Where has all the skewness gone? The decline in high-growth (young) firms in the U.S.

October 2015

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The pace of business dynamism and entrepreneurship in the U.S. has declined over recent decades. We show that the character of that decline changed around 2000. Since 2000 the decline in dynamism and entrepreneurship has been accompanied by a decline in high-growth young firms. Prior research has shown that the sustained contribution of business startups to job creation stems from a relatively small fraction of high-growth young firms. The presence of these high-growth young firms contributes to a highly (positively) skewed firm growth rate distribution. In 1999, the difference in the growth rate of the firm growing at the 90th percentile and the 50th percentile of the growth rate distribution was about 31 percentage points. This differential was 16 percent larger than the growth rate difference of firms at the 50th and 10th percentiles. However, we show that the 90-50 differential fell substantially in the post-2000 period. By 2007, the 90-50 differential was only 4 percent larger than the 50-10, and it continued to exhibit a trend decline through 2011. Both the declining share of young firms and the declining propensity for young firms to be high-growth firms are contributing factors. In addition, key sectors have exhibited a sharp decline in positive skewness in the post-2000 period—specifically the high tech sector. This sector exhibited an increase in dispersion and skewness in firm growth rates during the 1990s before the sharp decline.

* Board of Governors of the Federal Reserve System, University of Maryland and NBER, U.S. Census Bureau, and U.S. Census Bureau, respectively. We thank the Kauffman Foundation for financial support, Kristin McCue and seminar participants at Chicago Booth and George Mason University for helpful comments. The main findings in this paper previously circulated in a paper titled "The Secular Decline in Business Dynamism in the U.S.". The previous paper has been broken into two parts. The current paper focuses on the decline in high-growth firms and skewness. Any opinions and conclusions expressed herein are those of the author(s) and do not necessarily represent the views of the U.S. Census Bureau, of the Federal Reserve System, or of the Board of Governors or its staff. All results have been reviewed to ensure that no confidential information is disclosed. Corresponding author: John Haltiwanger, haltiwan@econ.umd.edu, (301) 405-3504 (phone), (301) 405-3542 (fax).

High-growth firms and especially high-growth young firms played critical roles in the robust U.S. job and productivity growth of the 1980s and 1990s. During this era, the pace of business startups was very high. Most of these startups would fail within the first five years, but a small fraction of young firms grew very fast. Such high-growth young firms yielded a sustained and disproportionate contribution of startups to job creation. Moreover, the evidence shows that these high-growth young firms were relatively more innovative and productive, so their rapid growth contributed positively to productivity growth as more resources were shifted to these growing firms.[1] An accompanying feature of these patterns is that young firms exhibited positive skewness in their growth rate distribution.

In this paper, we document that the contribution of high-growth (young) firms to U.S. job creation and the patterns of positive skewness in the firm growth rate distribution are changing. We present evidence that the post-2000 period has seen a decline in high-growth firms and especially high-growth young firms. An implication of this is that the positive skewness of the firm growth rate distribution has declined dramatically in the post-2000 period. In 1999 the difference between the 90th percentile and 50th percentile in the employment-weighted firm growth rate distribution was 31 percentage points.[2] This difference was 16 percent higher than the difference between the 50th and 10th percentile in 1999, reflecting considerable positive skew. But starting around 2000 this difference exhibited a trend decline. By 2007, the 90-50 differential was only 4 percent larger than the 50-10. The trend decline in skewness continued through 2011.

These findings provide helpful perspective and insights about the decline in U.S. business dynamism and entrepreneurship over the last few decades. Our findings suggest that the character of that decline changed around 2000. Prior to 2000, declining dispersion in firm growth rates was not accompanied by declining skewness. But in the

[1] See Haltiwanger, Jarmin, and Miranda (2013) and Decker, Haltiwanger, Jarmin, and Miranda (2014) for evidence about the role of high-growth young firms and their contribution to job creation and productivity growth. These papers use cross sectional averages using data for the 1980s, 1990s and 2000s. But as we show in this paper, the patterns they emphasize are dominated by the patterns of the 1980s and 1990s. Acemoglu et al. (2013) show that for the innovative intensive sectors it is the young firms that are most innovation intensive.

[2] We focus on trends in measures of dispersion and skewness in this paper. Statistics reported in this paragraph are from Hodrick-Prescott trends as discussed below.

post-2000 period the decline in dispersion is accompanied by a decline in skewness. We show that this reflects starkly different patterns across sectors. In the pre-2000 period, the decline in dispersion is driven by sectors like the Retail Trade sector that exhibits little or no skewness in any period. But in the post-2000 period, sectors like the high tech sector exhibited sharp declines in dispersion and skewness after having exhibited rising dispersion and skewness in the pre-2000 period. These different patterns by sector suggest that the causes and consequences of the decline in dynamism and entrepreneurship likely vary by sector and time period. Moreover, the data indicate a homogenization of the U.S. economy—sectors that previously differed widely in terms of both dispersion and skew are converging on increasingly similar patterns of dynamism. We discuss these issues further below.

While we focus our analysis on the U.S., an economy for which we have detailed microdata suitable for the task, there is a growing literature on business dynamics across developed countries. Bravo-Biosca, Criscuolo, and Menon (2013) find that the large contribution of young firms and high-growth firms to job creation we find in the U.S. holds in many European and other developed countries as well. Using a similar cross-country sample, Criscuolo, Gal and Menon (2014) find that young firm activity fell between 2001 and 2011 in most countries, though the Great Recession renders secular inference difficult on their data sample. Davis and Haltiwanger (2014) show that job reallocation fell from 2002 to 2009 in several developed countries, though most saw smaller declines than the United States. Our analysis may point to useful research avenues for those studying this topic outside the U.S., and it highlights the need for continued improvement in cross-country business dynamics data infrastructure.

The paper proceeds as follows. Section II describes the skewness of the firm growth rate distribution in the context of theories of business dynamics and entrepreneurship. Section III describes the data and the measures of firm growth, dispersion and skewness that we use in our analysis. Section IV presents basic facts about the declining pace of business dynamism focusing on the 90-10 differential in firm growth rates. Section V presents new evidence on the changing patterns of high-growth firms and skewness. Concluding remarks are in section VI.

II. Entrepreneurship and Skewed Distributions of Firm Growth Rates

The U.S. economy is very dynamic. At any given time, we observe new firms starting up and others shutting down. Some firms grow, hiring additional workers or adding new facilities, while others reduce employment and get smaller. Firm growth distributions summarize the activity of these growing and shrinking businesses and, in this sense, reflect the character and nature of the resource reallocation taking place in the economy.

Several factors can contribute to the distribution of firm growth rates being positively skewed especially for young firms and in turn economies and sectors where startups play a critical role for economic growth. First, models of firm dynamics suggest the uncertainty entrants face about their likely profitability and the subsequent selection and learning dynamics of young firms imply both dispersion and skewness in the growth rate distributions for young firms (Jovanovic (1982)). Uncertainty implies that firms enter small. Those that learn they are highly productive and profitable grow rapidly while those that learn they are not contract and potentially exit. Second, this up-or-our dynamic of young firms will be amplified if the distribution of productivity/profitability across firms is itself skewed. Since it is well known that the size distribution of firms is highly skewed, many have hypothesized that the distribution of productivity/profitability is also skewed. For example, it is common to assume that the distribution of productivity/profitability across firms is pareto to match the size distribution. A pareto distribution of productivity/profitability combined with uncertainty, selection and learning will yield highly disperse and skewed distributions of growth rates for young firms. Moreover, if the innovations to the productivity/profitability distribution are also drawn from a skewed distribution then this implies potential skewness in the growth rates even for mature firms.[3]

A related but different source of skewness of the distribution of growth rates for young firms stems from the hypothesis that variation in productivity at the firm level stems from endogenous innovation. Acemoglu et al. (2013) hypothesize that it is young firms that have the greatest propensity to make major innovations. In their model, firms enter as either high or low types. High types have the capacity to make major innovations. High types invest intensively in R&D and a fraction of those investments succeed, and such firms grow very rapidly. Given their assumption that young firms are more likely to be high types (in their model firms can revert to

[3] Such skewness in innovations to productivity would yield skewness in the growth rate distribution in the Ericson and Pakes (1996) model. See Syverson (2011) for a recent survey of the literature on the relationship between the growth dynamics of firms and productivity.

being low types, an absorbing state), young firms exhibit both greater dispersion and skewness in growth outcomes.

Another related hypothesis is that entrepreneurs exhibit ex ante heterogeneity in type. For example, Schoar (2010) suggests that it is helpful to distinguish between "subsistence" and "transformational" entrepreneurs in the context of firms in emerging economies. "Subsistence" entrepreneurs are small businesses created out of necessity or choice for the entrepreneur to provide income for themselves and perhaps a few others (in many cases, family members). "Transformational" entrepreneurs, by contrast, are those whose goal is to make a major product or process innovation that will yield a large firm that generates income and work for many people.

Hurst and Pugsley (2012) present evidence suggesting that most startups in the U.S. were created with little intent for innovation or growth. Moreover, they find that most business owners report significant non-pecuniary motivations, such as being one's own boss, for starting a business (Hurst and Pugsley (2012, 2014)). These businesses are akin to Schoar's "subsistence" category although we might call these "lifestyle" or "mainstream" entrepreneurs in the context of advanced economies. They further argue and find some evidence that there are some sectors dominated by the "be your own boss" entrepreneurs, which often include skilled craftsman, skilled professionals, and small shop keepers (*e.g.*, dry cleaners).

The "transformational" entrepreneurs can be thought as akin to the high types in the Acemoglu et al. (2013). Empirical evidence in the latter paper shows that the fraction of the economy which is innovation intensive is relatively small and concentrated in the high tech sectors. They also show that in such sectors high-growth firms are more likely to be young firms.

Putting these related hypotheses together, skewness in the growth rate distribution of young firms is more likely to be present in some sectors than others. Sectors which are dominated by "mainstream" or "lifestyle" entrepreneurs might have high rates of dispersion in growth due to high rates of turnover. However, such businesses would not exhibit much skewness since such firms have little prospect or aspiration for growth. Skewness in growth rates is more likely in innovative and dynamic sectors where there is high growth potential.

In light of the evidence that the pace of entrepreneurship has declined in the U.S. in recent decades, this discussion raises the question of what types of entrepreneurs have declined.

They implications are very different since high growth "transformation" entrepreneurs are tied to job creation and productivity growth. We examine this question in this paper by examining the changing pattern of skewness of the growth rate distribution of firms overall, in specific sectors and for different types of firms.

III. Business Dynamics Data

Most of the findings reported in this paper are based on the Census Bureau's Longitudinal Business Database (LBD).[4] The LBD covers the universe of establishments and firms in the U.S. nonfarm business sector with at least one paid employee. The LBD includes annual observations beginning in 1976, and in this paper we use the data through 2011.[5] It provides information on detailed industry, location and employment for every establishment. Employment observations in the LBD are for the payroll period covering the 12th day of March in each calendar year.

A unique advantage of the LBD is its comprehensive coverage of both firms and establishments. Only in the LBD is firm activity captured up to the level of operational control instead of being based on an arbitrary taxpayer ID.[6] The ability to link establishment and firm information allows firm characteristics such as firm size and firm age to be tracked for each establishment. Firm size measures are constructed by aggregating the establishment information to the firm level using the appropriate firm identifiers. The construction of firm age follows the approach adopted for the Business Dynamics Statistics (BDS) and based on our prior work (see, *e.g.*, Becker et al. (2006), Davis et al. (2007) and Haltiwanger, Jarmin and Miranda (2013)). Namely, when a new firm ID arises for whatever reason, we assign the firm an age based on the age of the

[4] We note that the LBD employment and job creation numbers track closely those of the County Business Patterns and Statistics of U.S. Business programs of the U.S. Census Bureau (see Haltiwanger, Jarmin and Miranda (2009)) as they all share the Census Bureau's Business Register (BR) as their source data. Further details about the LBD and its construction can be found in Jarmin and Miranda (2002).

[5] More recent versions of the LBD become available each year. There is now a 2013 version available. We use the version through 2011 since it is for this version that we have attached consistent NAICS codes to the firm- and establishment-level data.

[6] A closely related database at the Bureau of Labor Statistics tracks quarterly job creation and destruction statistics (Business Employment Dynamics). The BED has advantages in terms of both frequency and timeliness of the data. However, the BED only can capture firm dynamics up to the level of establishments that operate under a common taxpayer ID (EIN). There are many large firms that have multiple EINs—it is not unusual for large firms operating in multiple states to have at least one EIN per state.

oldest establishment that the firm owns in the first year in which the new firm ID is observed. The firm is then allowed to age naturally (by one year for each additional year it is observed in the data), regardless of any acquisitions and divestitures as long as the firm continues operations as a legal entity. We utilize the LBD to construct annual establishment-level and firm-level growth rates. The measures we construct abstract from net growth at the firm level that is due to M&A activity. We provide a brief description of these measures next.

We start with establishment-level statistics since our firm-level statistics build on these measures. Let E_{it} be employment in year *t* for establishment *i*. In the LBD, establishment employment is a point-in-time measure reflecting the number of workers on the payroll for the payroll period that includes March 12th. We measure the establishment-level employment growth rate as follows:

$$\gamma_{it} = (E_{it} - E_{it-1})/Z_{it}$$

where

$$Z_{it} = 0.5 * (E_{it} + E_{it-1}).$$

This growth rate measure has become standard in analysis of establishment and firm dynamics, because it shares some useful properties of log differences but also accommodates entry and exit (See Davis, Haltiwanger and Schuh (1996), and Törnqvist, Vartia, and Vartia (1985)). We refer to this as the DHS growth rate. This critically permits us to construct measures of firm- and establishment-level volatility such as job reallocation that incorporate the contribution of entry and exit.

Computing firm-level growth rates is more complex given changes in ownership due to mergers, divestitures, or acquisitions. In these instances, net growth rates computed from firm-level data alone will reflect changes in firm employment due to adding and/or shedding continuing establishments. This occurs even if the added and/or shed establishments experience no employment changes themselves. To avoid firm growth rates capturing changes due to M&A and organizational change, we compute the period *t-1* to period *t* net growth rate for a firm as the employment-weighted average DHS net growth rate of all establishments owned by the firm in period *t*, including acquisitions and the net growth attributed to establishments owned by the firm

in period *t-1* that it has closed before period *t.*[7] For any continuing establishment that changes ownership, this method attributes any net employment growth to the acquiring firm. Note, however, if the acquired establishment exhibits no change in employment, there will be no accompanying change in firm-level employment induced by this ownership change. The general point is that this method for computing firm-level growth captures only "organic" growth at the establishment level and abstracts from changes in firm-level employment due to M&A activity.

Most of our analysis in this paper focuses on measures of business dynamics at the firm level. Moreover, given our interest in high-growth firms and skewness, most of our analysis uses measures based on the percentiles of the employment-weighted firm growth rate distribution. In particular, we utilize changes over time in the differences between the 90th and 10th percentiles to describe trends in dynamism. Similarly, we examine trends in the skewness of firm growth rate distributions by comparing the 90-50 and 50-10 differentials over time. These robust statistics are computed for the universe of firms in the relevant analysis group (*e.g.*, all firms, continuers, sector, etc.).

Focusing on firm growth rates also helps facilitate the analysis of young firms (since young establishments differ from young firms considerably). As noted above, we are using measures of firm growth that capture only organic growth. In this analysis, we examine the distributions where we include all firms and where startups and exits are excluded allowing us to focus on continuing firms. Before proceeding to that analysis, we note that we have conducted our analysis of indicators of declining business volatility using a variety of measures at the firm and establishment level. As shown in appendix A and discussed briefly below, we find that the overall and sectoral patterns of declining dynamism are robust to using alternative measures of volatility including job reallocation at the firm and establishment level, measures of the standard deviation of firm- and establishment-level growth and within-firm and within-establishment measures of volatility.

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[7] To construct organic firm-level growth rates, consult the formulas for establishments detailed above then let Z_{Jt}^{f} be a measure of employment for firm J:

$$Z_{Jt}^{f} = \sum_{i \in J} Z_{it},$$

that is, the sum of Z_{it} for all establishments owned by firm J at time t. Then the firm growth rate is given by

$$\gamma_{Jt}^{f} = \sum_{i \in J} (Z_{it}/Z_{Jt}^{f})\gamma_{it}.$$

IV. The Decline in Business Dynamism

We examine declining business dynamism by studying the differential between the 90th and the 10th percentiles of the firm growth rate distribution, to which we refer as the 90-10 differential. Large 90-10 differentials indicate large amounts of reallocation activity across firms, and a decline in 90-10 differentials indicates a decline in the pace of reallocation. Figure 1 shows the 90-10 differential from the employment-weighted distribution of firm-level net employment growth rates. The 90-10 differentials for all firms (including entry and exit) as well as for continuing firms are both depicted. To facilitate focusing on the trends, the Hodrick-Prescott trend is also included (given the use of annual data, the Hodrick Prescott smoothing parameter used is 100).[8] It is apparent that there is a secular decline in the 90-10 differential of among both all firms and continuing firms only. Moreover, the Hodrick-Prescott trend helps draw out another pattern. There is a sharp decline in dispersion from the late 1980s to the early 1990s, the second half of the 1990s exhibits a more modest decline, and then there is a sharp decline again in the post-2000 period.

If declining dispersion were entirely accounted for by changes in entry and exit patterns, then only the "all firm" series in Figure 1 should trend down. The finding that there is declining dispersion both for all firms and for continuing firms implies that declining dispersion cannot be driven simply by a decline in entry and exit rates. Figures 2a and 2b show the pattern of firm entry and exit rates, both unweighted (2a) and weighted by employment (2b). The firm entry rate (what we also often call the startup rate) exhibits a pronounced secular decline. The firm exit rate generally does not (though when weighting by employment as in Figure 2b there is a clear decline from the 1980s to the 1990s). Since 2008 the rate of net entry has turned negative.[9]

The trends in Figure 1 are not confined to the specific measures or data used here. Davis et al. (2010) show that the declining pace of job flows is evident in the Business Employment Dynamics (BED). They also show that the declining trend in the pace of

[8] We have found that our results are largely robust to using a 3-year moving average of the dispersion and skewness measures. This is not surprising given the patterns in Figure 1. We discuss this more below.
[9] This is a point emphasized by Hathaway and Litan (2014).

job destruction is closely linked to the secular decline in the inflow rate to unemployment (both at the national and sectoral level). Davis, Faberman, and Haltiwanger (2012) show that the declining pace of job flows in the BED is matched by a declining pace of worker flows in the Job Openings and Labor Turnover (JOLTS) data. They find that excess worker reallocation (worker reallocation over and above job reallocation, sometimes called churn) has also exhibited a trend decline.[10] Similar findings on the secular decline in churn have been documented and analyzed by Lazear and Spletzer (2012) using the JOLTS data. Hyatt and Spletzer (2013) use the worker and job flows data from the Quarterly Workforce Indicators (QWI) based on linked employer-employee data to examine trends in employment dynamics. They show that the patterns that others have found in the BED and JOLTS are also evident in the QWI data on hires, separations, job creation and job destruction. In Appendix A, using the same data as in Figure 1 we show that a variety of alternative measures of firm- and establishment-level volatility exhibit a pronounced decline over the same period.

The decline in the pace of overall firm volatility does mask an increase in the pace of firm volatility among publicly traded firms through 2000, as documented by Comin and Philippon (2005). Davis et al. (2007) confirm the Comin and Philippon findings using linked LBD-Compustat data that have both privately held and publicly traded firms. They show that the decline in the pace of business volatility among privately held firms overwhelms the rise in firm volatility for publicly traded firms. We use the distinction between privately held and publicly traded firms in our analysis below since, as we shall see, it offers some clues about the acceleration in the decline in volatility in the post-2000 period.

A common finding in the recent literature is that the decline in dispersion shown in Figure 1 is largely occurring within cells defined by industries, firm size classes and firm age classes (see, *e.g.*, Davis et al. (2007), Hyatt and Spletzer (2013), Decker et al. (2014), and Davis and Haltiwanger (2014)). We confirm this finding for the data we use for Figure 1 (see appendix B). We find that compositional shifts can account for a relatively small fraction of the decline in dispersion in business growth rates.

[10] Davis and Haltiwanger (2014) show that the declines in job and worker reallocation are also associated with the declines in employment rates in the U.S.

Specifically, we find that only 15 percent of the decline in job reallocation rates (an alternative measure of business volatility that is highly correlated with the 90-10 dispersion measure) is accounted for by all compositional effects taken into account simultaneously (firm age, firm size, multi-unit status, and indicators of whether a firm is part of a national chain).[11] Like others, we find that this relatively small combined effect masks substantial individual composition effects working in opposite directions. The shift toward older firms accounts for about 26 percent of the decline in job reallocation rates by itself, but this is offset by the 13 percent increase in job reallocation due to the shift toward more volatile industries. The declining share of young firms combined with the higher degree of dispersion for young compared to older firms accounts for the former. The shift away from low-dispersion, goods-producing sectors like Manufacturing to high-dispersion sectors like Retail Trade and Services accounts for the latter. These findings motivate our focus on changing patterns of dispersion and in turn skewness within cells defined by sectors and firm age classes in what follows.

Figure 3 shows the trends in the 90-10 differential (using Hodrick-Prescott trends) for selected sectors. The Retail Trade and Services sectors exhibit large declines in dispersion over the entire period; we study Services in more detail below. Interestingly, the Information sector and the Finance, Insurance, and Real Estate (FIRE) sector exhibit flat or increasing dispersion until about 2000 and then sharply decline thereafter. While the various sectors of the economy began the 1980s with large differences in levels of dispersion, the post-2000 trends have resulted in a convergence of dispersion patterns across the board.

