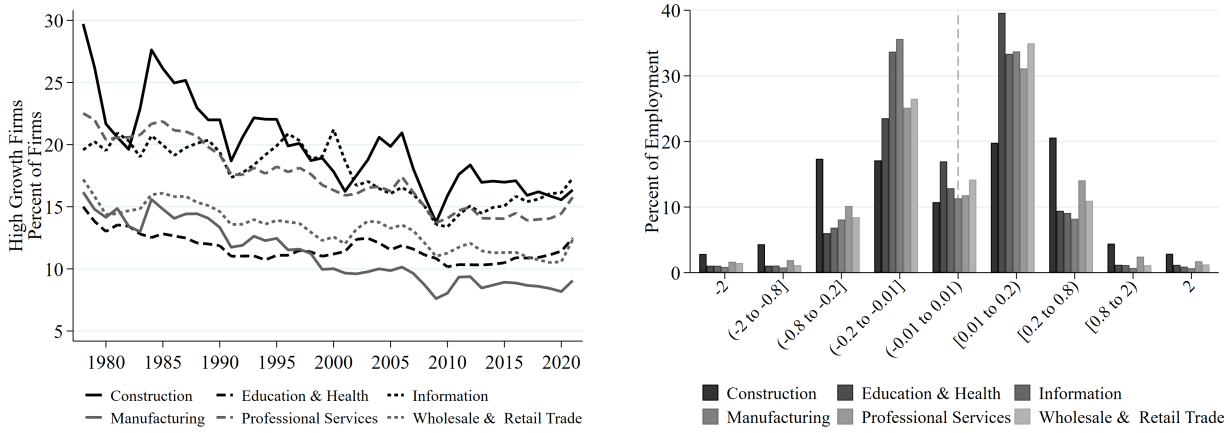
there is less of a systematic relationship. For very young firms, the smallest and largest

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.

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 10 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 show a more modest rebound. Nonetheless, the share of high-growth firms in all sectors in 2020 remains well below the levels in 1978.

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 that the high-growth firm 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 10 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

Figure 10: 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.

2), it generally has longer tails at both ends including firm death and entry. These patterns highlight that the construction 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 11, 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.

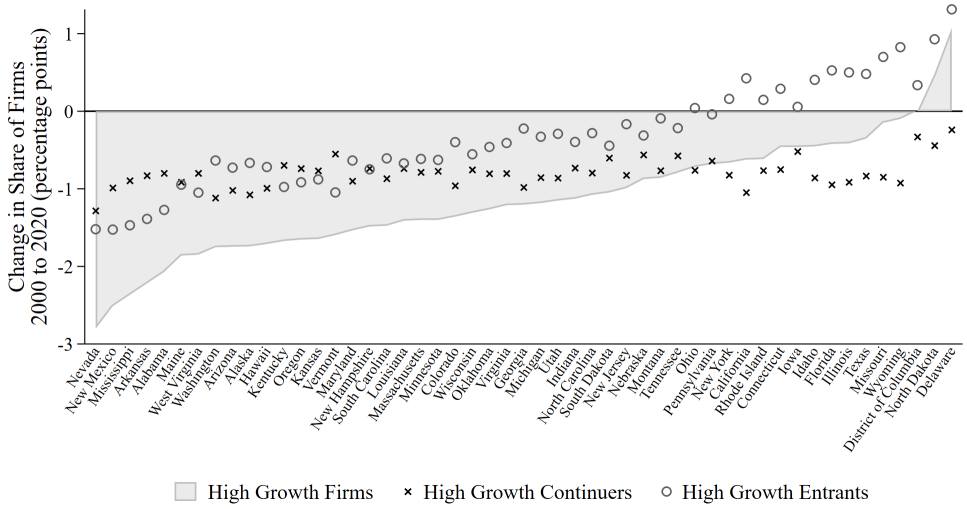
Figure 11: State's Share of High-Growth Firms versus Share of All Firms

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 12. 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 changes in the high-growth entrant share and high-growth continuer share 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 by 1.5 percentage points (14.8% to 13.3%) and its share of high-growth continuers falling by 1.3 percentage points (3.8% to 2.5%). Unlike Figure 11, these statistics are not normalized by the region's overall share of firms.