Figure 4 shows the share of employment accounted for by young firms for the same sectors as well as the entire economy. Neither FIRE nor Information exhibit the declines in young firm activity through 2000 exhibited by sectors such as Services and Retail Trade. The share of employment accounted for by young firms in the Information sector rises in the second half of the 1990s and then starts to decline after 2000. Figures 3 and 4 together highlight that not all sectors have exhibited a monotonic decline in

[11] We use job reallocation for this purpose since this measure of business volatility readily lends itself to shift-share decompositions. It is possible to decompose non-parametric dispersion measures such as the 90-10 using methods like those used in Juhn, Murphy and Pierce (1993). Such methods are not exact decompositions like that used for job reallocation.

indicators of business dynamism and entrepreneurial activity.[12] That said, Figure 4 also shows that the aggregate economy has seen a decline in young firm activity.[13]

The Information industry includes only a subset of sectors typically associated with high tech. Included are industries such as Software Publishing (NAICS 5112) and Internet Service Providers and Web Search Portals (NAICS 5161), but there are other high tech industries in Manufacturing such as Computer Hardware and Peripherals (NAICS 3341). For this purpose, we follow a study by Hecker (2005) from the Bureau of Labor Statistics by defining the high tech sector based on the 14 4-digit NAICS industries with the largest shares of STEM workers. The 14 industries are listed in Table A.1 in the appendix.[14]

Figure 5 shows the Hodrick-Prescott trends of the 90-10 differential for the high tech sector, privately held firms and publicly traded firms (with all firms included as a point of reference). For the high tech sector, we find rising dispersion through 2000 and then sharply declining dispersion in the post-2000 period. Focusing on the high tech sector is of interest since it is a critical sector for innovation and productivity growth. As Fernald (2014) highlights, much of the surge in productivity growth in the overall U.S. economy in the 1990s is due to a surge in productivity in the IT-producing and IT-using sectors. Moreover, he finds that there has been a trend slowdown in productivity shortly after 2000 driven by a slowdown in IT-producing and IT-using industries.

Figure 5 also shows patterns for privately held vs. publicly traded firms. Due to wide data availability, much research has focused on publicly traded firms, so relating results on public firms to results for the broader universe of firms is useful. Davis et al. (2007) show that, in terms of dynamism, public firms have been far from representative. Figure 5 updates their analysis. Privately held firms exhibit declining dispersion throughout the entire time period. Publicly traded firms exhibit rising dispersion through

[12] We show in appendix Figure A.2 that these patterns for the 90-10 differential also hold for job reallocation.
[13] The economywide decline in young firm activity reflects a combination of trends in entry rates, young firm exit rates, and growth rates of continuer young firms, with declining entry rates being the most important. These series are shown on Figure A.4 in the appendix. The figure suggests that the trend in young firm activity reflects changes in both the entry margin and the exit margin, particularly prior to 2000, with growth rates of continuing young firms playing little or no role until at least 2007.
[14] Haltiwanger, Hathaway and Miranda (2014) use this same high tech classification and show that there has been a rising pace of job reallocation and entrepreneurial activity in the high tech sector through 2000 and a decline thereafter.

2000 (consistent with the recent literature) but then falling dispersion in the post-2000 period, joining the trend exhibited by privately held firms. Davis et al. (2007) highlight that the rising dispersion of publicly traded firms before 2000 is driven by the rapid growth of new publicly traded firms in the 1980s and 1990s. Those cohorts exhibited an especially high degree of volatility. We further update the Davis et al. (2007) results in appendix C and show that the post-2000 cohort of new publicly traded firms does not exhibit the rapid growth of the 1980s and 1990s cohorts nor the volatility. These trends among public firms suggest interesting avenues for further research while highlighting this paper's theme of broad-based declining dynamism since 2000. A greater understanding of the causes of declining dynamism among public firms may shed light on trends among U.S. firms more generally.

The different patterns by sector and by firm type (privately and publicly traded) already offer a hint that the character of the decline in business dynamism changed around 2000. Prior to 2000 the decline was dominated by sectors like Retail Trade and Services while sectors like Information and high tech (which overlap) exhibited an increase in indicators of dynamism. Moreover, publicly traded firms exhibited an increase in dispersion through 2000 but a decline thereafter. One early conclusion is that the acceleration of the decline in dispersion around 2000 reflects changes in sectors like high tech and Information and publicly traded firms.

V. High-growth Firms and Skewness

In this section, we explore the changing patterns of high-growth firms and skewness in the firm growth rate distributions over time. Before doing so, it is useful to first review in more detail what we know about the cross sectional patterns of firm growth and skewness over the last several decades in the U.S.

V.I. Cross Sectional Patterns of Business Dynamics and Growth

Using data from the 1980s, 1990s and 2000s, Haltiwanger, Jarmin and Miranda (2013) and Decker et al. (2014) show that on average young firms exhibit an "up or out" dynamic in the U.S. That is, they exhibit a high failure rate as evidenced by the very high rate of job destruction from exit. But conditional on survival, they exhibit a much higher mean net growth rate than

their more mature counterparts. Decker et al. (2014) show that the high mean net growth rate of young firms is driven by enormous skewness in growth rates of young firms. The median young firm (or more generally the median firm of any age) exhibits little or no growth. Young firms exhibit much higher dispersion of growth rates (which is a finding that is well known since Dunne, Roberts and Samuelson (1989) and Davis, Haltiwanger and Schuh (1996)). A novel finding in Decker et al. (2014) is that young continuing firms exhibit enormous skewness in growth rates. The 90-50 differential for young continuing firms (less than five years old) is on average about 63 percentage points, while the 50-10 differential is about 46 percentage points. This contrasts with a fairly symmetric growth rate distribution for mature firms, with both a 90-50 differential and a 50-10 differential of about 22 percentage points. Thus, growth rates for young firms exhibit both more dispersion and more (positive) skewness than do growth rates for mature firms.

It is the very high growth of a relatively small number of young firms that accounts for the high mean net growth rate of young, surviving firms and in turn the long-lasting contribution of startups and young firms to job creation.[15] The high exit rates of young firms imply that after five years about 50 percent of the jobs created by an entering cohort have been eliminated from such exit. But high-growth young firms almost fully compensate for these losses so that a typical entering cohort has about 80 percent of the employment from entry. Taken together, startups plus high-growth firms (which are disproportionately young) account for 70 percent of firm-level gross job creation on average.

One pattern emphasized by Decker et al. (2014) is that the median firm, regardless of firm age, has near-zero growth. This property holds across many different classifications of firms. The median firm in each of the major sectors has close to zero growth (averaged across time), and the median firm in any given year also has close to zero growth. For the overall economy and in all major sectors, the median firm growth rate (using the employment-weighted distribution) is typically less than 1 percent in absolute value. In contrast, there is substantial variation in employment-weighted mean firm growth rates across sectors and time. Such differences in the patterns of means and medians reflect differences in the patterns of skewness in the firm growth rate distribution across sectors and time. The differences in means and

[15] The findings in this paragraph summarize findings from Decker et al. (2014).

medians are large in magnitude. For example, in 2009 when the employment-weighted mean firm growth rate was -5.1 percent, the median of the employment-weighted firm growth rate distribution was only about -1.5 percent. By 2011, the employment-weighted mean firm growth rate had recovered to 1.6 percent while the median was 0 percent.

For our purposes, the low absolute value of median firm growth rates implies that there is a close correspondence between statements about the 90-50 differential and the 90th percentile itself since to a first approximation the 90-50 differential is equal to the 90th percentile. In this respect, there is a close correspondence in statements about variation in the 90-50 differential and high-growth firms. That is, when the 90-50 differential declines the 90th percentile has typically fallen as well. Since we exclusively focus on employment-weighted distributions this implies that when the 90-50 differential declines the fraction of activity (employment) accounted for by high-growth firms declines.

In what follows, we show patterns for both the 90-50 and the 90th percentile for completeness, but the above discussion indicates that this is somewhat redundant. We often also contrast the difference between the 90-50 and the 50-10 differentials. This is our method for quantifying changes in the pattern of skewness. It could obviously be true that there is a decline in high-growth firms (the 90th percentile) and the 90-50 without a change in skewness if the 50-10 is changing at the same pace.

V.II. The Changing Nature of High-Growth Firms and Skewness

We now turn to the main contribution of this paper: the evolution of the distribution of firm growth rates over time. Figure 6 shows the differences in the 90th and 50th percentiles and the 50th and the 10th percentiles for all firms and for continuing firms. We use HP filtered data to focus on the trends, but our main points are robust to other trend definitions. For example, Figure 7 shows the 90-50 and 50-10 differentials as centered 3-year moving averages.[16] Several patterns are evident in Figures 6 and 7. First, both for all firms and for continuing firms, the 90-50 differential substantially exceeded the 50-10 differential in the pre-2000 period. In 1999, the

[16] The 3-year MA patterns exhibit more cyclical variation than the HP trends, as is evident in Figure 7. The 50-10 differential is highly countercyclical consistent with the well-known finding that job destruction is highly countercyclical. The 90-50 differential is less cyclical although it does decline substantially in the Great Recession. Still it is evident in Figure 7 that the 90-50 is substantially above the 50-10 during the cyclical expansion in the second half of the 1990s and that this difference is smaller in magnitude in the cyclical expansion in the mid 2000s.

90-50 differential is 16 percent higher than the 50-10. Second, this skewness is substantially reduced in the post-2000 period. By 2007, the 90-50 differential is only 4 percent higher than the 50-10. By 2011, the 90-50 differential is lower than the 50-10 differential for all firms and for continuing firms. It is true that positive skewness is procyclical so that some caution has to be used in interpreting the patterns in 2011 given the Great Recession. Using the HP trends should mitigate this concern, and even just looking at the patterns from 2000 to 2007 shows a substantial decline in skewness prior to the Great Recession.[17] Third, the patterns for all firms and continuing firms are quite similar. Thus, the patterns are not being driven simply by the patterns of entering and exiting firms. We know from Figure 2a that there is a declining startup rate without an accompanying decline in the exit rate. This alone will yield declining skewness in the all-firm distribution, but it is apparent that this is not the only factor since the pattern is similar for continuers.

To verify that the patterns for the 90-50 are largely mimicked by the patterns of the 90th percentile, Figure 8 shows the patterns of the 90th percentile for all and continuing firms (HP trends). There is a decline in high-growth firms over this period of time that accelerates in the post-2000 period. But putting Figure 8 into the context of Figures 6 and 7, the decline in the 90th percentile in the pre-2000 period is associated with a decline in dispersion but not a decline in skewness. It is only during the post-2000 period that this also yields a decline in skewness.

To dig deeper, Figure 9 shows the 90-50 and 50-10 differentials (HP trends) for young and mature continuing firms.[18] Young continuing firms exhibit a modest decline in both 90-50 and 50-10 differentials before 2000. After 2000, there is a greater decline in the 90-50 than in the 50-10 for young continuing firms, so skewness among the young continuing firms is reduced substantially over this period. For the older continuing firms there are relatively modest changes over the entire period, but the decline in the 90-50 accelerates for the older firms in the post-2000 period. Figure 10 shows the patterns for the 90th percentile (HP trends) by firm age over time. Consistent with Figure 9, the 90th percentile for young continuing firms exhibits only a modest

[17] Recall that the skewness for 2007 represents the growth rate distribution for firms between March 2006 and March 2007. So even the 2008 distribution (March 2007 to March 2008) reflects the distribution prior to the sharp downturn in the second half of 2008.

[18] Examining the 90-50 for young firms using all firms is not as informative since entry and exit dominate the all-firm distribution for young firms. The 90th percentile for all young firms is essentially at the DHS upper bound of 2 (entry) as more than 10 percent of employment of young firms inclusive of entry is at startups.

decline through 2000 and then sharply declines thereafter.[19] The 90th percentile for older firms is much lower than that for young firms indicating that high growth is concentrated in young firms. Older firms do exhibit an acceleration of the decline in the 90th percentile in the post 2000 period.

In comparing the patterns in Figures 9 and 10 with those in Figures 6-8, it is striking that the 90th percentile for the overall distribution is declining throughout the 1980s and 1990s but the 90th percentile for young and mature separately are relatively stable over this period. The overall pattern is thus driven by the shift of activity away from young to older firms. But during the 1980s and 1990s this composition effect primarily yields a decline in dispersion and not skewness. As we will see below, this reflects some offsetting patterns in skewness for select sectors over this period of time.

Figure 11 shows the 90-50 and 50-10 differentials by selected broad sectors (again using the HP trends). Some sectors like Information exhibited an increase in skewness through 2000 and then a sharp decline thereafter. Particularly after 2000, the general pattern in the figure is convergence: within-sector 90-50 and 50-10 differentials converge toward equality, and dispersion levels for all sectors decline and converge. The result is that previously high-dispersion, high-skew sectors like Services or Information increasingly resemble low-dispersion, low-skew sectors like Manufacturing. Figure 12 shows a similar pattern for high tech for both all and continuing firms. The high tech sector has especially high skewness in the 1990s. This declines sharply in the post-2000 period. The 90-50 differential is 28 percent larger than the 50-10 differential in 1999. It is only 8 percent larger in 2007 and 4 percent larger in 2011. Figure 13 shows that the skewness in publicly traded firms' growth rates increased in the 1990s and has also fallen since the early 2000s. Figure 14 shows analogous patterns for the 90th percentile of publicly traded and high tech firms.

The evidence of the rising and then falling dispersion and skewness of publicly traded firms is complementary to our evidence on high tech firms. As we noted above, Davis et al. (2007) show that the rising volatility of publicly traded firms is attributable to the rapidly

[19] While the Great Recession was associated with a large decline in startup activity, the post-2000 decline in the HP filtered 90th percentile for young firms does not only reflect post-2007 data. Appendix Figure A.5 reports unfiltered 90th percentile data for continuing young firms. The essential finding of Figure 10 can be clearly seen: the 90th percentile is remarkably stable prior to 2000 (aside from temporary drops in the early 1980s and 1991 recessions), but after 2000 it falls in a stair-step pattern, moving sideways during the 2000s at a lower level than in the 1980s and 1990s before plunging with the Great Recession.

growing 1980s and 1990s cohorts of new publicly traded firms that also exhibited high volatility. The number of IPOs can itself be viewed as an indicator of the dynamism of the economy, and the 1980s and 1990s had many IPOs that grew quickly. That rapid growth of new IPOs in the 1980s and 1990s apparently also yielded an increase in skewness for publicly traded firms. As the post-2000 cohort of IPOs exhibited much less growth (as we show in appendix C), dispersion and skewness of publicly traded firms declined. It is interesting that the patterns of high growth and skewness for publicly traded firms roughly mimic those for high tech firms. Of course, this overlap in patterns is not a surprise since high tech firms played an important role in the 1980s and 1990s cohorts of new publicly traded firms. Newly traded high tech firms from the 1990s accounted for almost 40 percent of high tech publicly traded employment in 2001.

To sum up, there has been a sharp decline in the skewness of the firm growth rate distribution including all firms and for continuing firms only starting around 2000. Given that the median firm has about zero growth, an equivalent statement is that there has been a sharp decline in the 90th percentile of the firm growth rate distribution without an equivalent increase in the 10th percentile. The implication is that the decline in dispersion in the post-2000 period is driven mostly by the decline in the 90-50. Looking within groups, young continuing firms exhibited a sharp decline in the 90-50 relative to the 50-10 in the post 2000 period—and, equivalently, young continuing firms exhibited a decline in the 90th percentile given that the median young firm has about zero growth. Other key groups with within-group declines in skewness include the information sector, the high tech sector and publicly traded firms.

The decline in skewness in the post-2000 period represents a change in the character of the declining dispersion in firm growth rates. Prior to 2000 the decline in dispersion was disproportionately accounted for by industries like Retail Trade and Services. Retail Trade stands out as a sector where there is not much evidence of skewness in the firm growth rate distribution at any time, so the decline in dispersion in Retail Trade is driven equally by a decline in the 90-50 and the 50-10. In contrast, in the post-2000 period sectors like high tech and publicly traded firms exhibited sharp declines in dispersion and skewness after having exhibited rises in dispersion and skewness in the 1990s.

Our use of employment-weighted distributions raises the question of whether movements in the 90th percentile growth rate reflect changes in actual firm growth rates or changes in weights. That is, does a decline in the 90th percentile reflect a broad decline in growth rates and

corresponding absence of "superstar" high-growth firms, or does it reflect a decline in the number of firms whose growth rates are high enough to meet previous thresholds? The typically high-growth nature of small firms makes the question particularly relevant, as a decline in aggregate 90th percentiles could simply reflect the existence of fewer small firms. We consider this question in Figures 15a and 15b. Figure 15a shows average growth rates of firms in the top decile, disaggregated by size class, where the cutoff for the top decile is the growth rate of the 90th percentile firm (employment weighted) as of 1979 (so the cutoff is constant across the time series). Figure 15b shows, for each size class, the share of that size class's employment that is at firms with growth rates in the top decile, again defined at 1979 (due to the high volatility of this series, we report three-year centered moving averages). Figures 15a and 15b consist of data on continuing firms only; Figures A.9a and A.9b report the same measures for all firms.

Figure 15a shows trends in growth rates that are remarkably flat and, in some cases, even rising. High-growth small firms have maintained growth rates that exceed 80 percent, while larger firms (at least 250 employees) also show high growth rates with mostly flat trends. The data show no signs of an absence of "superstar" high-growth firms, suggesting that the decline in the 90th percentile broadly is likely to simply reflect fewer high-growth firms rather than a drop in the growth rate ceiling. Figure 15b confirms this, with most firm size classes seeing a declining portion of their activity occurring at high-growth firms. There are still firms with extremely high growth, but they account for less employment than they once did—within every firm size class.

Table 1 summarizes our findings. Using the HP-filtered time series data described above, we report the annualized change in 90-50 and 50-10 differentials for selected categories of firms. We report these changes separately for the pre- and post-2000 periods. The table illustrates the finding that, in many cases, the decline in growth rate dispersion in the pre-2000 period involved similar declines in the 90-50 and the 50-10 differentials (*i.e.*, declining dispersion did not mean declining skewness); after 2000, though, the 90-50 differential declines much more than the 50-10 differential. While there are a few exceptions to the pre-2000 element of this pattern, for all groupings of firms the post-2000 period is characterized by 90-50 declines that outpace 50-10

declines.[20] As discussed above, the skewness decline is particularly notable in Services, Information, and the high tech sector. Retail stands out for having a different pattern than other sectors, with a slight skewness increase before 2000 and an only minor decline in skewness after 2000.

The findings summarized on Table 1 suggest that the drivers of the post-2000 decline in overall skewness were young firms as well as firms in the Information and Services sectors and those that can be described as high tech. Publicly traded firms also see a notable decline in skewness after 2000, as do firms in Finance, Insurance, and Real Estate. Additionally, the overall decline can be partly thought of as a composition effect across firm age, with an increasing share of activity coming from low-skewness mature firms; but the industrial composition effect works in the opposite direction, with the overall trend reflecting the overwhelming declines seen within sectors.

V.III. Retail vs. High Tech: Interpretation through the lens of industry differences

In the context of the discussion from section II, it is useful to compare and contrast the patterns of the Retail Trade sector and the high tech sector. The Retail Trade sector has been undergoing a transformation in the business model of firms over the last several decades (see Doms et al. (2004), Foster et al. (2006), Jarmin, Klimek and Miranda (2009), and Foster et al. (2015)). Single-establishment firms have been displaced by establishments operated by large national chains in virtually all major Retail Trade categories. Information technology and globalization have enabled large, national (and indeed multinational) firms in Retail Trade to develop their distribution and supply chains in new ways. The evidence shows that establishments of large, national chains are both more productive and more stable. Thus, for Retail Trade the decline in business dynamism has arguably been benign, with falling dispersion of firm growth rates and a decline in startups that has been productivity enhancing. The industry has not exhibited much skewness in firm growth rates, and the decline in dispersion is due to a decline in both the 90-50 and the 50-10. Relating back to the discussion in section II, the typical startup in Retail Trade has been a "Mom and Pop" business that better fits the characterization of

[20] Note that the Information row of Table 1 reports slight pre-2000 declines in dispersion, but this is largely a function of endpoints as Figures 8 and 11 show moderately rising dispersion and somewhat flat skewness from the mid-1980s through 2000.

a “mainstream” business. Viewed from this perspective, the decline in “Mom and Pop” retail stores has not been a decline in transformational entrepreneurship.

Now consider the high tech sector, a sector with rapid job and productivity growth in the late 1980s and through the 1990s. This sector exhibited rising entrepreneurship and dynamism over this period. It also exhibited a high level of skewness of the firm growth rate distribution over this period that was also increasing through 2000. That skewness is consistent with the presence of and contribution of the type of high-growth transformational entrepreneurs discussed in section II. Since 2000 the sector has exhibited declining dynamism, entrepreneurship and skewness in firm growth rates. Remarkably the skewness in firm growth rates has largely been eliminated in 2011 even though the sector had amongst the highest levels of skewness in the 1980s and 1990s.

To explore this further, we disaggregate the high tech sector into several NAICS industries: Manufacturing (except pharmaceutical and aerospace), Information, Services, and both pharmaceutical and aerospace manufacturing. Figure 16a reports 90-50 and 50-10 differentials for these industries of high tech. Figure 16b describes the share of high tech employment accounted for by these industries. The figures show that the moderate decline in dispersion for the high tech sector shown on Figure 5 hides interesting industry dynamics. The high tech sector was once dominated by the manufacture of goods like computers, peripherals, communications equipment, and semiconductors, but the sector has been overtaken by activities like internet publishing and service provision, data hosting and processing services, computer system design services, and software publishing. Services and Information are characterized by higher employment dynamics than the Manufacturing areas, so this composition effect puts upward pressure on overall high tech dispersion. The within-industry declines in dynamism outweigh the composition effect, though, with the post-2000 period seeing particularly dramatic dispersion declines among Services and Information firms.

Unlike Retail, the high tech dispersion patterns are closely linked to changes in skewness (as shown on Figure 16a). In what is now a familiar pattern from other areas of the economy, the skewness of the main high tech industries declined rapidly in the post-2000 period. The Information industry, in particular, saw roughly constant skewness (with rising dispersion) before 2000 but a rapid move toward symmetry after 2000 driven mainly by a dampening of the top end of the growth distribution. Unlike other manufacturers (see Figure 11), the

Manufacturing portion of high tech had a substantial high-growth skew prior to 2000, but in the post-2000 period its growth distribution has come to resemble the rest of the broader U.S. Manufacturing industry. Most of the high-tech industries have almost no skew by the end of the time series, with only Services showing resilient skewness (though at a much lower level than the high skewness of the 1990s). In results not shown, we find that the share of activity accounted for by young firms in these high tech industries has been very volatile over our time sample, with the high tech Services and Information industries seeing young shares as high as 20 percent and 14 percent of employment, respectively, in 2001. Each of Services, Information, and Manufacturing have seen significant young share declines since 2000. More broadly, declining skewness is now ubiquitous across the components of the high tech sector, with even popular modern "Silicon Valley" industries like software publishing and data processing losing their high-growth characteristics.

While the reasons for this decline in dispersion and skewness in the high tech sector are not yet understood, these patterns are inherently different from the patterns for Retail Trade. Something has happened to the incentives or the ability to be a high-growth firm in the high tech sector. Determining the reasons for this change should be a high priority.

V.IV. Services

The Services industry has seen a very large decline in dispersion and skewness while also accounting for a large and increasing share of employment in the U.S. Figure 3 shows that the 90-10 differential in Services, while consistently the largest of any industry, has fallen sufficiently that by 2011 it was smaller than the 90-10 differentials for all other major sectors as of 1979, with the exception of Manufacturing. This large decline is largely a result of a dramatic decline in skewness, particularly since 2000, as shown on Figure 11.

On Figure 17a we report 90-50 and 50-10 differentials for selected industries within Services. The figure reveals considerable heterogeneity across Services industries. At the low end, Health Care and Social Assistance displays levels of dynamism that are similar to the broad FIRE sector in the U.S., not much higher than Manufacturing; this industry primarily includes businesses that provide medical care. At the high end, Administrative and Support Services drive the high dynamism observed for Services generally. Administrative and Support Services

include businesses like facilities support providers, travel agencies, telemarketers, and temporary help services.

Each of the Services industries shown has seen declines in both dispersion and skewness, with skewness being nearly eliminated or even reversed by 2011. As such, the large decline seen in U.S. Services generally is at least partly driven by declines within more detailed industries, even highly dynamic ones. Several industries have converged on similar levels of dispersion, but Health Care and Social Assistance remains significantly less dynamic than other Services industries. Each of the selected industries has seen steady declines in the share of employment accounted for by young firms (not shown), with the analogous pattern that Health Care and Social Assistance is clearly the "oldest" of the industries even after significant aging among the others.

Figure 17b shows the employment composition of Services across the selected Services industries. While each of the Services industries has increased its share of total U.S. employment (not shown), within Services itself the Other Services category has lost share to other industries.[21] Administrative and Support Services—the most dynamic of the Services industries—saw increased activity share until around 2000, when it began to level off or even fall. Meanwhile, Health Care and Social Assistance—the "oldest" and least dynamic of the Services industries—has gradually increased its share throughout the sample. Therefore, the accelerated decline in dynamism of Services generally since 2000 is in part a composition effect resulting from increased activity in healthcare industries and the relatively slower growth of more dynamic segments of the Services industries.

VI. Concluding Remarks

There has been a pervasive decline in business dynamism over the last several decades in the U.S. as indicated by a decline in various summary indicators of dispersion in firm growth rates. We have added to the core facts about this decline by focusing on the changing patterns of skewness in the firm growth rate distribution. We find that prior to 2000 the decline in the

[21] "Other Services" firms run the gamut of (typically small) services, ranging from auto repair and drycleaning to funeral homes and parking lots.

dispersion of firm growth rates was accounted for by roughly equal declines in the 90-50 and the 50-10 differentials in firm growth rates. However, since 2000 the decline in dispersion has been driven primarily by a decline in the 90-50 differential. The decline in the 90-50 has been so substantial that skewness in the firm growth rate distribution has largely been eliminated, both within the major sectors of the economy and in the overall firm growth rate distribution.

Why might we care that the decline in dynamism is accompanied by a decline in skewness in the firm growth rate distribution in the post-2000 period? Evidence shows that high-growth young firms have disproportionately accounted for job creation and productivity growth. The pattern for the U.S. used to be that in any given year, most newly entered firms would fail while a few would grow very fast. These high-growth young firms yielded substantial skewness in the firm growth rate distribution. Now the U.S. has a much lower pace of startups, and those that do enter are less likely to be high-growth firms. The implication is that startups and high-growth young firms contribute less to U.S. job creation in the post-2000 period. We do not yet fully understand the labor market implications of a reduced role of young firms in job creation, but the evidence highlights the importance of further research on the topic.

Aggregate productivity growth depends not only on innovations and technology investments within firms but also on the economy's ability to reallocate resources from businesses with lower productivity to businesses with higher productivity. Evidence suggests that young firms devote disproportionately more resources to innovation, so the high growth of young firms is particularly important for aggregate productivity growth (Acemoglu et al. (2013); Foster, Haltiwanger, and Krizan (2001, 2006); Foster, Haltiwanger, and Syverson (2008)). If rapid firm-level growth reflects efficient movement of labor toward high-productivity producers, then the increasing rarity of high growth may be a cause for concern. While we have highlighted the year 2000 as a turning point for trend growth rates across several categories of firms, that year should not be interpreted as precise—nor should we necessarily expect the effect of changes in reallocative patterns on aggregate productivity to be instantaneous. Further research is necessary to determine whether the patterns we describe are related to the well-known finding by Fernald (2014) of a trend break in US productivity growth around 2003.

While we have attempted to describe in detail several aspects of declining skewness in the U.S. using industry, size, and age comparisons, we have not discovered and described the underlying causes of these trends. Theory suggests several possible candidates. In canonical

models of firm dynamics, rapid growth of individual firms results from revelations about, or changing realizations of, firm-level productivity or demand conditions. Firms may sometimes operate below optimal scale as a result of credit constraints or imperfect information about their own quality, and high growth follows the loosening of these constraints as the firm size distribution evolves to better reflect the underlying firm productivity distribution. In other research, we empirically study the relationship between productivity and establishment growth in the high tech Manufacturing sector and find that recent changes in growth patterns reflect declining sensitivity of businesses to productivity shocks rather than declining productivity dispersion or persistence (Decker et al. (2015)). Those findings point in the direction of increasing adjustment frictions or changes in market structure that somewhat insulate businesses from the competitive pressures that typically drive productivity responsiveness.

Alternatively, changes in employment growth patterns could reflect an optimally changing role of the employment adjustment margin for firm growth. For example, it might be that, historically, young businesses with high draws of productivity and profitability rapidly expanded employment, while more recently innovative businesses grow by adding machines or expanding internationally. Moreover, the growing role of intangible forms of investment could change the relationship between specific inputs (like employment) and firm productivity or profitability conditions. If the cause of declining skewness is benign like those just described, our results are still of critical importance for job growth; but the interpretation and driving forces may be quite different.

The theoretical propositions outlined above highlight several potential explanations for the changing growth patterns we have described, ensuring that this significant puzzle will be the subject of further research. The temporal, sectoral, and age heterogeneity in the skewness patterns that we have described here provides considerable empirical discipline for the topic.

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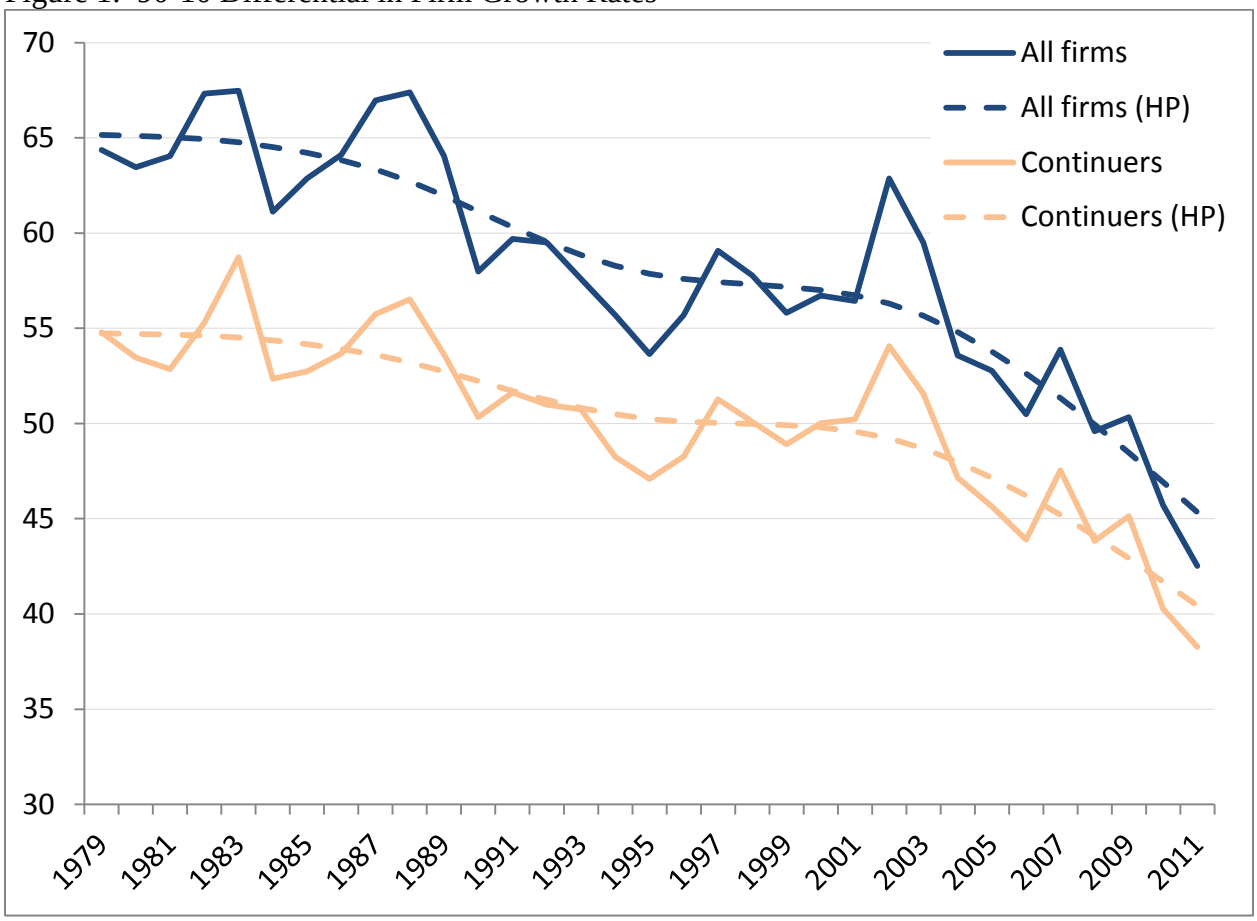
Table 1: Annual Declines in 90-50 and 50-10 Differentials

	Pre-2000		Post-2000	
	90-50	50-10	90-50	50-10
All firms	-0.17	-0.21	-0.76	-0.30
Young firms	-0.15	-0.35	-0.78	-0.20
Mature firms	-0.03	-0.15	-0.49	-0.21
High tech	0.05	0.08	-1.07	-0.59
Publicly traded	0.21	0.00	-0.47	-0.32
FIRE	-0.08	-0.01	-0.70	-0.32
Information	-0.16	-0.11	-1.55	-0.53
Manufacturing	-0.13	-0.09	-0.24	-0.06
Retail	-0.41	-0.49	-0.76	-0.62
Services	-0.56	-0.33	-1.19	-0.65

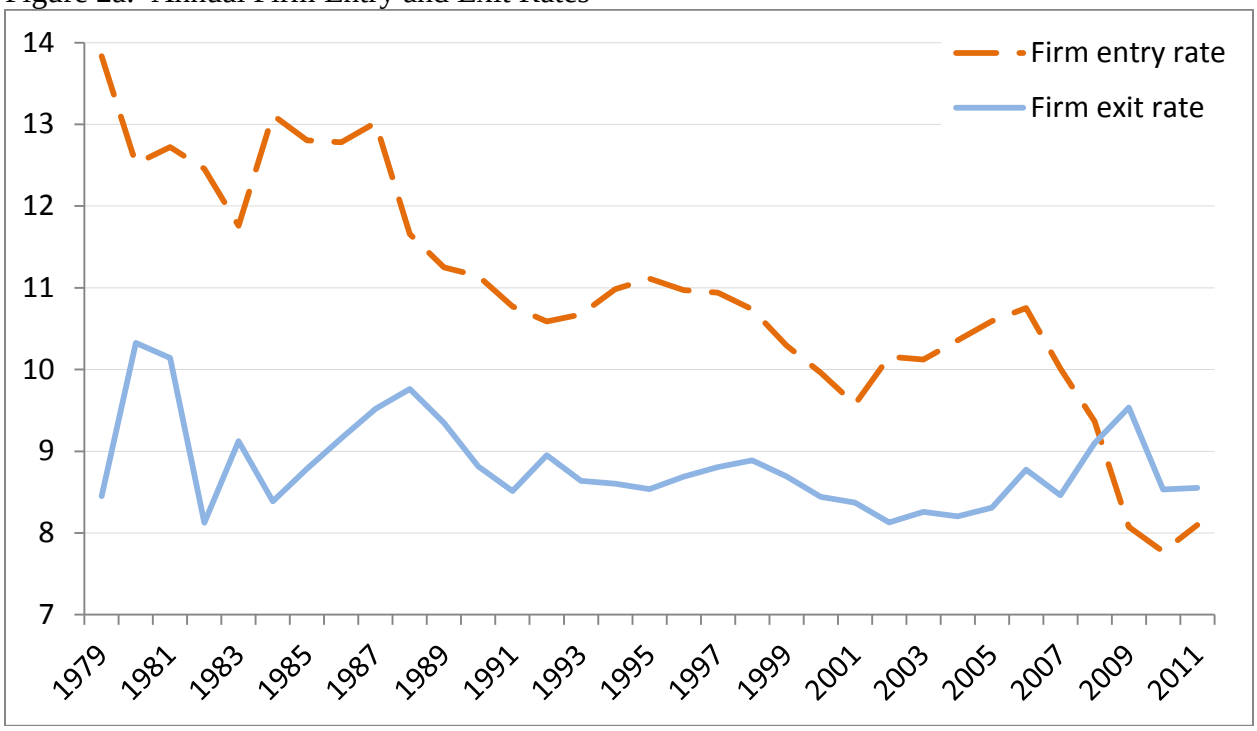
Note: Declines are expressed in percentage points (annualized). The pre-2000 period begins in 1979 with the exceptions of "Young firms" and "Mature firms" which begin in 1981. The post-2000 periods for all firm groups end in 2011. Young firms have age less than five. High tech is defined as in Hecker (2005). FIRE, Information, Manufacturing, Retail, and Services are defined on a consistent NAICS basis. Author calculations from the Longitudinal Business Database and Compustat.

Figure 1: 90-10 Differential in Firm Growth Rates



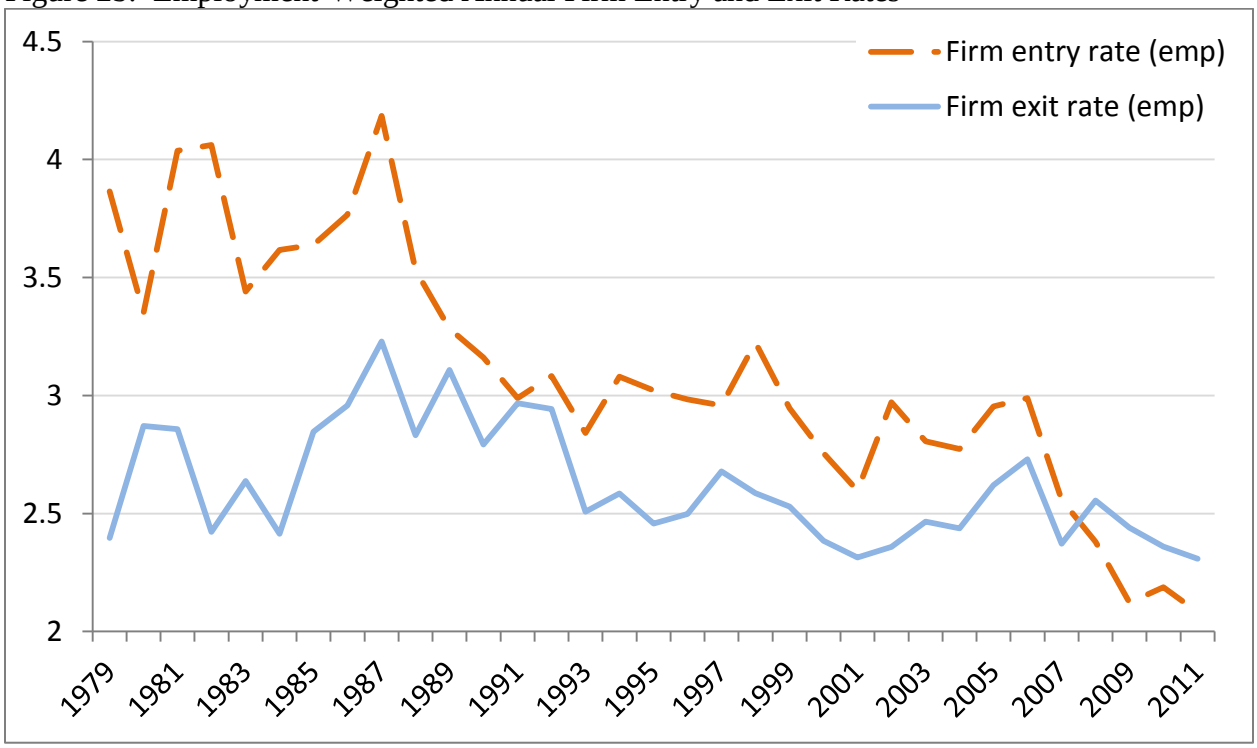
Note: Y axis does not start at zero. The 90-10 differential is the difference between the 90th and the 10th percentile of the employment-weighted distribution of firm employment growth rates. HP filter uses parameter set to 100. Author calculations from the Longitudinal Business Database.

Figure 2a: Annual Firm Entry and Exit Rates



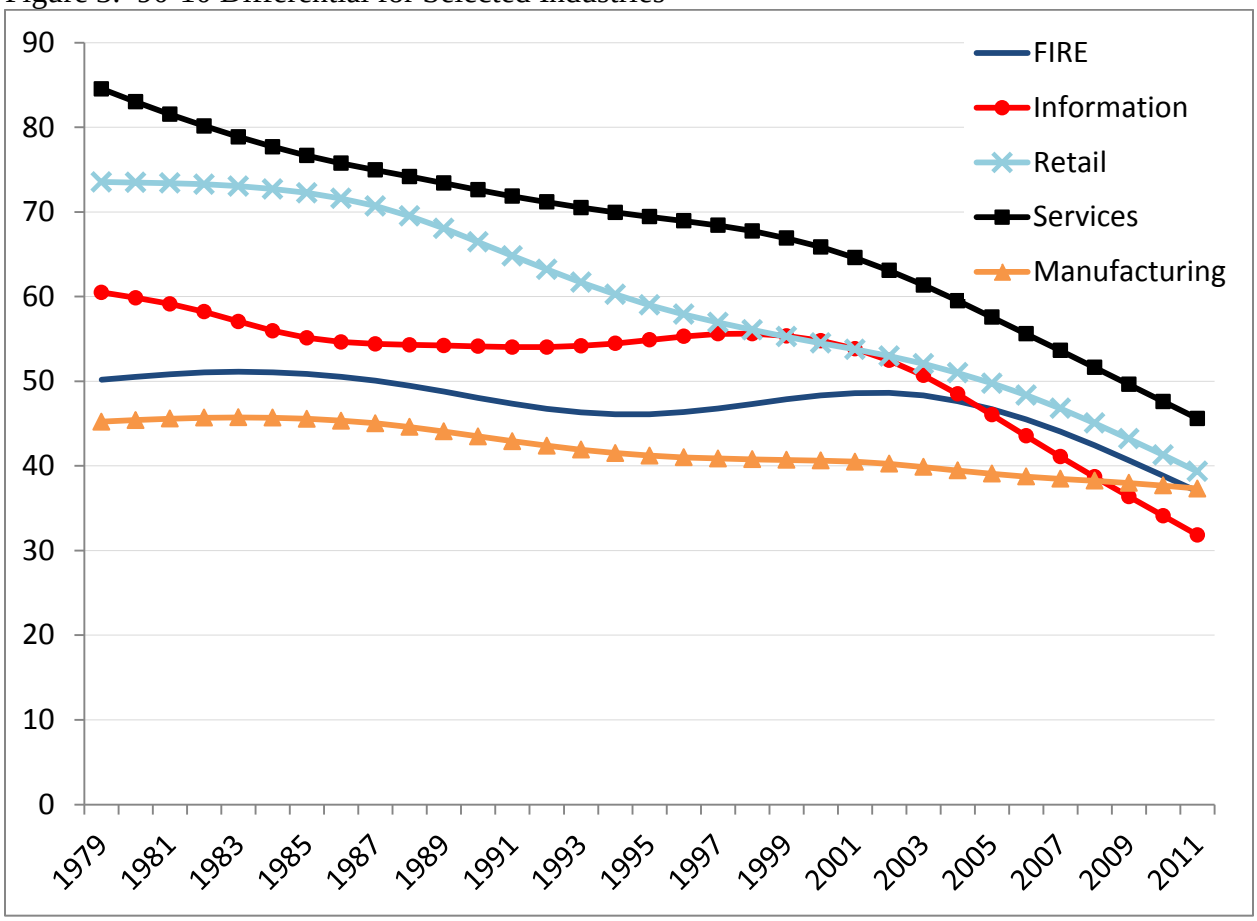
Note: Y axis does not start at zero. Firm entry rate is new firms as a percent of all firms. Firm exit rate is exiting firms as a percent of all firms. Author calculations from the Business Dynamics Statistics.