FIGURE 12: 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 remarkable patterns emerge in Figure 12. 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 are primarily driven by differences in the decline of entry.

4 Examples of Use Cases for Future Research

In this section, we highlight various research avenues that can be enabled by the three primary advantages of this new, publicly available dataset—namely, (1) detailed information on the distribution of firm growth rates extending beyond birth and death rates (e.g., high- versus low-growth); (2) a long time-series (covering 1978-2021) with consistent measures; (3) and coverage of different firm types by age (i.e., startups versus established firms), size, industry, and geography. Below, we discuss several example questions—covering a wide range of topics from firm diversification to employment protection laws—along with their underlying motivation and how specifically the BDS-HG data can help.

How does the enforceability of non-competes impact the growth of firms? Prior studies show that non-competes can not only reduce long-term wages, but also suppress the rate of entrepreneurship (Starr et al. 2018; Marx 2022; Jeffers 2024). It is not clear how they may impact the growth prospects of existing firms. For instance, large incumbent firms may benefit from stronger enforceability of non-competes by being able to retain key employees, who may otherwise be well-positioned to leave and start their own firms. Leveraging state-level legal changes in the enforceability of non-competes (e.g., Jeffers 2024), BDS-HG can be used to construct the dependent variable of the number of firms in each growth-bin at the state-year level.

How do changes in the market structure influence a firm's decision to enter through diversification? Diversification is a central strategic choice that enables firms to expand into new markets and thereby reduce risk (Gort 1962; Rumelt 1982; Silverman

1999). Among others, an important factor in influencing the performance implications of diversification is the underlying market structure (Caves et al. 1980; Montgomery 1985; Christensen and Montgomery 1981). Future research can extend this line of work by highlighting the dynamic effects of market structure—most notably, the rising levels of concentration in various industries (Autor et al. 2020)—on both the firm's decision to enter through diversification and the subsequent performance implications of diversification. BDS-HG can be used to construct the independent variable characterizing the (changing) degree of competition in the same market defined at the sector-state level. Competition could be further broken down by the types of firms in terms of size and age.

What explains the rise of startups with zero growth? As discussed with Figure 4, there are multiple potential explanations why firms are increasingly experiencing little to no change in employment, especially among young firms. While one possibility is that a declining share of startups are born with growth aspirations (Hurst and Pugsley 2011), another is that entrepreneurial firms face greater barriers in attaining the resources necessary for growth (c.f., Alvarez and Barney 2017). BDS-HG can be used to construct the dependent variable on the share of startups with zero employment change at the sector-state-year level.

How does foreign import competition impact entry and growth of domestic firms? While trade is understood to benefit the global economy through efficiency gains via specialization, it has been shown to have deleterious effects on the labor market (Autor et al., 2013). Less understood is how rising competition from imports heterogeneously affects the growth prospects of domestic firms in different industries and regions. BDS-HG can be used to construct the dependent variable reflecting the number of firms in

each growth-bin at the sector-state-year level.[16]

How do changes in bank lending affect young firms' growth distributions? Bank loans are a common source of financing for young businesses (Robb and Robinson, 2014). Accordingly, an increase in banks' small business lending leads to an increase in firm entry (for evidence at the state level, see Cetorelli and Strahan 2006). However, little is known about its impact on the growth distribution of these firms. For example, bank lending may primarily affect young firms with low risk but little growth potential and have only minimal impact on young firms with high risk and high growth potential. BDS-HG can be used to construct the dependent variable reflecting the number of firms in each growth-bin among young firms at the state-year level.

How does employment protection affect distribution of firm growth? Employment protection laws are known to lower employment rates (Autor et al., 2006) and affect firm size distribution (Hopenhayn and Rogerson, 1993), but there is little evidence on its effects on firm growth distribution. For example, employment protection laws may reduce firm growth, or limit contraction, or both. Also, these effects may differ along firm size and age. BDS-HG can be used to construct dependent variables that measure growth rate distributions by firm age and size, at the state-year level.