Figure 2b: Employment-Weighted Annual Firm Entry and Exit Rates



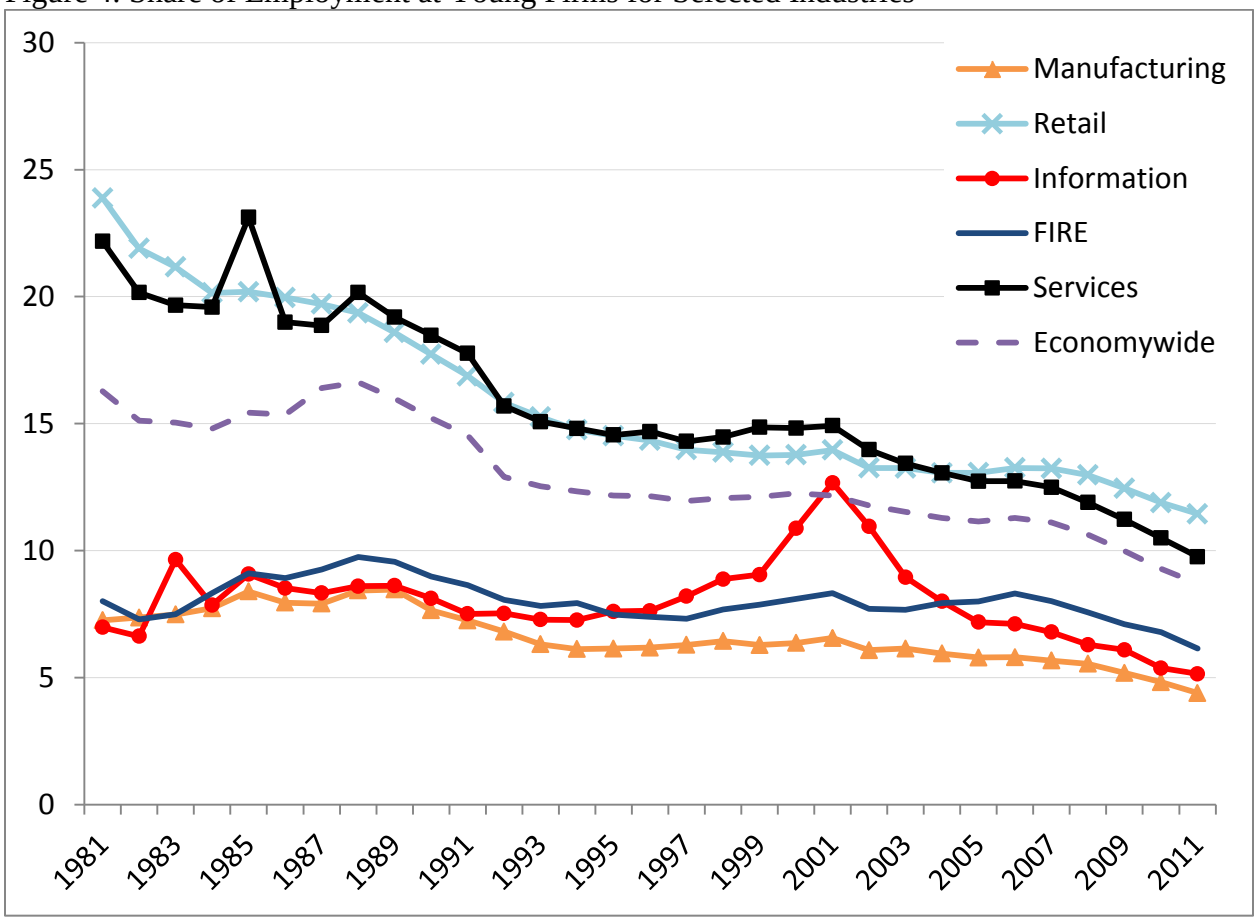
Note: Y axis does not start at zero. Firm entry rate is new firm employment as a percent of all employment. Firm exit rate is exiting firm employment as a percent of all employment. Author calculations from the Business Dynamics Statistics.

Figure 3: 90-10 Differential for Selected Industries



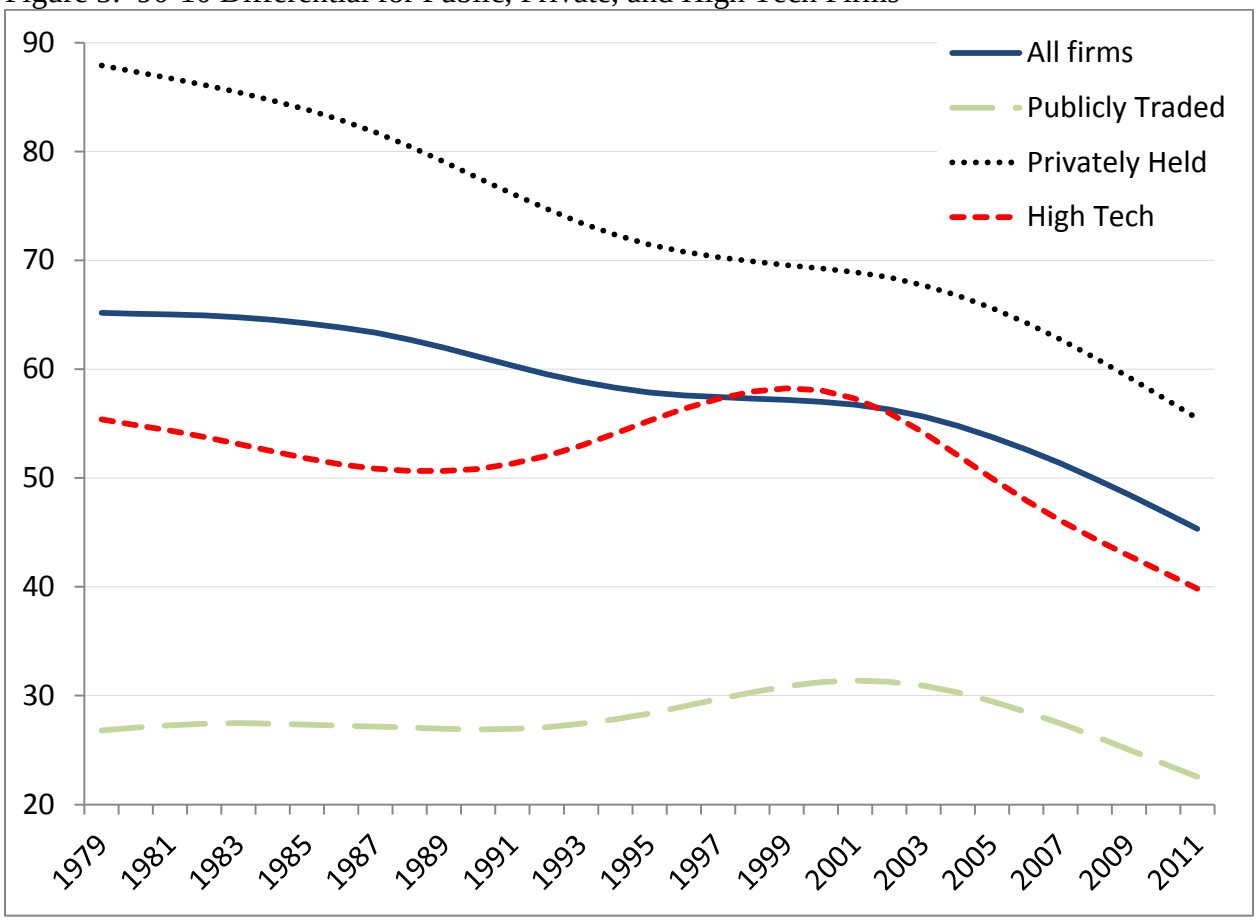
Note: The 90-10 differential is the difference between the 90th and the 10th percentile of the employment-weighted distribution of firm employment growth rates. HP filter uses parameter set to 100. Industries are defined on a consistent NAICS basis. Data include all firms (new entrants, exiters, and continuers). Author calculations from the Longitudinal Business Database.

Figure 4: Share of Employment at Young Firms for Selected Industries



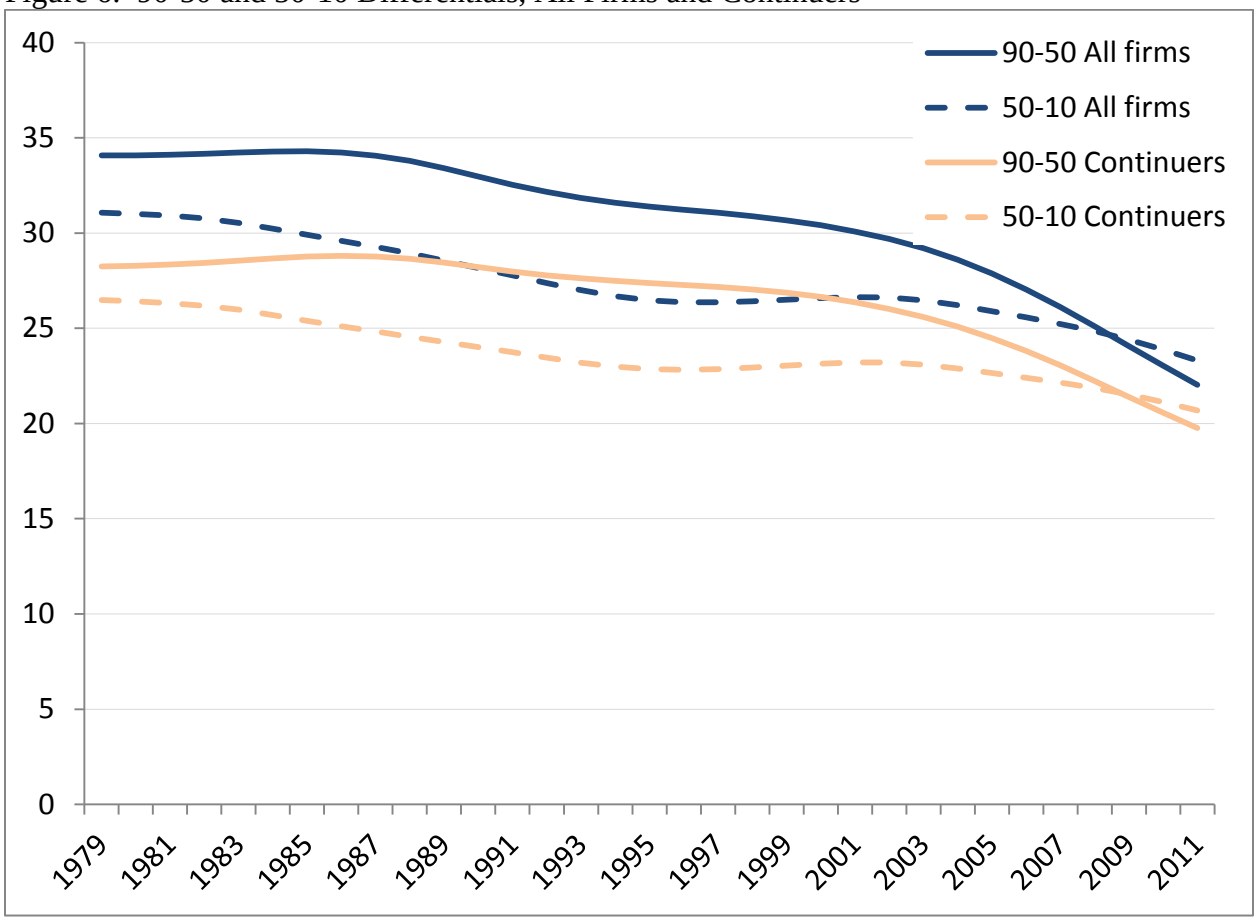
Note: Young firms have age less than 5. Industries are defined on a consistent NAICS basis. Data include all firms (new entrants, exiters, and continuers). Author calculations from the Longitudinal Business Database.

Figure 5: 90-10 Differential for Public, Private, and High Tech Firms



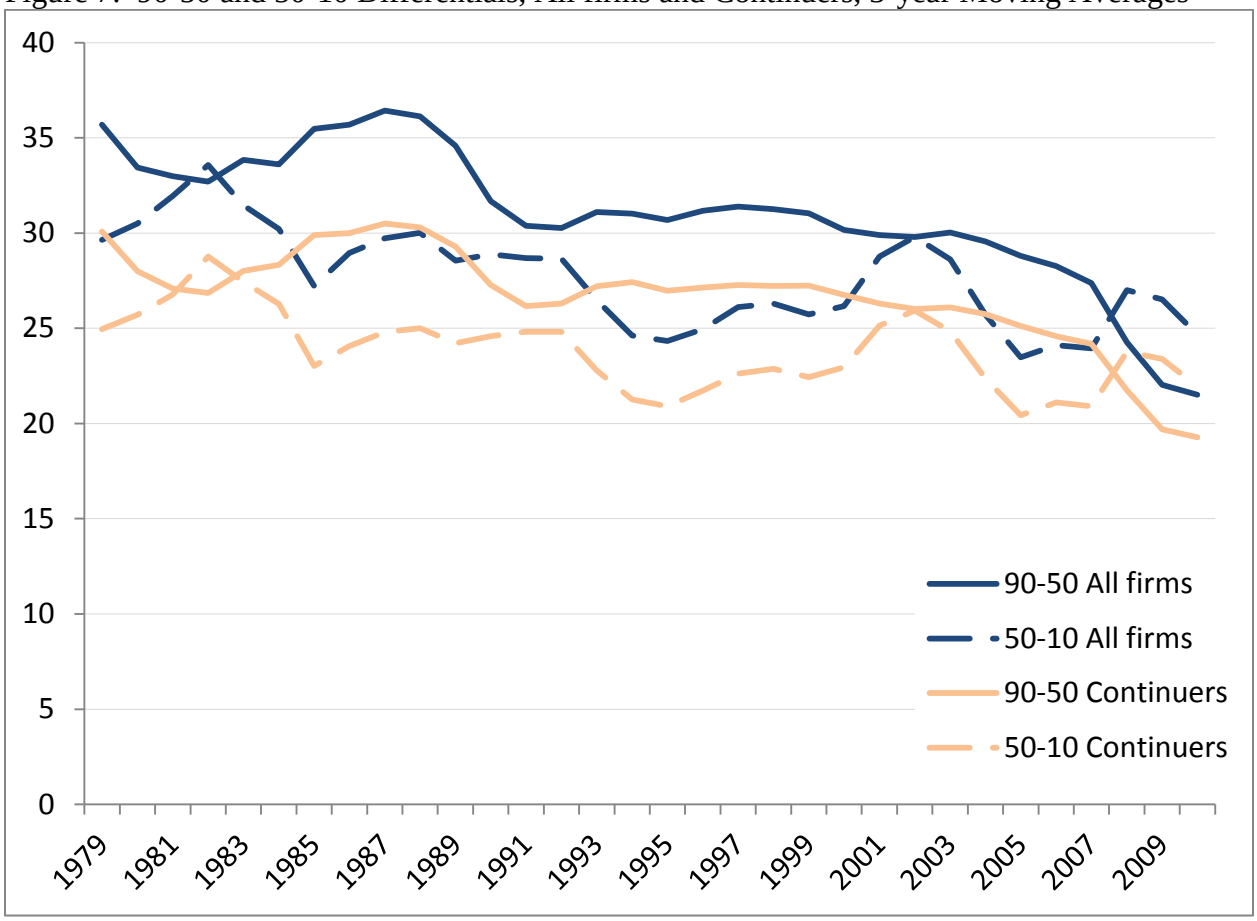
Note: Y axis does not begin at zero. The 90-10 differential is the difference between the 90th and the 10th percentile of the employment-weighted distribution of firm employment growth rates. Data are HP trends using parameter set to 100. High tech is defined as in Hecker (2005) (see Appendix Table A.1). Data include all firms (new entrants, exiters, and continuers). Author calculations from Compustat and the Longitudinal Business Database.

Figure 6: 90-50 and 50-10 Differentials, All Firms and Continuers



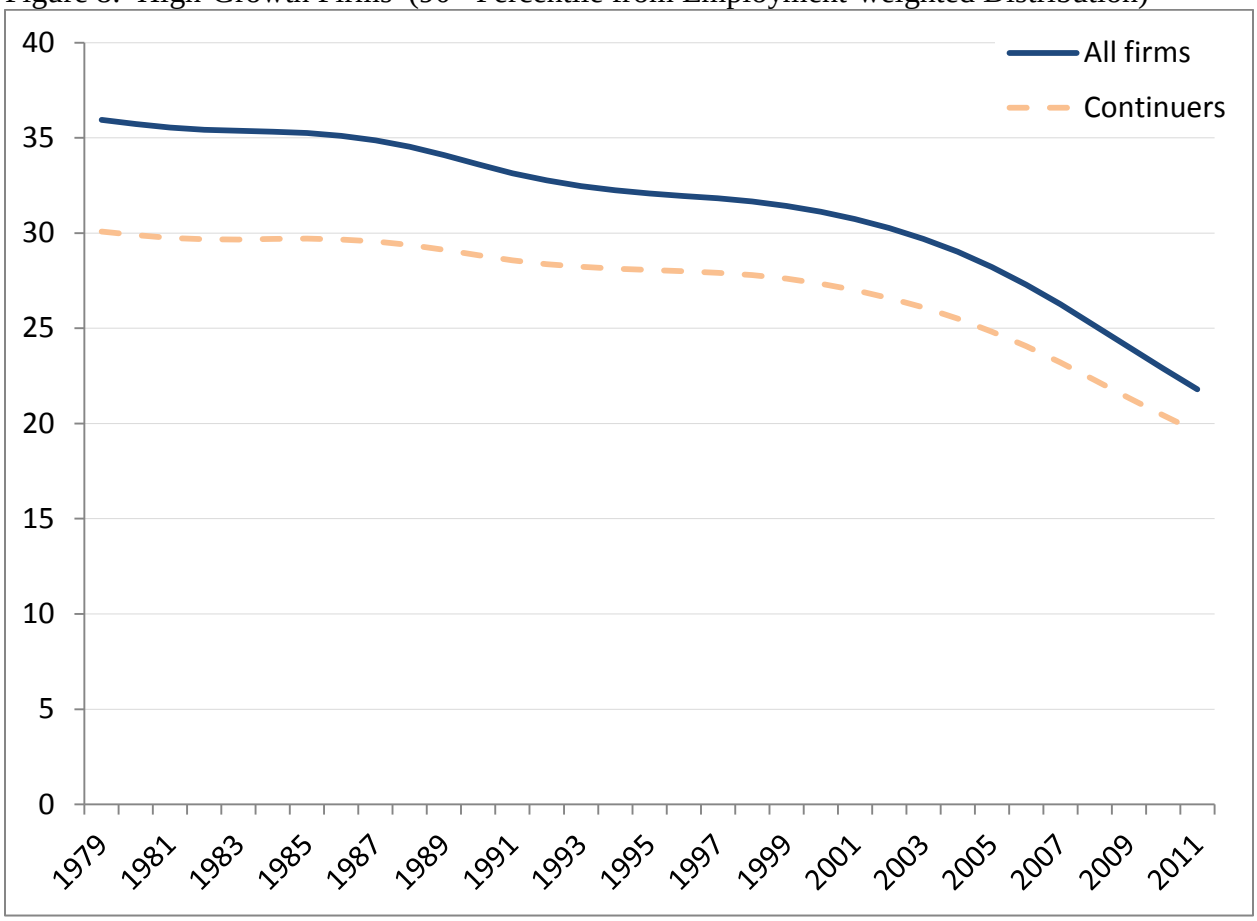
Note: The 90-50 differential and the 50-10 differential are the difference between the 90th and the 50th percentile and the 50th and 10th percentile, respectively, of the employment-weighted distribution of firm employment growth rates. Data are HP trends using parameter set to 100. Author calculations from the Longitudinal Business Database.

Figure 7: 90-50 and 50-10 Differentials, All firms and Continuers, 3-year Moving Averages



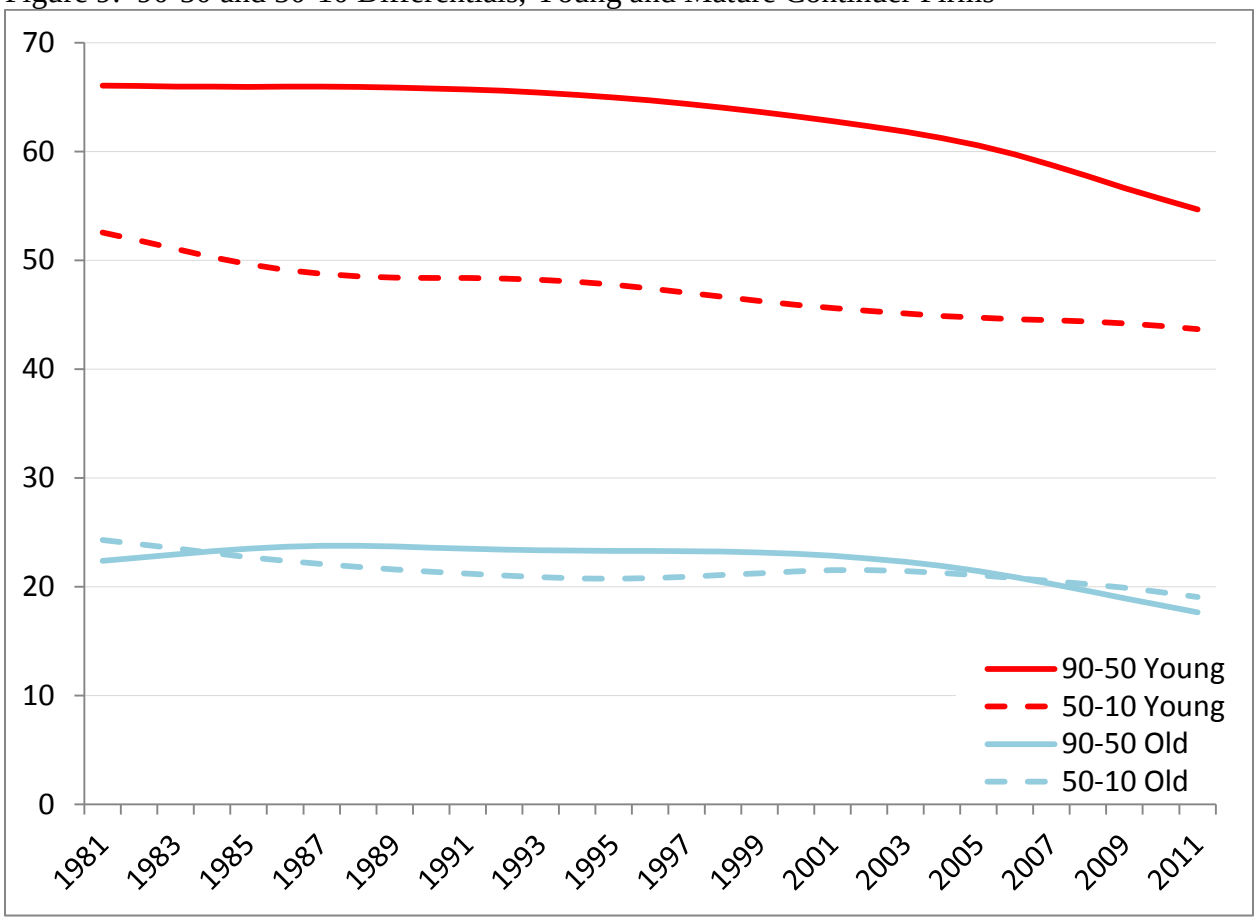
Note: The 90-50 differential and the 50-10 differential are the difference between the 90th and the 50th percentile and the 50th and 10th percentile, respectively, of the employment-weighted distribution of firm employment growth rates. Chart reflects 3-year centered moving averages. Author calculations from the Longitudinal Business Database.

Figure 8: High-Growth Firms (90th Percentile from Employment-weighted Distribution)



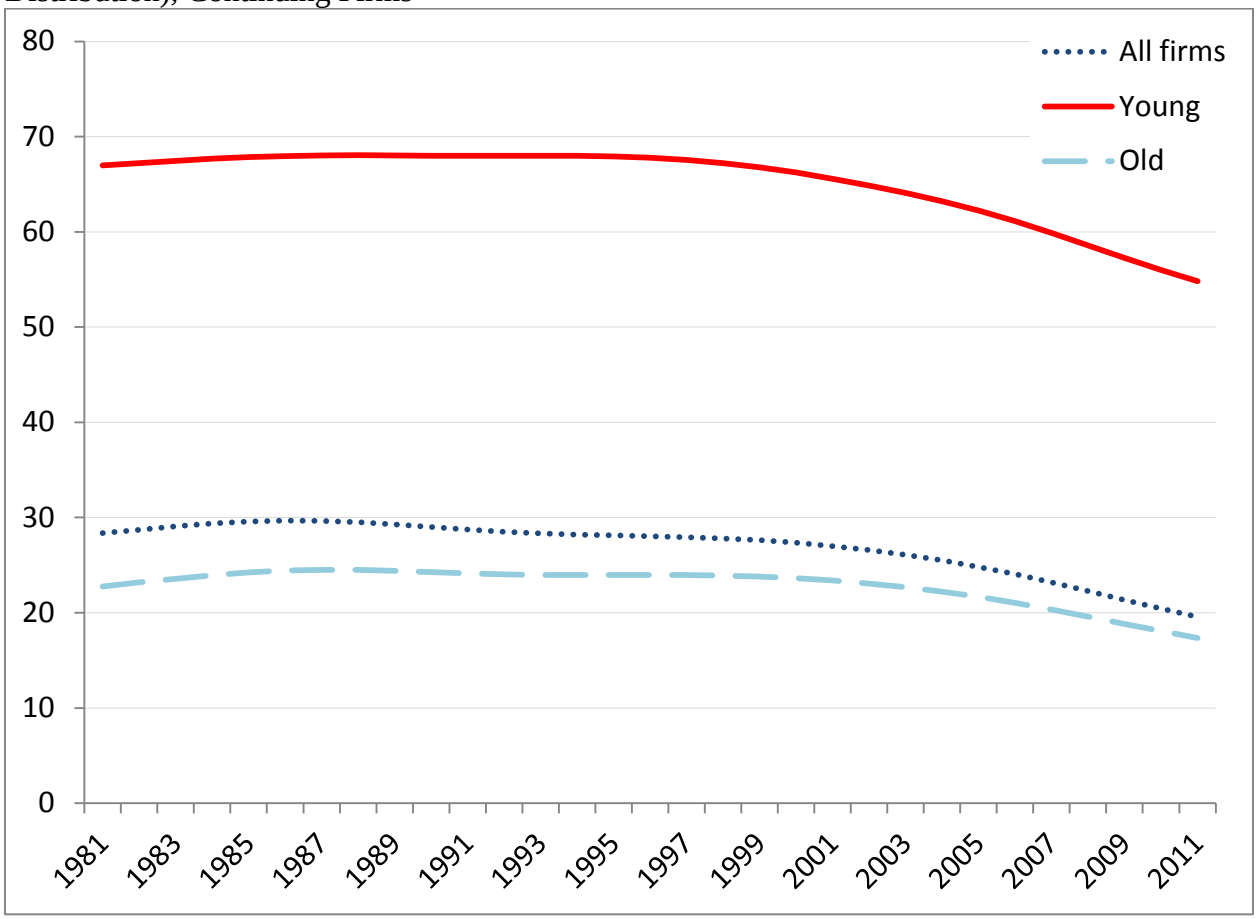
Note: The 90th percentile is based on the employment-weighted distribution of firm employment growth rates. Data are HP trends using parameter set to 100. Author calculations from the Longitudinal Business Database.

Figure 9: 90-50 and 50-10 Differentials, Young and Mature Continuer Firms



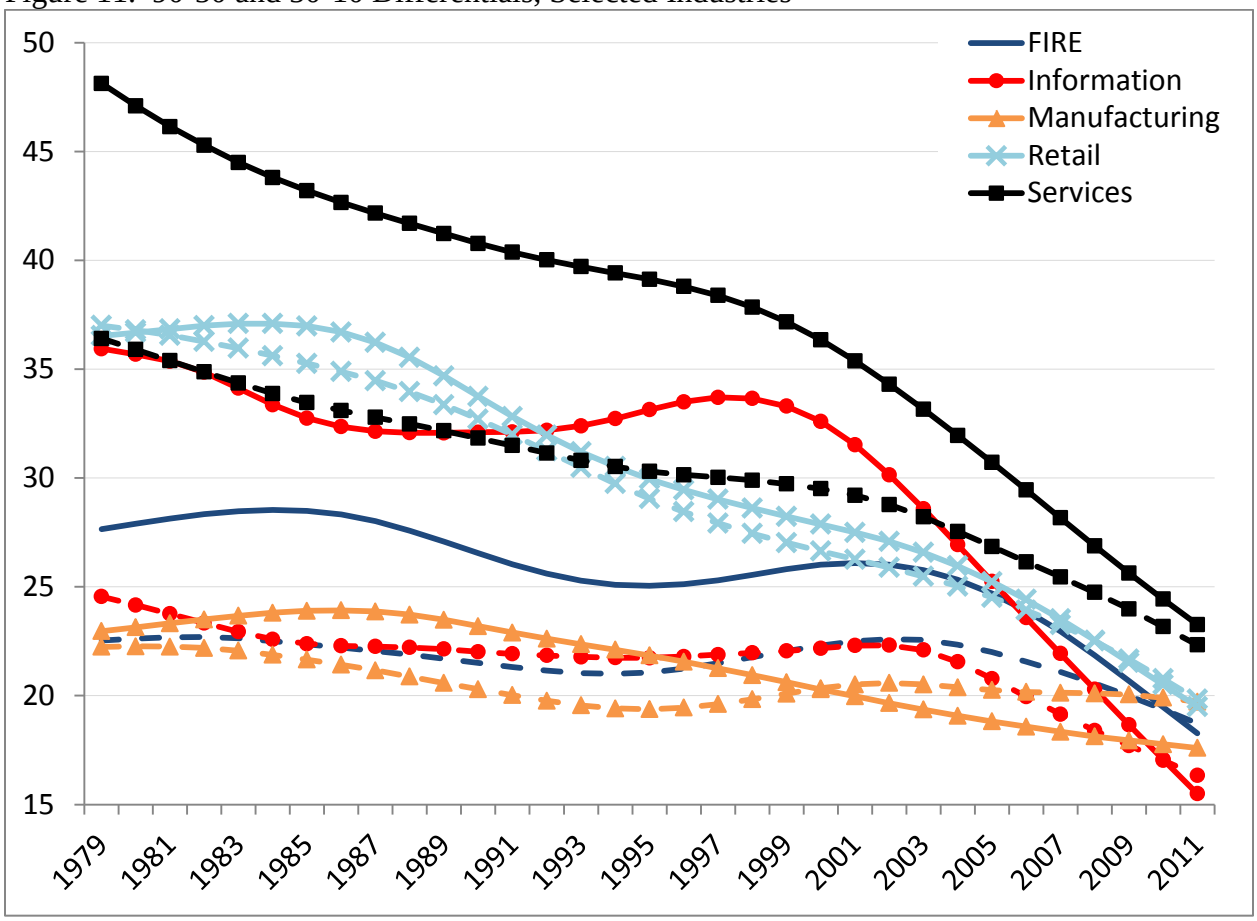
Note: The 90-50 differential and the 50-10 differential are the difference between the 90th and the 50th percentile and the 50th and 10th percentile, respectively, of the employment-weighted distribution of firm employment growth rates. Young firms have age less than 5. Data are HP trends using parameter set to 100. Data include continuers only. Author calculations from the Longitudinal Business Database.

Figure 10. High-Growth Firms by Firm Age (90th Percentile of Employment-weighted Distribution), Continuing Firms



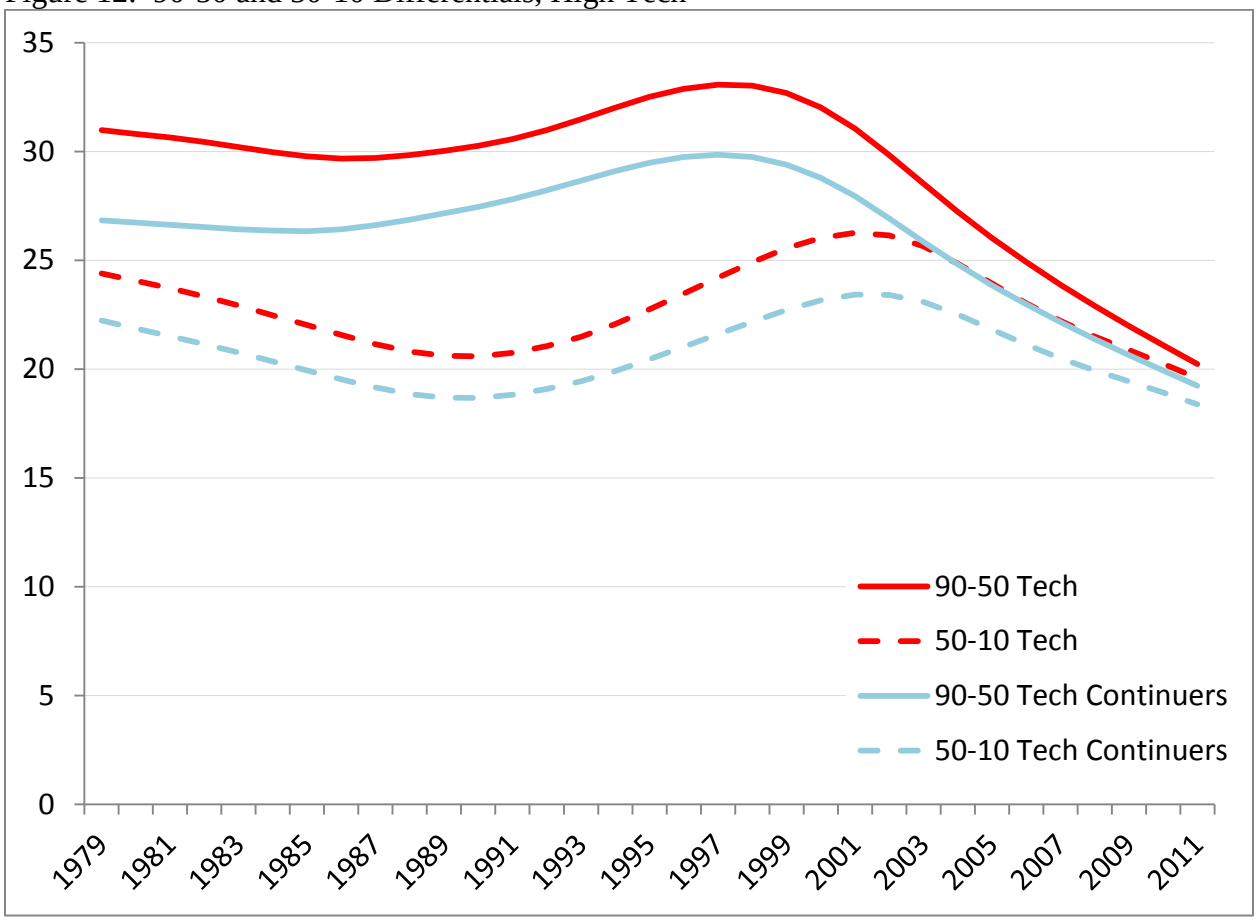
Note: The 90th percentile is based on the employment-weighted distribution of firm employment growth rates. Data are HP trends using parameter set to 100. Data include continuers only. Author calculations from the Longitudinal Business Database.

Figure 11. 90-50 and 50-10 Differentials, Selected Industries



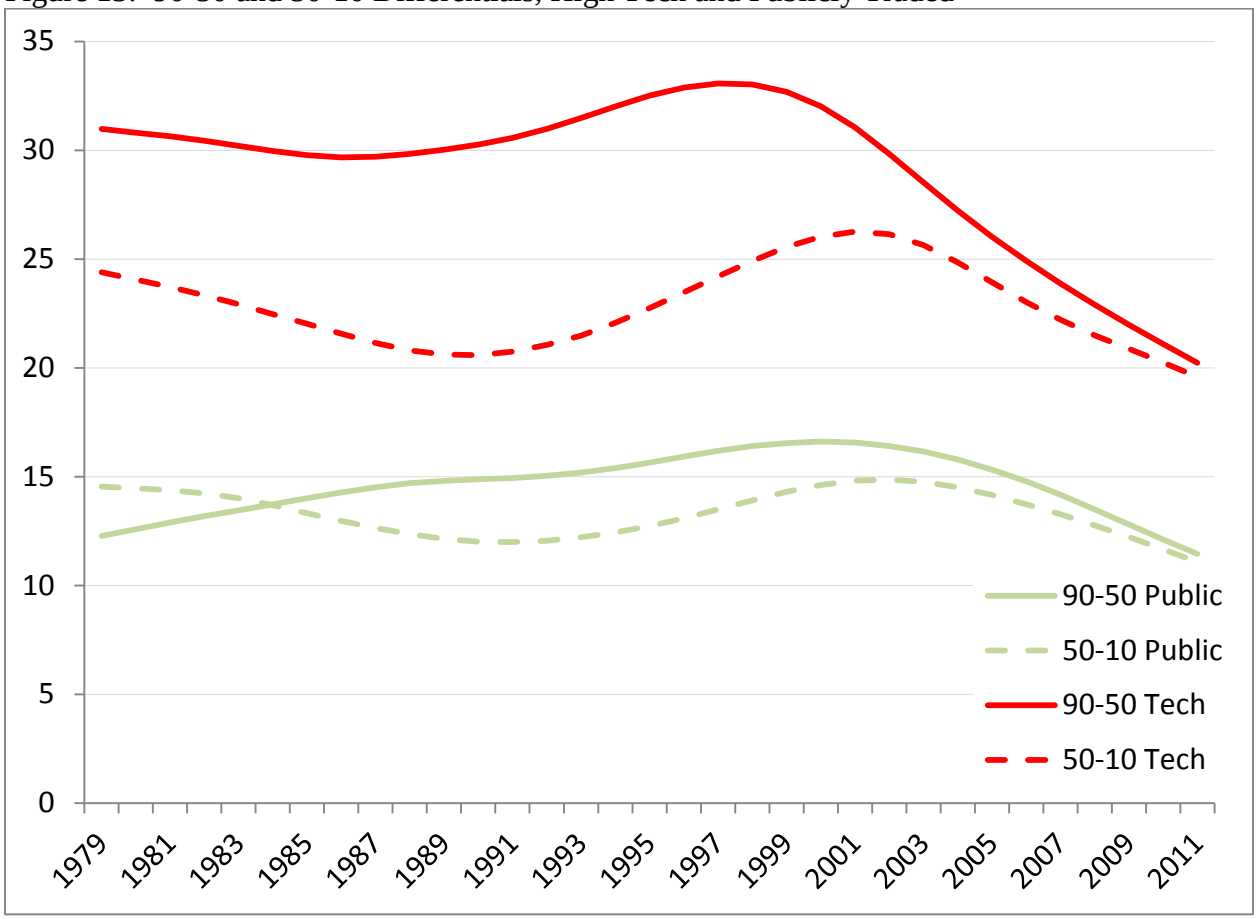
Note: Y axis does not start at zero. Solid lines indicate 90-50 differential; dashed lines indicate 50-10 differential. The 90-50 differential and the 50-10 differential are the difference between the 90th and the 50th percentile and the 50th and 10th percentile, respectively, of the employment-weighted distribution of firm employment growth rates. Data are HP trends using parameter set to 100. Industries are defined on a consistent NAICS basis. Data include all firms (new entrants, continuers, and exiters). Author calculations from the Longitudinal Business Database.

Figure 12: 90-50 and 50-10 Differentials, High Tech



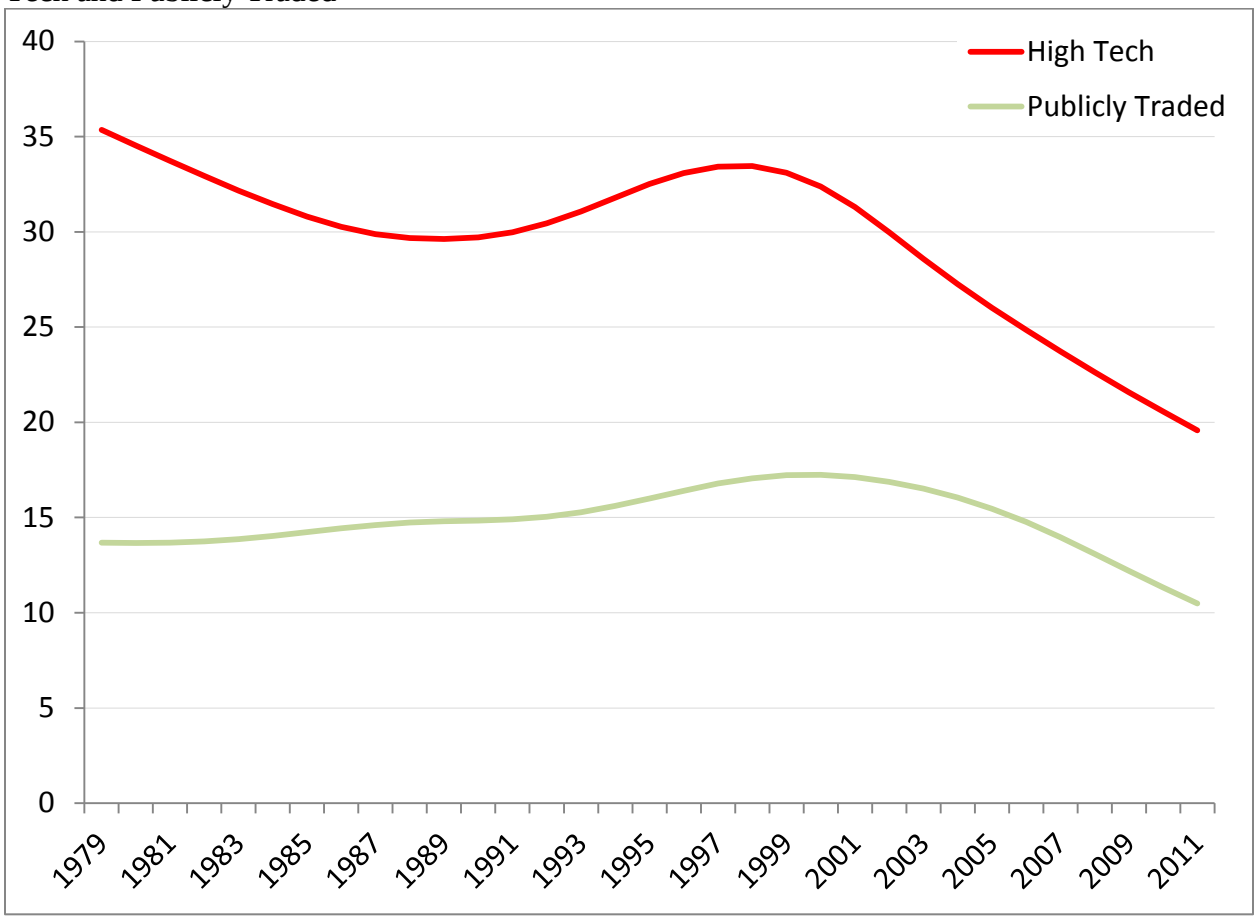
Note: Solid lines indicate 90-50 differential; dashed lines indicate 50-10 differential. The 90-50 differential and the 50-10 differential are the difference between the 90th and the 50th percentile and the 50th and 10th percentile, respectively, of the employment-weighted distribution of firm employment growth rates. Data are HP trends using parameter set to 100. High tech is defined as in Hecker (2005) (see Appendix Table A.1). Author calculations from the Longitudinal Business Database.