How does the type of innovative firms relate to firm growth? A core question in the innovation literature is the role of startups and established firms in generating radical versus incremental innovation (Tushman and Anderson 1986; Tripsas 1997; Christensen 1997; Benner 2010; Akcigit and Kerr 2018). In a follow-on extension, Garcia-Macia et al. (2019) have shown that there is a mapping between these dynamics and the evolution of the shape of the firm growth rate distribution. The working hypothesis is that disruptive

[16] As noted above, the Fall 2024 release will include more granular statistics at the sector $\times$ state level.

innovations by young firms will lead to fat right tails in the growth rate distribution. BDS-HG provides a unique public domain database for investigating these questions.

What are the causes and consequences of changes in US business dynamism? Business dynamism has declined in the U.S. over the last several decades (at least through 2021). Alternative hypotheses include changes in adjustment costs, changes in the distribution of firm productivity including slowing diffusion, and rising market power. BDS-HG offers the richest public-domain data on the changing shape of the firm growth rate distribution available. Changes in the shape alone are informative (e.g., the increased share of inactive firms is an indication of rising nonconvex adjustment frictions). The variation by geography and industry in the BDS-HG can help researchers test some of these consider alternative hypotheses.

How does the U.S. firm growth rate distribution compare to other OECD countries? The measurement approach described in Section 2 was designed to be maximally comparable to similar statistics collected as part of the OECD's DynEmp program (Desnoyers-James et al., 2019). Research by the OECD suggests that though many countries experienced significant declines in business dynamism, there is significant cross country variation that can be used to evaluate economic policy (Calvino et al., 2020). By combining BDS-HG data with the OECD's DynEmp statistics, researchers could better understand how the evolution of the firm growth rate distribution in the US compares to other OECD countries. Moreover, the presence of the U.S. in such a dataset would offer additional cross country policy variation, providing a more complete picture of the relationship between dynamism and economic policy.

5 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 firms demonstrating little to no employment change. 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.

Beyond these trends, our hope is that this new, publicly available dataset will help facilitate future research in management, economics, and other related disciplines. 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.[17]

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

References

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.

Alvarez, Sharon A and Jay B Barney (2017) "Resource-based theory and the entrepreneurial firm," *Strategic entrepreneurship: Creating a new mindset*, 87–105.

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.

Autor, David H, John J Donohue III, and Stewart J Schwab (2006) "The costs of wrongful-discharge laws," *The review of economics and statistics*, 88 (2), 211–231.

Autor, David H, David Dorn, and Gordon H Hanson (2013) "The China syndrome: Local labor market effects of import competition in the United States," *American economic review*, 103 (6), 2121–2168.

Baum, Joel AC and Stephn J Mezias (1993) "Competition, institutional linkages, and organizational growth," *Social Science Research*, 22 (2), 131–164.

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

Benner, Mary J (2010) "Securities analysts and incumbent response to radical technological change: Evidence from digital photography and internet telephony," *Organization Science*, 21 (1), 42–62.

Calvino, Flavio, Chiara Criscuolo, and Rudy Verlhac (2020) "Declining business dynamism: Structural and policy determinants."

Carroll, Glenn R and Michael T Hannan (1989) "Density delay in the evolution of organizational populations: A model and five empirical tests," *Administrative Science Quarterly*, 411–430.

Caves, Richard E, Michael E Porter, and Michael Spence (1980) *Competition in the open economy: A model applied to Canada* (150): Harvard University Press.

Cetorelli, Nicola and Philip E Strahan (2006) "Finance as a barrier to entry: Bank competition and industry structure in local US markets," *The journal of Finance*, 61 (1), 437–461.

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.

Christensen, Clayton M (1997) *The innovator's dilemma: when new technologies cause great firms to fail*: Harvard Business School Press.

Christensen, H Kurt and Cynthia A Montgomery (1981) "Corporate economic performance: Diversification strategy versus market structure," *Strategic Management Journal*, 2 (4), 327–343.

Coad, Alex (2024) *Scale-ups and High-Growth Firms: Theory, Definitions, and Measurement*: Springer Nature.

Crane, Leland Dod and Ryan Decker (2019) "Business Dynamics in the National Establishment Time Series (NETS)/Leland Crane, Ryan Decker."

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 and John Haltiwanger (2023) "Surging Business Formation in the Pandemic: Causes and Consequences," *Brookings Papers on Economic Activity*, 3–24.

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.

Eisenhardt, Kathleen M and Claudia Bird Schoonhoven (1990) "Organizational growth: Linking founding team, strategy, environment, and growth among US semiconductor ventures, 1978-1988," *Administrative science quarterly*, 504–529.

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.

Garcia-Macia, Daniel, Chang-Tai Hsieh, and Peter J Klenow (2019) "How destructive is innovation?" *Econometrica*, 87 (5), 1507–1541.

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 (1962) *Diversification and integration in American industry*: Greenwood Press.

Guzman, Jorge and Scott Stern (2020) "The state of American entrepreneurship: New estimates of the quantity and quality of entrepreneurship for 32 US States, 1988–2014," *American Economic Journal: Economic Policy*, 12 (4), 212–243.

Haltiwanger, John C (2022) "Entrepreneurship during the COVID-19 pandemic: Evidence from the business formation statistics," *Entrepreneurship and Innovation Policy and the Economy*, 1 (1), 9–42.

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.

Hopenhayn, Hugo and Richard Rogerson (1993) "Job turnover and policy evaluation: A general equilibrium analysis," *Journal of political Economy*, 101 (5), 915–938.

Hurst, Erik and Benjamin Wild Pugsley (2011) "What do small businesses do?"Technical report, National Bureau of Economic Research.

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

Jeffers, Jessica S (2024) "The impact of restricting labor mobility on corporate investment and entrepreneurship," *The Review of Financial Studies*, 37 (1), 1–44.

Khaire, Mukti (2010) "Young and no money? Never mind: The material impact of social resources on new venture growth," *Organization Science*, 21 (1), 168–185.

Lucas Jr, Robert E (1978) "On the size distribution of business firms," *The Bell Journal of Economics*, 508–523.

Marx, Matt (2022) "Employee non-compete agreements, gender, and entrepreneurship," *Organization Science*, 33 (5), 1756–1772.

Montgomery, Cynthia A (1985) "Product-market diversification and market power," *Academy of management journal*, 28 (4), 789–798.

Nagaraj, Abhishek and Matteo Tranchero (2023) "How does data access shape science? Evidence from the impact of US census's research data centers on economics research,"Technical report, National Bureau of Economic Research.

Nelson, Richard R and Sidney G. Winter (1982) *An evolutionary theory of economic change*: Harvard University Press.

Robb, Alicia M and David T Robinson (2014) "The capital structure decisions of new firms," *The Review of Financial Studies*, 27 (1), 153–179.

Rumelt, Richard P (1982) "Diversification strategy and profitability," *Strategic management journal*, 3 (4), 359–369.

Silverman, Brian S (1999) "Technological resources and the direction of corporate diversification: Toward an integration of the resource-based view and transaction cost economics," *Management science*, 45 (8), 1109–1124.

Sivadasan, Jagadeesh, Natarajan Balasubramanian, Ravi Dharwadkar, and Charlotte Ren (2024) "How do US firms grow? New evidence from a growth decomposition," *Strategic Management Journal*.

Starr, Evan, Natarajan Balasubramanian, and Mariko Sakakibara (2018) "Screening spinouts? How noncompete enforceability affects the creation, growth, and survival of new firms," *Management Science*, 64 (2), 552–572.

Sterk, Vincent, Petr Sedláček, and Benjamin Pugsley (2021) "The nature of firm growth," *American Economic Review*, 111 (2), 547–579.

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

Tripsas, Mary (1997) "Unraveling the process of creative destruction: Complementary assets and incumbent survival in the typesetter industry," *Strategic management journal*, 18 (S1), 119–142.

Tushman, Michael L and Philip Anderson (1986) "Technological discontinuities and organizational environments," *Administrative Science Quarterly*, 439–465.