Figure 13: 90-50 and 50-10 Differentials, High Tech and Publicly Traded



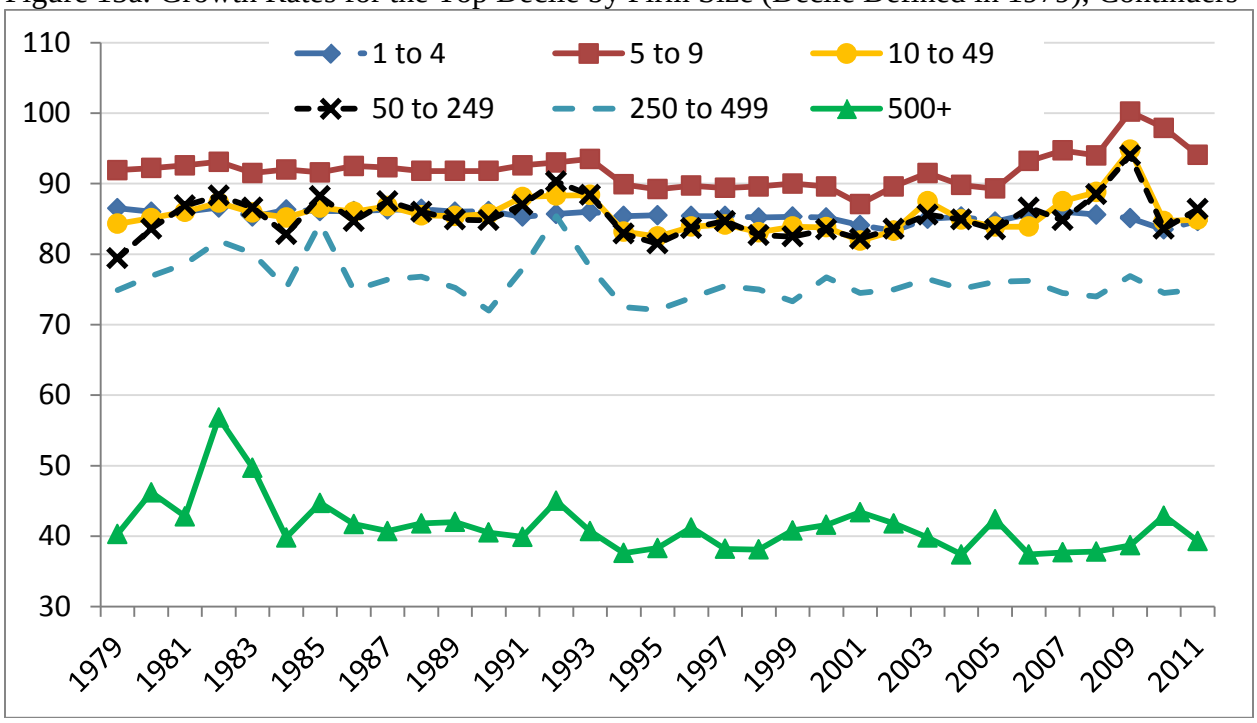
Note: Solid lines indicate 90-50 differential; dashed lines indicate 50-10 differential. The 90-50 differential and the 50-10 differential are the difference between the 90th and the 50th percentile and the 50th and 10th percentile, respectively, of the employment-weighted distribution of firm employment growth rates. Data are HP trends using parameter set to 100. High tech is defined as in Hecker (2005) (see Appendix Table A.1). Data include all firms (new entrants, continuers, and exiters). Author calculations from Compustat and the Longitudinal Business Database.

Figure 14: High-Growth Firms (90th Percentile of Employment-weighted Distribution), High Tech and Publicly Traded



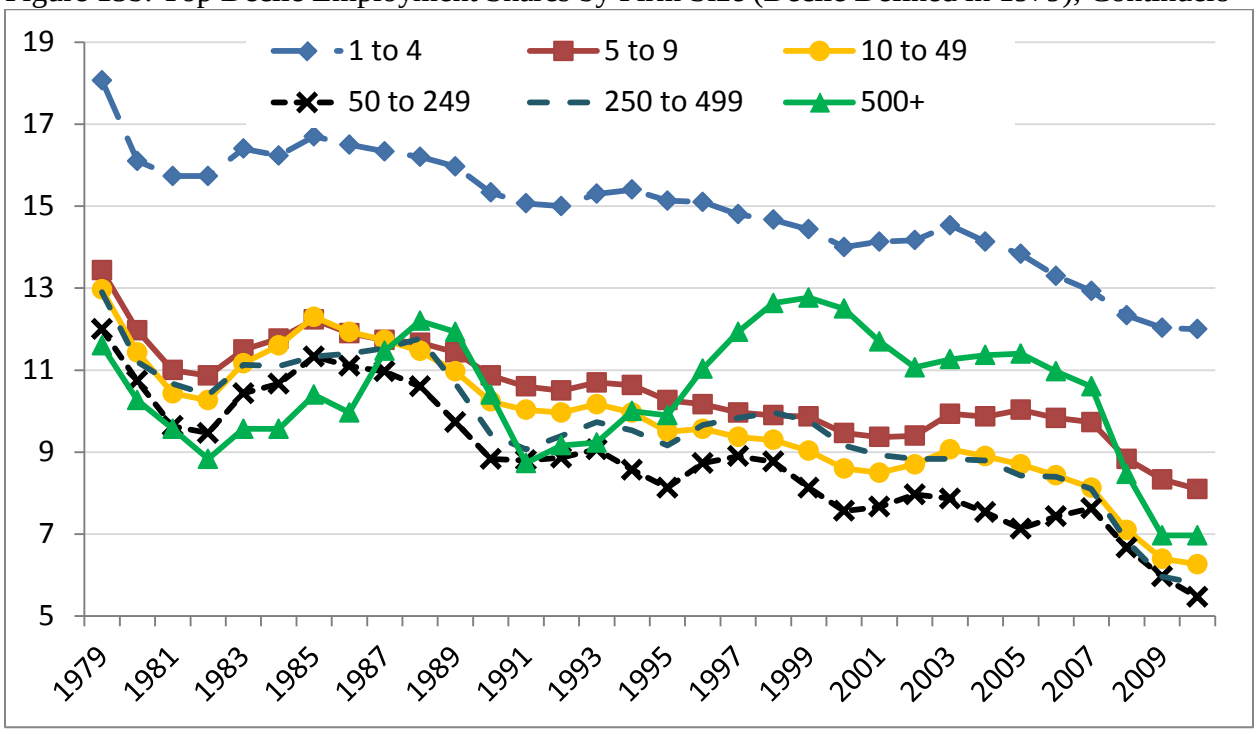
Note: The 90th percentile is based on the employment-weighted distribution of firm employment growth rates. Data are HP trends using parameter set to 100. High tech is defined as in Hecker (2005) (see Appendix Table A.1). Data include all firms (new entrants, continuers, and exiters). Author calculations from Compustat and the Longitudinal Business Database.

Figure 15a: Growth Rates for the Top Decile by Firm Size (Decile Defined in 1979), Continuers



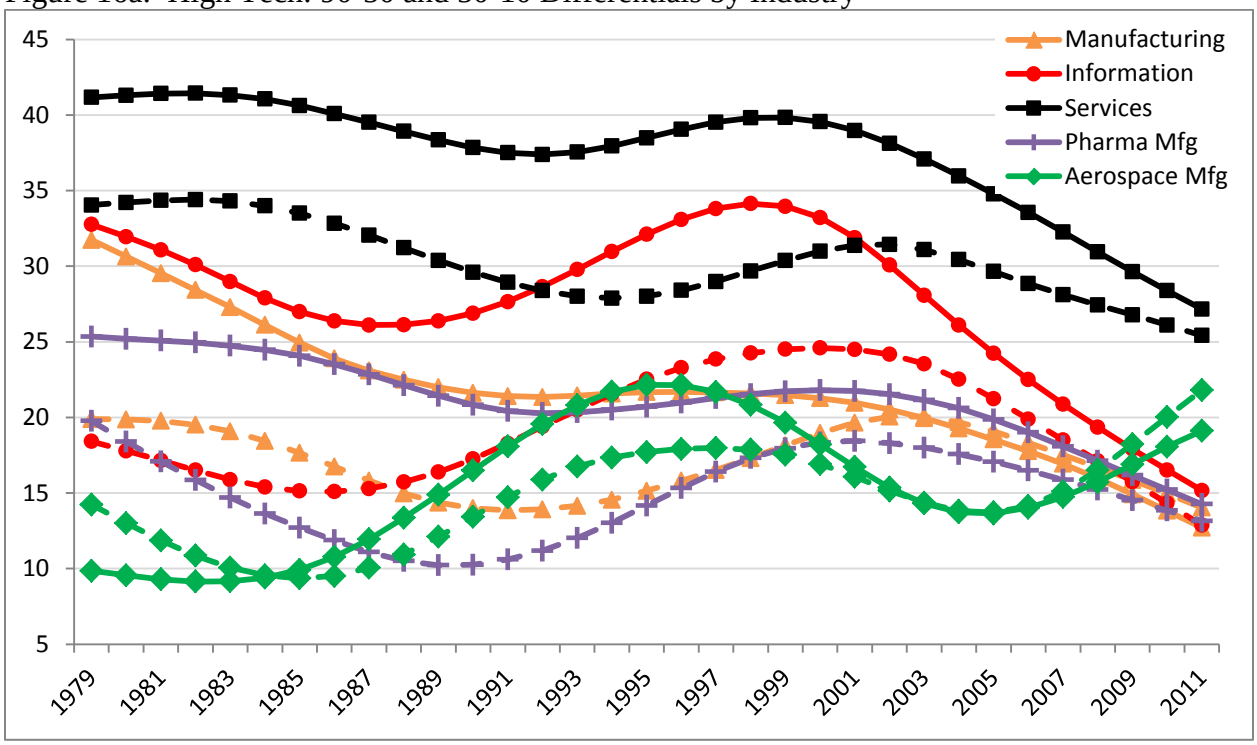
Note: Y axis does not start at zero. Chart depicts employment-weighted average growth rates by size class for firms with growth rates exceeding the 90th percentile (employment-weighted distribution) as of 1979. Author calculations from the Longitudinal Business Database.

Figure 15b: Top Decile Employment Shares by Firm Size (Decile Defined in 1979), Continuers



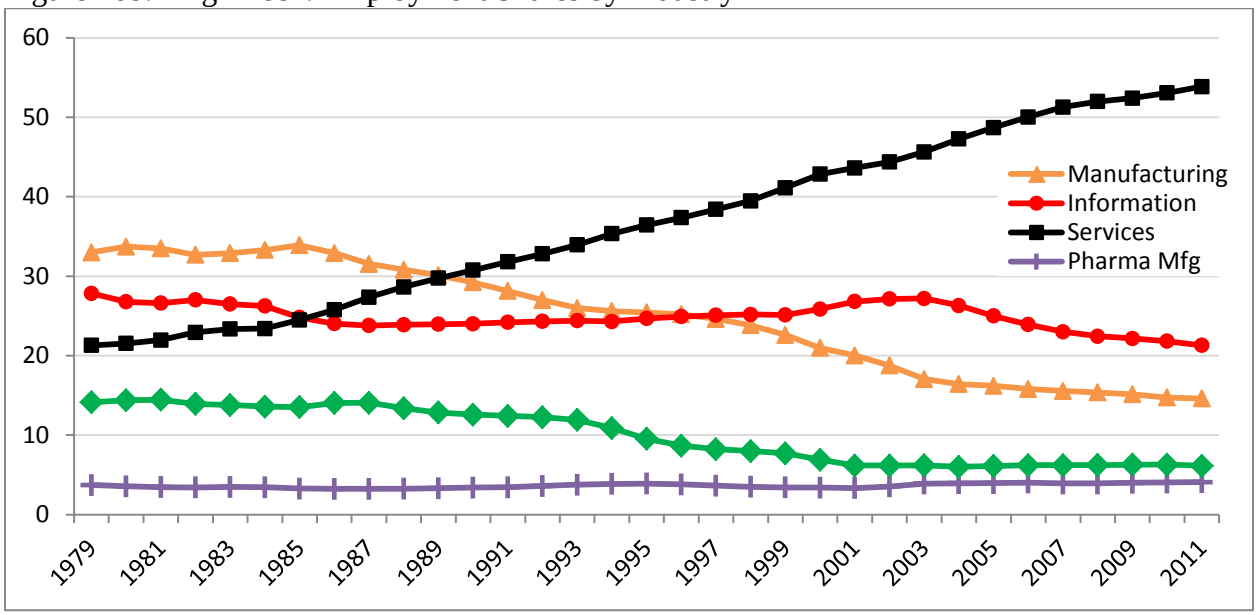
Note: Y axis does not start at zero. Chart depicts the share of employment of each size class that is at firms with growth rates exceeding the 90th percentile (employment-weighted distribution) as of 1979, as 3-year centered moving averages. Author calculations from the Longitudinal Business Database.

Figure 16a: High Tech: 90-50 and 50-10 Differentials by Industry



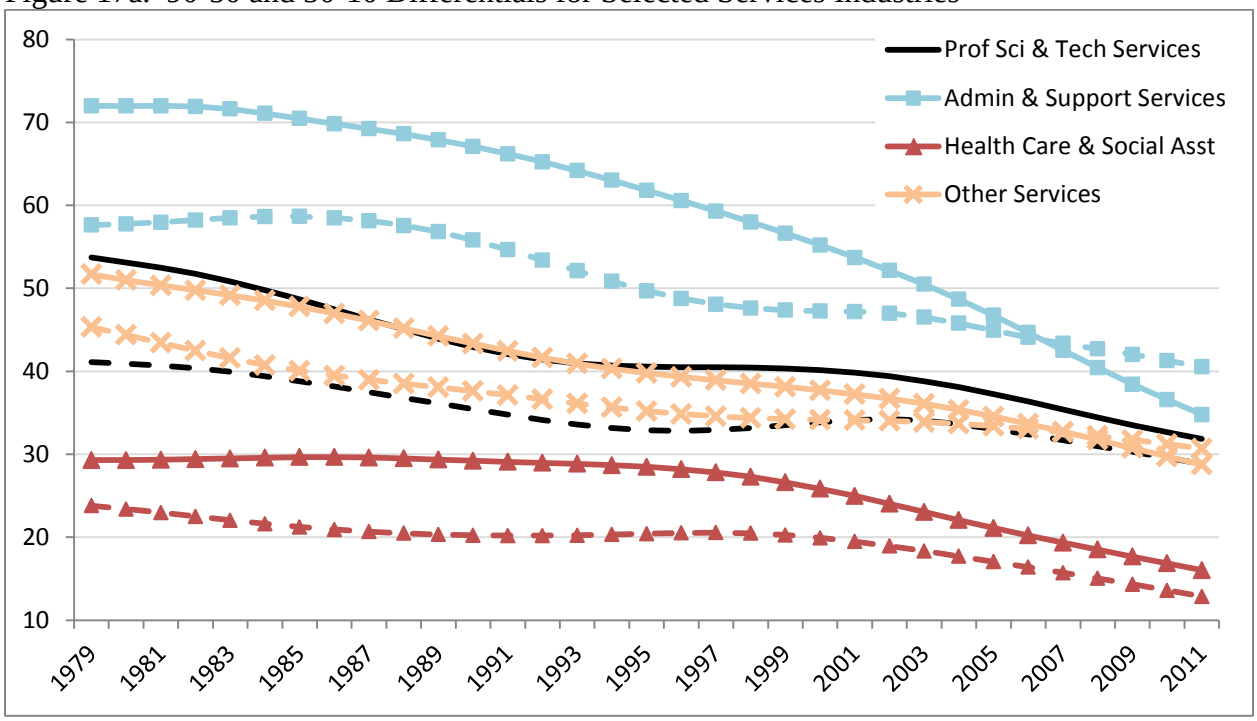
Note: Y axis does not start at zero. Solid (dashed) lines indicate 90-50 differential (50-10 differential). The 90-50 differential (50-10 differential) is the difference between the 90th and the 50th percentile (50th and 10th percentile) of the employment-weighted distribution of firm employment growth rates. Data are HP trends using parameter at 100. High tech is defined as in Hecker (2005) (see Appendix Table A.1). "Manufacturing" is all Manufacturing high tech except pharmaceuticals and aerospace. Industries are defined on a consistent NAICS basis. Data include all firms (new entrants, continuers, and exiters). Author calculations from the Longitudinal Business Database.

Figure 16b: High Tech: Employment Shares by Industry



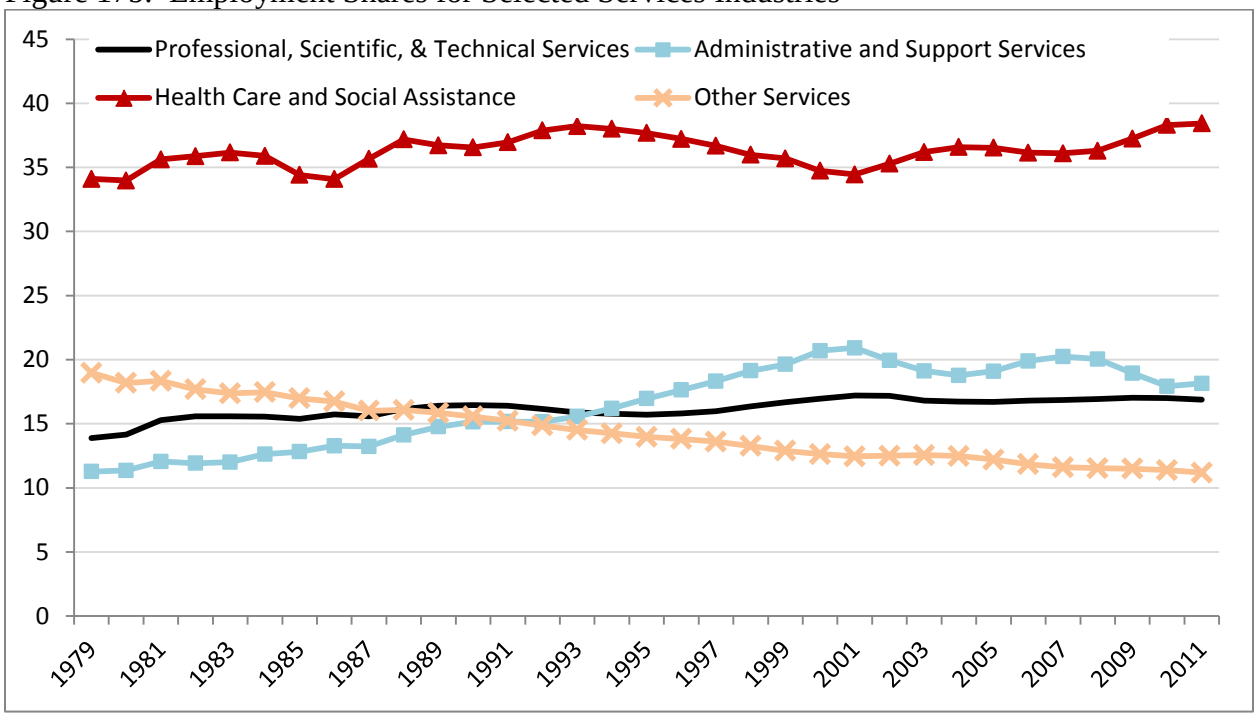
Note: High tech is defined as in Hecker (2005) (see Appendix Table A.1). "Manufacturing" is all Manufacturing high tech except pharmaceuticals and aerospace. Industries are defined on a consistent NAICS basis. Data include all firms (new entrants, exiters, and continuers). Author calculations from the Longitudinal Business Database.

Figure 17a. 90-50 and 50-10 Differentials for Selected Services Industries



Note: Y axis does not start at zero. Solid (dashed) lines indicate 90-50 differential (50-10 differential). The 90-50 differential (50-10 differential) is the difference between the 90th and the 50th percentile (50th and 10th percentile) of the employment-weighted distribution of firm employment growth rates. Data are HP trends using parameter at 100. Industries are defined on a consistent NAICS basis. Data include all firms (new entrants, continuers, and exiters). Author calculations from the Longitudinal Business Database.

Figure 17b: Employment Shares for Selected Services Industries



Note: Share of total Services employment. Industries are defined on a consistent NAICS basis. Data include all firms (new entrants, exiters, and continuers). Author calculations from the Longitudinal Business Database.

Appendix A.1

A. Alternative Measures of Volatility

We have conducted robustness analysis of the patterns of business dynamics using a variety of measures of both establishment-level and firm-level volatility. One measure we use is the job reallocation rate (the sum of job creation and destruction). It is a summary measure of the pace of reallocation and corresponds to an employment-weighted cross sectional absolute deviation measure of dispersion (centered at zero). We also use a number of other measures of volatility based on firm- and establishment-level data. We compute the employment-weighted cross sectional standard deviation of firm (establishment) growth rates. We also compute percentiles of the employment-weighted firm growth rate distribution (*e.g.*, 90th percentile, 50th percentile and 10th percentile). Finally, we use the measure of within-firm (within-establishment) volatility developed in Davis et al. (2007) which we discuss below. All of the measures of volatility that we consider in this paper are employment weighted. Activity weighting measures of business volatility is of critical importance given the highly skewed nature of business activity. Activity-weighted measures are relevant if the focus is on volatility that contributes to aggregate job, output and productivity growth.

The measure of within-firm volatility follows Davis et al. (2007). Let γ_{it} be the firm level growth rate and let $z_{it} = 0.5 * (E_{it} + E_{it-1})$ be the size of firm *i* at time *t*, where E_{it} is employment. Let P_{it} denote the number of years from *t-4* to *t+5* for which $z_{it} > 0.$ Define the scaling quantity, $K_{it} = P_{it} / \sum_{\tau=-4}^{5} z_{i,t+\tau}$, and the rescaled weights, $\tilde{z}_{it} = K_{it} z_{it}$. By construction, $\sum_{\tau=-4}^{5} \tilde{z}_{it} = P_{it}$. The within-firm volatility measure with a degrees-of-freedom correction is given by

$$\tilde{\sigma}_{it} = \left[\sum_{\tau=-4}^{5} \left(\frac{\tilde{z}_{i,t+\tau}}{P_{it} - 1} \right) (\gamma_{i,t+\tau} - \overline{\gamma}_{it}^{w})^2 \right]^{1/2}, \qquad (1)$$

where $\overline{\gamma}_{it}^{w}$ is firm *i*'s size-weighted mean growth rate from *t-4* to *t+5*, using the z_{it} as weights. We construct this measure for all businesses in year *t* with a positive value for z_{it}. In other words, we compute (1) on the same set of firms as the contemporaneous dispersion measure.

The average magnitude of firm volatility at a point in time can be calculated using equal weights or weights proportional to business size. Following Davis et al. (2007) and to be consistent with our other measures, we focus on size-weighted volatility. In the size-weighted measures, the weight for business *i* at time *t* is proportional to z_{it}. This measure is a modified version of the within-firm volatility measures computed by Comin and Philippon (2005) being inclusive of short-lived firms and entry and exit. We compute this measure at the establishment level in an analogous fashion.

Figure A.1 presents six different measures: firm- and establishment-level job reallocation, firm and establishment employment-weighted cross sectional standard deviations of growth rates, and within-firm and within-establishment measures of volatility. All measures exhibit a pronounced secular decline. The cross sectional measures exhibit more high-frequency cyclical variation. All measures decline by over 10 percent over the time period depicted. All measures are also highly correlated (all pairwise correlations exceed 0.9) including the cross sectional (*e.g.*, job reallocation or cross sectional standard deviation) and within-business measures. For example, the correlation between the within-firm volatility measure and the job reallocation for firms is 0.93. Finally, it is apparent that firm-level measures are lower than establishment-level measures of volatility. This reflects the statistical aggregation that occurs across establishments of multi-establishment firms. It is striking, though, that the patterns are so highly correlated for establishment- and firm-level volatility. It might have been the case, for example, that the decline in firm volatility was due to an increased role of statistical aggregation since there has been a shift towards multi-unit establishment firms. In spite of the latter, we observe systematic declines in both firm- and establishment-level volatility.

B. The Changing Structure of the US Economy: The Role of Compositional Shifts

Methodological Approach

Our objective in this section is to quantify the contribution of compositional shifts by firm age and industry as well as other firm characteristics. This part of our analysis follows closely that of Davis et al. (2007) and Decker et al. (2014), and as such our

conclusions are similar to those found in those papers. We include similar analysis here since it helps provide a basis for our main analysis later in the paper. For this purpose, we consider 282 unique 4-digit NAICS (2002) industries, 7 unique firm age groups (0 through 5, and 6+), 8 firm size groups (1-9, 10-19, 20-49, 50-99, 100-249, 250-499, 500-000, and 1000+ employees), 50 states and the District of Columbia, 2 firm status groups (single or multiple location indicator), 3 chain groups (local, regional, or national capture based on whether the firm operates in multiple geographic locations) and 29 different years between 1982 and 2011.[22] Note that startups are simply those firms with age zero.

For this purpose, we focus on the establishment-level job flow measure—but robustness analysis (as well as a comparison with similar analyses in the recent literature) indicates that our findings are robust to using firm-level measures and to within-business vs. cross sectional measures of volatility. Changes in the pace of job flows can be readily decomposed using a shift-share decomposition. First we start with employment shares and job flows (job creation rate, job destruction rate and job reallocation rate measures) at a detailed cell level denoted by *c*. One can decompose job flow statistics for any given level of aggregation *i* as follows:

$$F_{it} - F_{it_o} = \Delta F_{it} = \sum_{c \in i} s_{ct_0} \Delta F_{ct} + \sum_{c \in i} F_{ct_0} \Delta S_{ct} + \sum_{c \in i} \Delta F_{ct} \Delta S_{ct}$$

where the change in the flow *F* from time *t* to the base year can be decomposed into three terms. The first term represents a within-cell component based on the change in flows for a particular cell between the current period *t* and the base period t_0 weighted by the initial shares of that cell. The second term represents a between-cell component that reflects changing shares, weighted by the flows in the base period. The third term represents a cross term relating changes in shares with changes in flows. We focus our attention on the overall and the within components. The difference between those two reflects the

[22] We thank Teresa Fort for the development of a methodology that reclassifies all establishments in the LBD to a consistent NAICS (2002) industry classification system. See Fort (2013) for details. Having a consistent classification system for our entire panel is critical for our analysis.

extent to which compositional changes (captured by both the between and the covariance terms) account for the difference.

This shift-share methodology yields counterfactual job flows holding constant alternative classifications of cells at their initial level. Given our focus on the declining trends, we focus our attention on long differences in the actual and counterfactual flows on a peak-to-peak basis. Specifically, we focus on the long difference in the flows from the peak in the late 1980s to the peak just before the Great Recession. To mitigate the influence of higher frequency variation, we consider the 3-year averages at each of these peaks. In particular, we use the 3-year average for the 1987-89 period and the 3-year average for the 2004-06 period.

How Much of the Decline is Accounted for by the Changing Composition of Businesses?

Figure A.3 illustrates the percent in the decline of job flows explained by changes in composition for selected components and overall. The difference between the actual rate and the within component is the part that is explained by composition shifts. We first examine the impact of controlling for shifts in detailed industry, firm age, and firm size, one at a time by themselves, in order to examine their independent impact. Results for their combined full interaction with multi-unit status and firm status are also provided. Finally, we also include an interaction with geography.

How much of this decline can be explained by compositional shifts across detailed industries? As anticipated above, shifts in detailed industry composition actually work in the "wrong" direction. If the changing industrial structure were the only influence on the secular trends in job creation, destruction and reallocation rates, we should have seen these rates rise, not fall, over time as employment shifted from Manufacturing to Retail Trade and Services. The job creation rate should have increased by about 20 percent, the job destruction rate by about 4 percent and the reallocation rate by about 13 percent if the only effect operating was the shift in industrial composition.

In contrast, the shifting age composition plays a major role in accounting for the declining pace of business dynamics. The shifting age composition accounts for 32 percent of the observed decline in job creation, 20 percent of the decline in job

destruction, and 26 percent of the decline in job reallocation. The change in the firm age composition is by far the most important of any of the individual factors we examine in accounting for the overall declines. The implication is that understanding the sources of the declines in the pace of entrepreneurship is critically important for understanding the decline in business dynamism.

The shift in economic activity toward large firms has similar but more muted effects. The explanatory power for this composition effect alone is about 10 percent for job creation, job destruction and job reallocation. In interpreting the effects of size, it is important to remember that business size and business age are correlated. Young businesses are small, as documented in Haltiwanger, Jarmin and Miranda (2013). However, there are many older small businesses so it is important to distinguish between those characteristics. Fort et al. (2013) show that the decline in the share of employment by young businesses (who are also small businesses) shows up in increased shares of older business, both large and small. As such, there is less of a noticeable trend in the share of activity by business size as opposed to business age. In addition, Haltiwanger, Jarmin and Miranda (2013) show the high pace of job creation of small businesses is actually mostly captured by business age. So it is not that surprising that size contributes less than age.

It is apparent that there are offsetting composition effects, with shifts toward less volatile older, larger and multi-establishment firms working one way and shifts toward the Service and Retail Trade sectors as well as the shifts towards activity in the south and west working in the opposite direction. The two most important individual factors are firm age and industry—and they are working in opposite directions. In evaluating all of these effects simultaneously, additional considerations become important as well. While there has been a shift towards Services and Retail, these are sectors where the decline in the employment share of young firms has been the largest. Figure A.3 shows that the fully saturated compositional exercise accounts for about 15 percent of the respective decline in job creation, job destruction and job reallocation. This holds whether or not we include interactions with geography.

Taking stock, compositional shifts can account for part of the decline in job flows, but most of the decline remains unaccounted for by these factors. Even though only 15

percent of the decline in business volatility is accounted for by all compositional effects taken into account simultaneously, this relatively small combined effect masks substantial individual composition effects working in opposite directions. Shifts toward older firms account for about 26 percent of the decline in business volatility (as measured by the decline in reallocation) by itself, but this is offset by the 13 percent increase in volatility due to the shift towards more volatile industries.

C. Changing Cohort Patterns for Publicly Traded Firms

Davis et al. (2007) showed that the rising volatility of publicly traded firms through 2000 is largely attributable to cohort effects. In particular, the 1980s and 1990s cohorts of new publicly traded firms were large, grew rapidly and exhibited very high volatility. These patterns are evident in Figures A.6 and A.7 which show the employment shares and the volatility of publicly traded firms using COMPUSTAT data so that a longer time series perspective can be provided. The contribution of the 1980s and 1990s cohorts reported and highlighted by Davis et al. (2007) is evident. But also observe that after about the year 2000 there are substantial changes. First, the cohort of new IPOs post 2000 is small and did not grow rapidly. Second, the post-2000 cohort is much less volatile than the 1980s and 1990s cohorts. Third, the 1980s and 1990s (and all cohorts) exhibited substantial declines in volatility post 2000. [23]

The contribution of cohort effects is presented in Figure A.8. Figure A.8 was constructed as follows. First, an employment-weighted regression of firm volatility on year effects was estimated. Those year effects are by construction the aggregate employment-weighted within-firm volatility. Second, cohort effects for each year of entering cohort of publicly traded firms were added to the specification. The year effects from this regression are an indicator of the extent to which cohort effects account for the rise and fall of within-firm volatility for publicly traded firms. Cohort effects account for a substantial fraction of the rise in volatility through 2000 consistent with the findings in Davis et al. (2007). But cohort effects account for little of the decline. This is not surprising given Figure A.7, which shows a sharp decline in within-cohort volatility for all cohorts but especially the 1980s and 1990s cohorts.

[23] Behavior of publicly traded firms reflects not only the behavior of existing public firms but also the margins of listing and delisting of public firms. See Doidge, Karolyi, and Stulz (2015) for a discussion of potential explanations for recent trends in both listing and delisting activity.

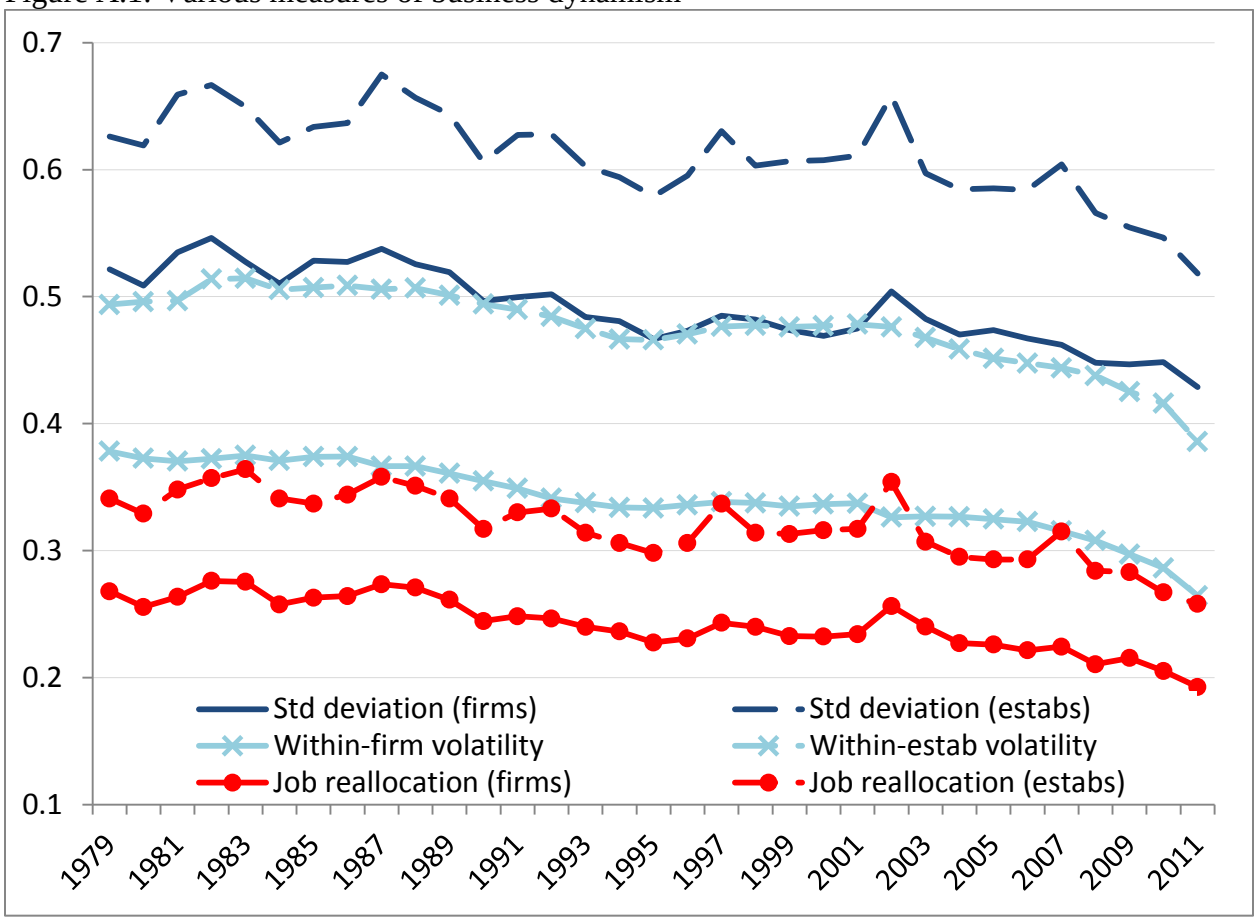
Appendix A.2: Tables and Figures

Table A.1: High-Technology Industries

NAICS Code	Industry
Information and Communications Technology (ICT) High-Tech	
3341	Computer and peripheral equipment manufacturing
3342	Communications equipment manufacturing
3344	Semiconductor and other electronic component manufacturing
3345	Navigational, measuring, electromedical, and control instruments manufacturing
5112	Software publishers
5161	Internet publishing and broadcasting
5179	Other telecommunications
5181	Internet service providers and Web search portals
5182	Data processing, hosting, and related services
5415	Computer systems design and related services
Miscellaneous High-Tech	
3254	Pharmaceutical and medicine manufacturing
3364	Aerospace product and parts manufacturing
5413	Architectural, engineering, and related services
5417	Scientific research-and-development services

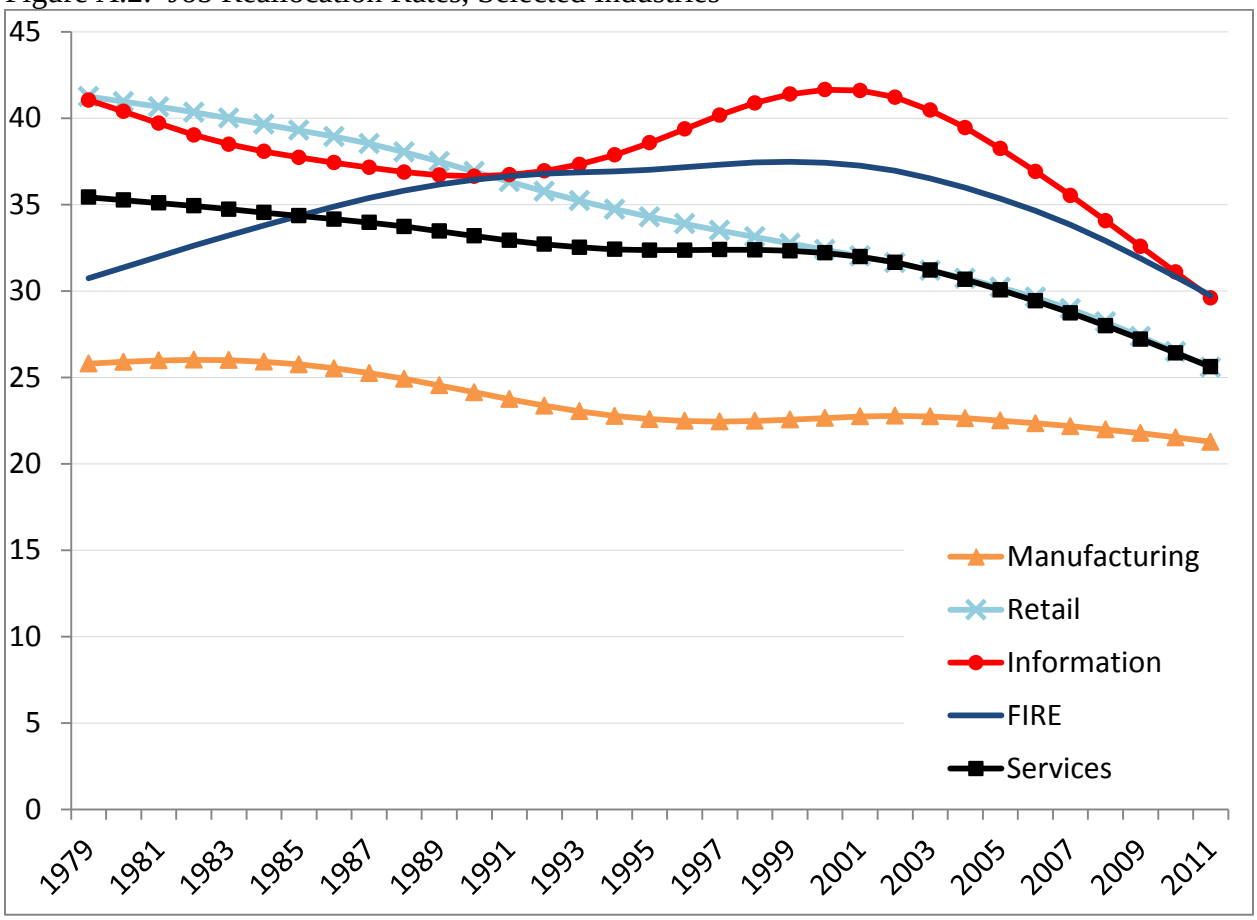
Source: Bureau of Labor Statistics, Hecker (2005)

Figure A.1: Various measures of business dynamism



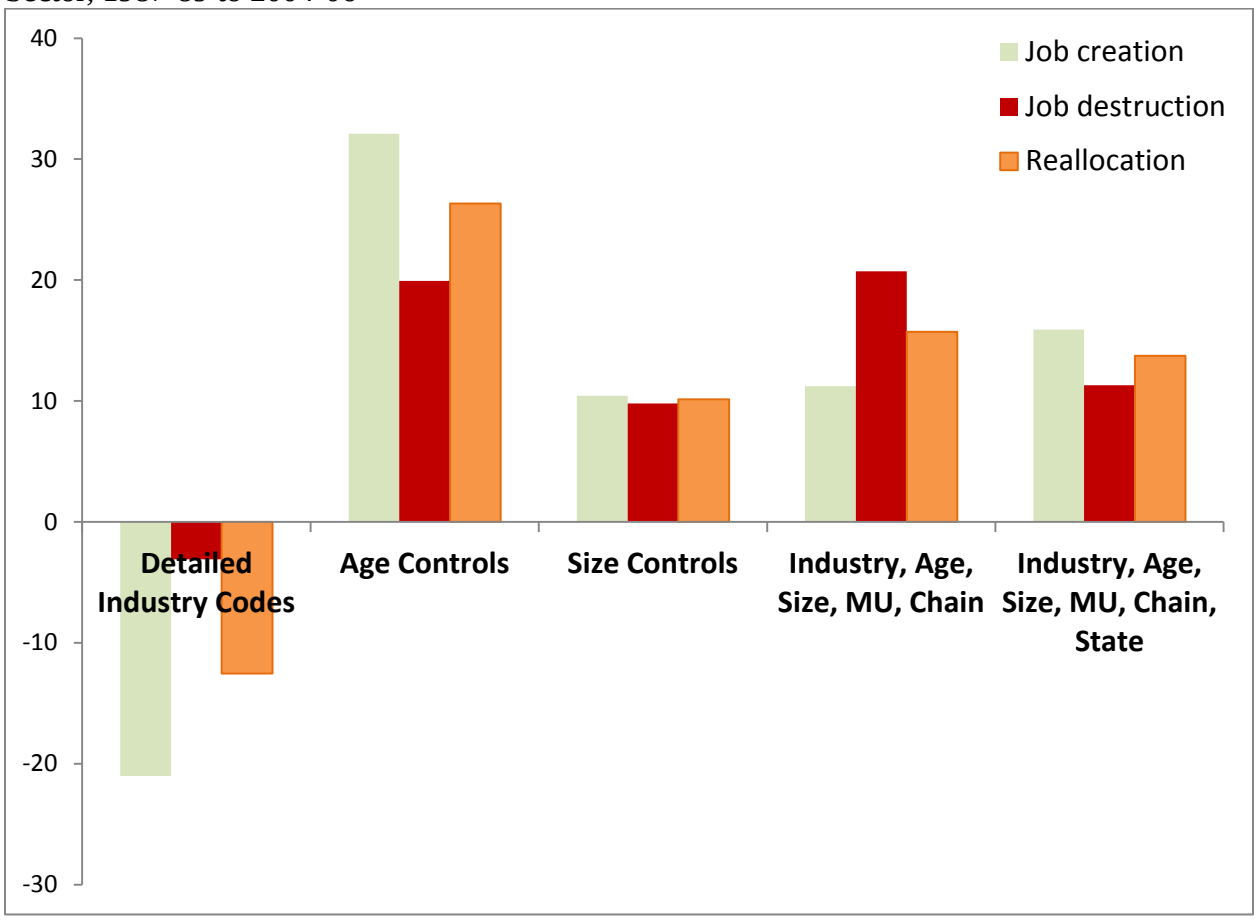
Note: Y axis does not start at zero. Author calculations from the Longitudinal Business Database.

Figure A.2: Job Reallocation Rates, Selected Industries



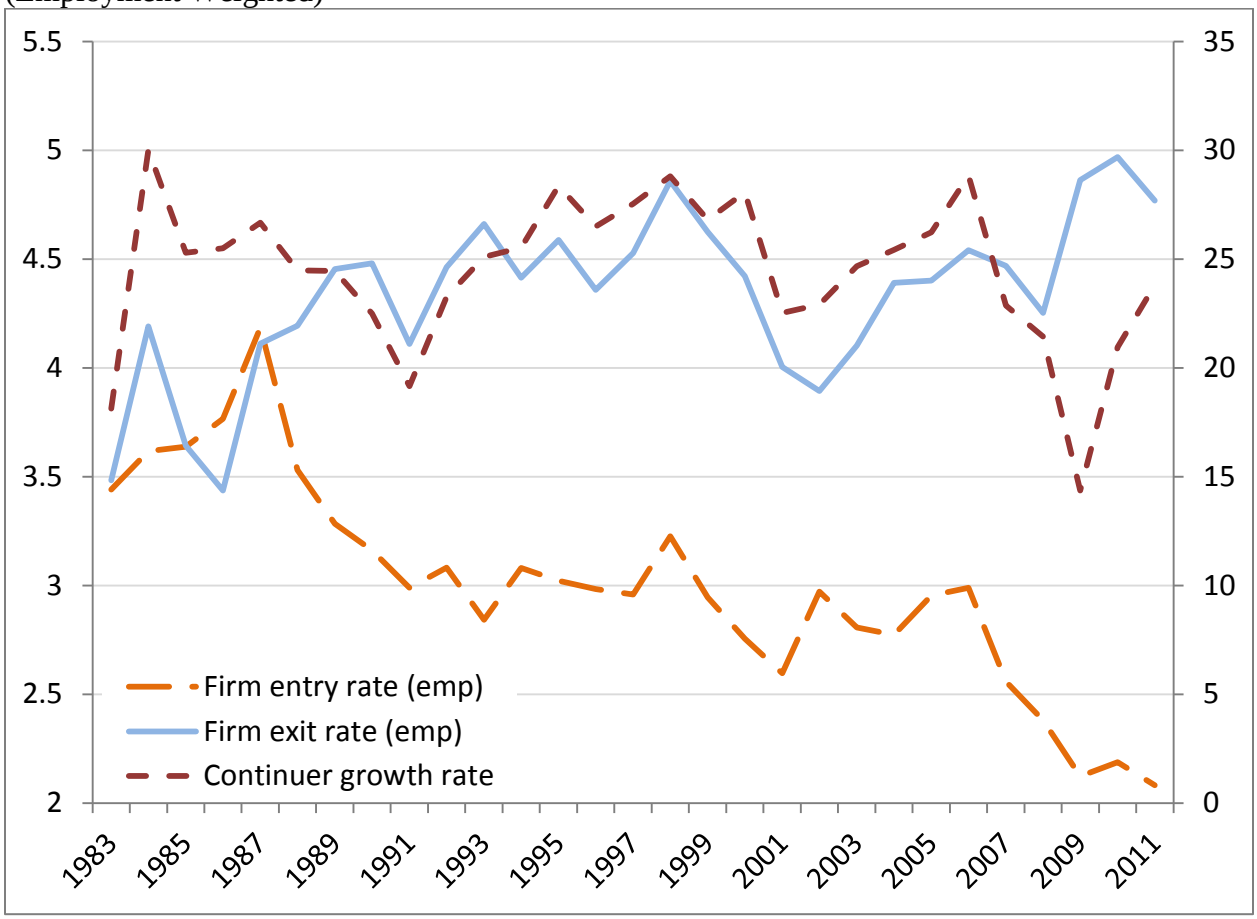
Note: Data are HP trends using parameter set to 100. Industries are defined on a consistent NAICS basis. Data include all firms (new entrants, continuers, and exiters). Author calculations from the Longitudinal Business Database.

Figure A.3: Percent of Decline in Job Flows Accounted for by Composition Effects, Private Sector, 1987-89 to 2004-06



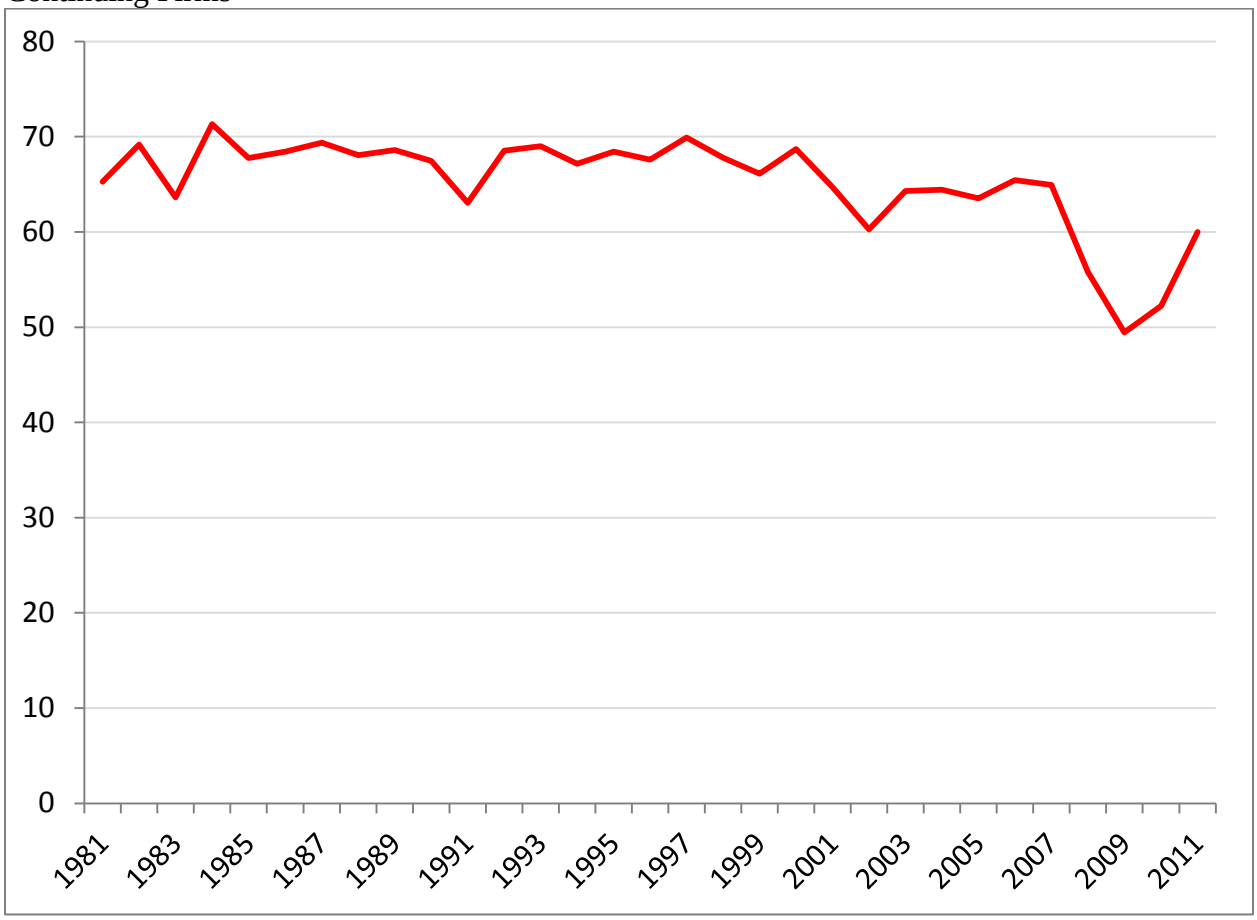
Note: Author calculations from the Longitudinal Business Database.

Figure A.4: Young Firm Entry Rate, Exit Rate, and Survival-Conditional Growth Rate (Employment Weighted)



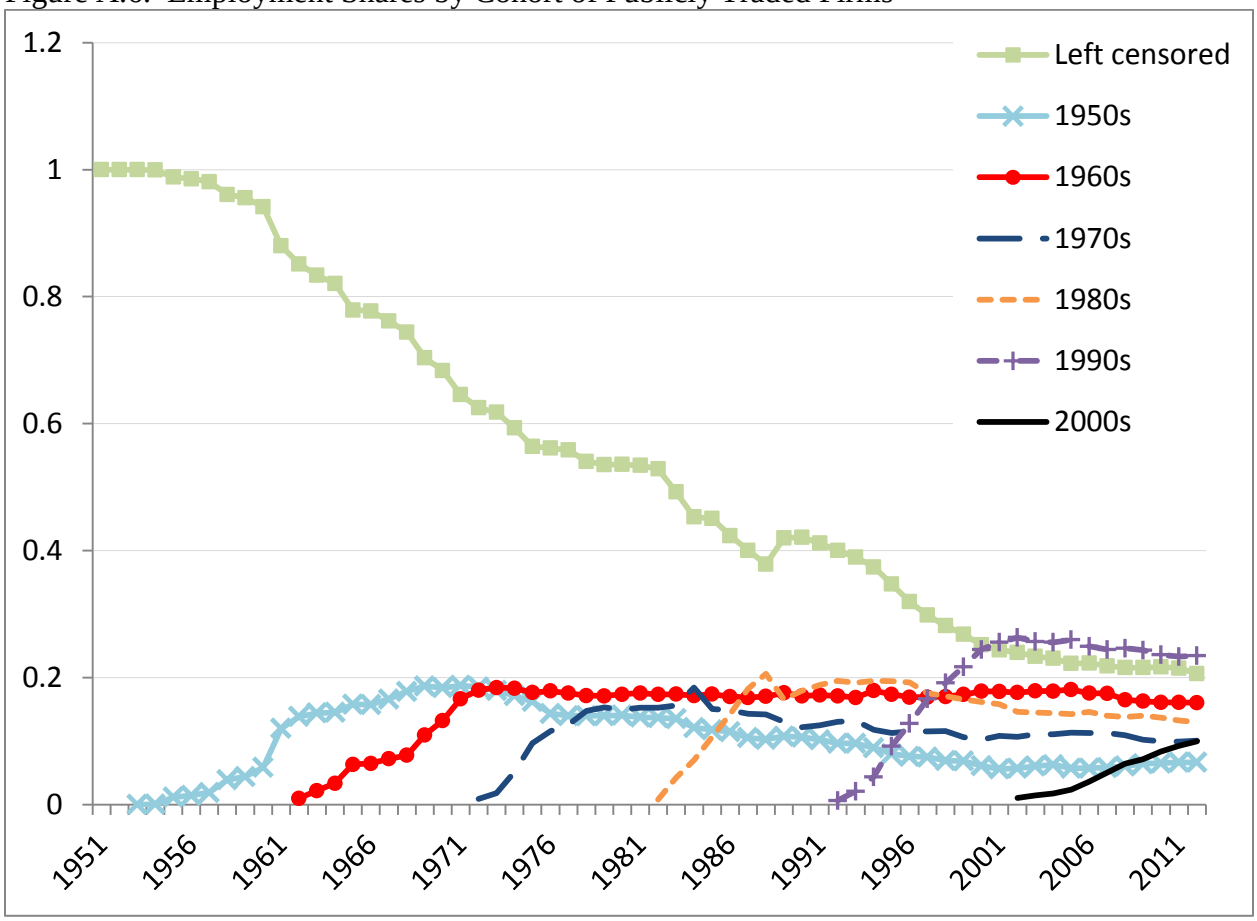
Note: Y axis does not begin at zero. Young firms have age five or less. Firm entry rate is new firm employment as a percent of all employment. Firm exit rate is employment at exiting young firms as a percent of all employment. Continuer growth rate is employment-weighted average growth rate among continuing young firms (*i.e.*, non-entering, non-exiting young firms). Author calculations from the Longitudinal Business Database.

Figure A.5: High-Growth Young Firms (90th Percentile of Employment-weighted Distribution), Continuing Firms



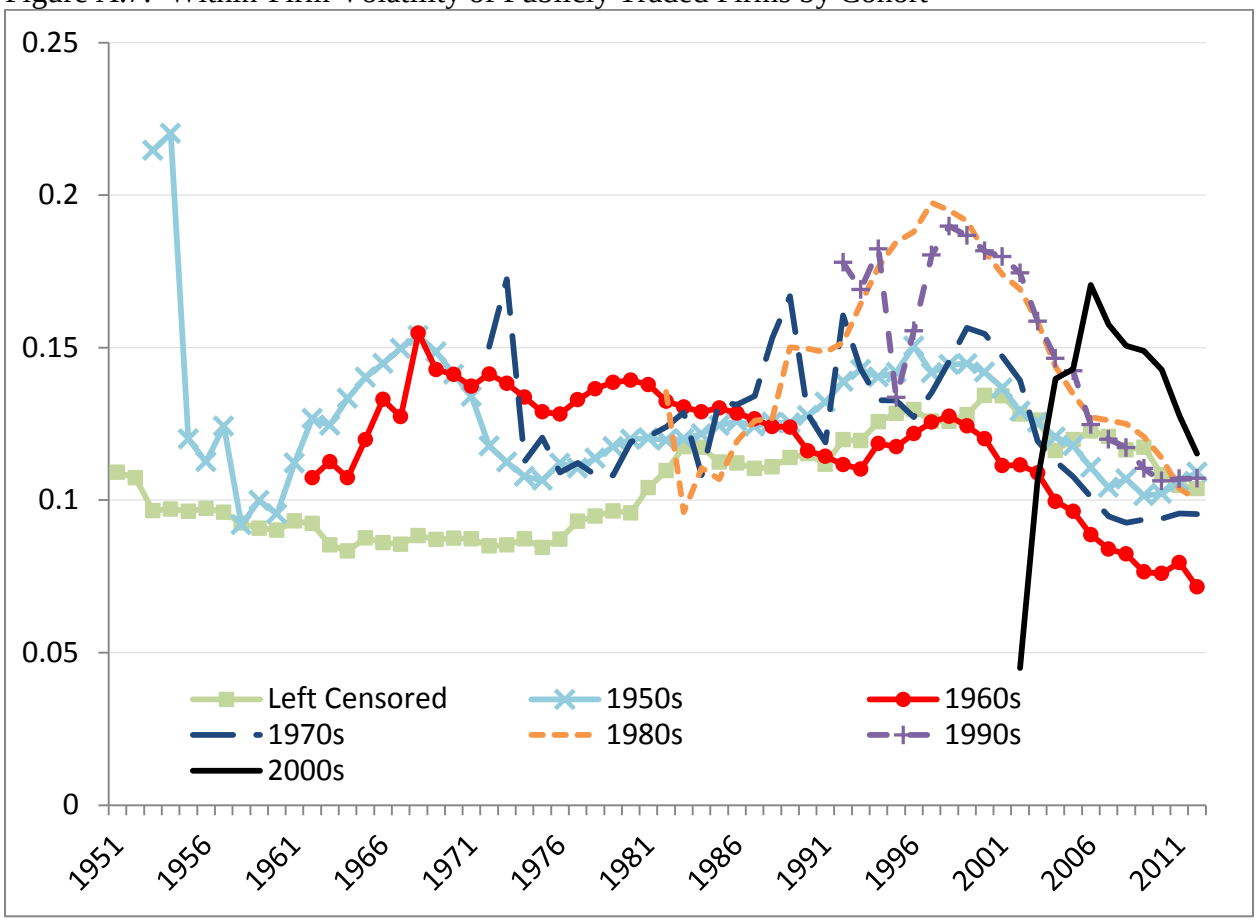
Note: The 90th percentile is based on the employment-weighted distribution of firm employment growth rates. Data include continuers only. Author calculations from the Longitudinal Business Database.

Figure A.6. Employment Shares by Cohort of Publicly Traded Firms



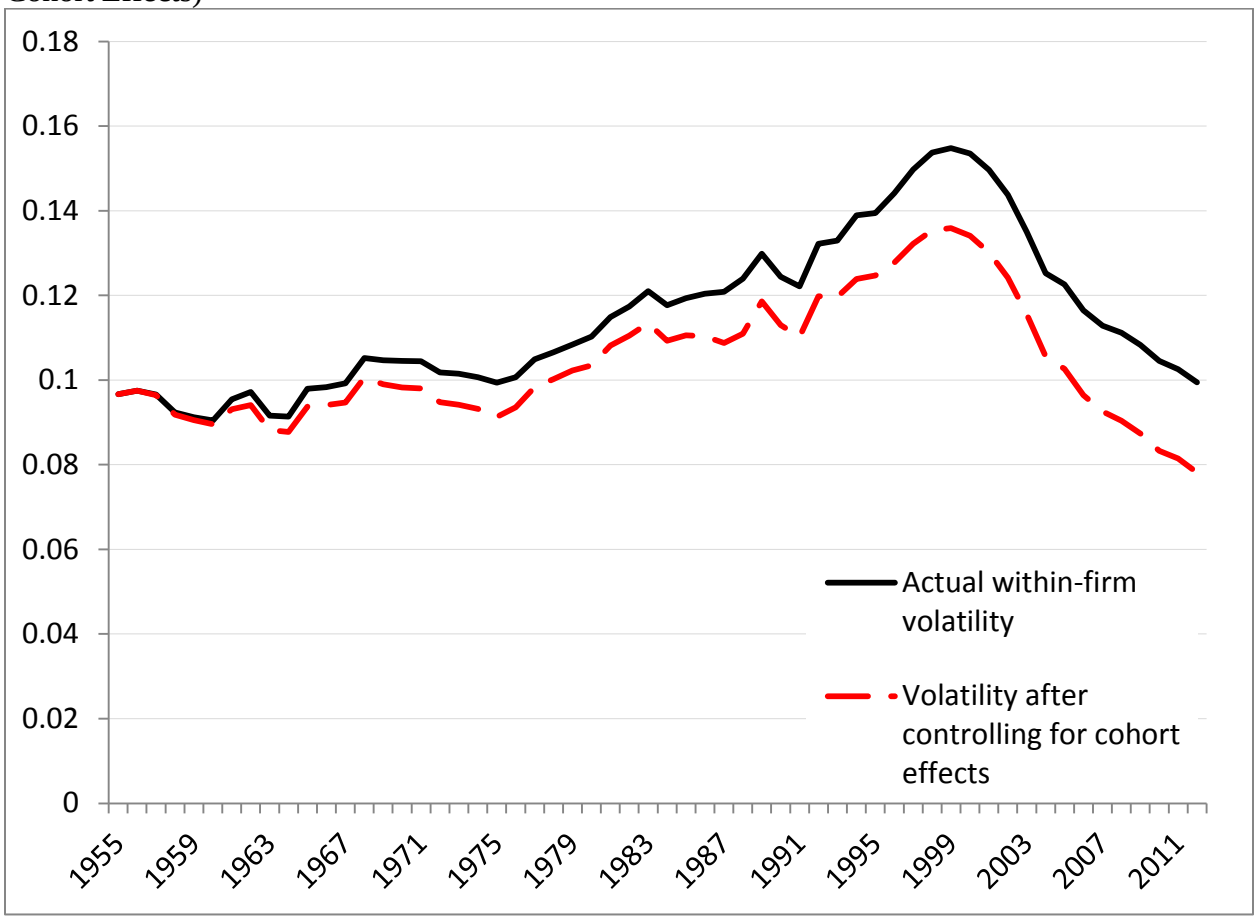
Note: Cohorts are defined by decade of initial public offering. Author calculations from Compustat.

Figure A.7: Within-Firm Volatility of Publicly Traded Firms by Cohort



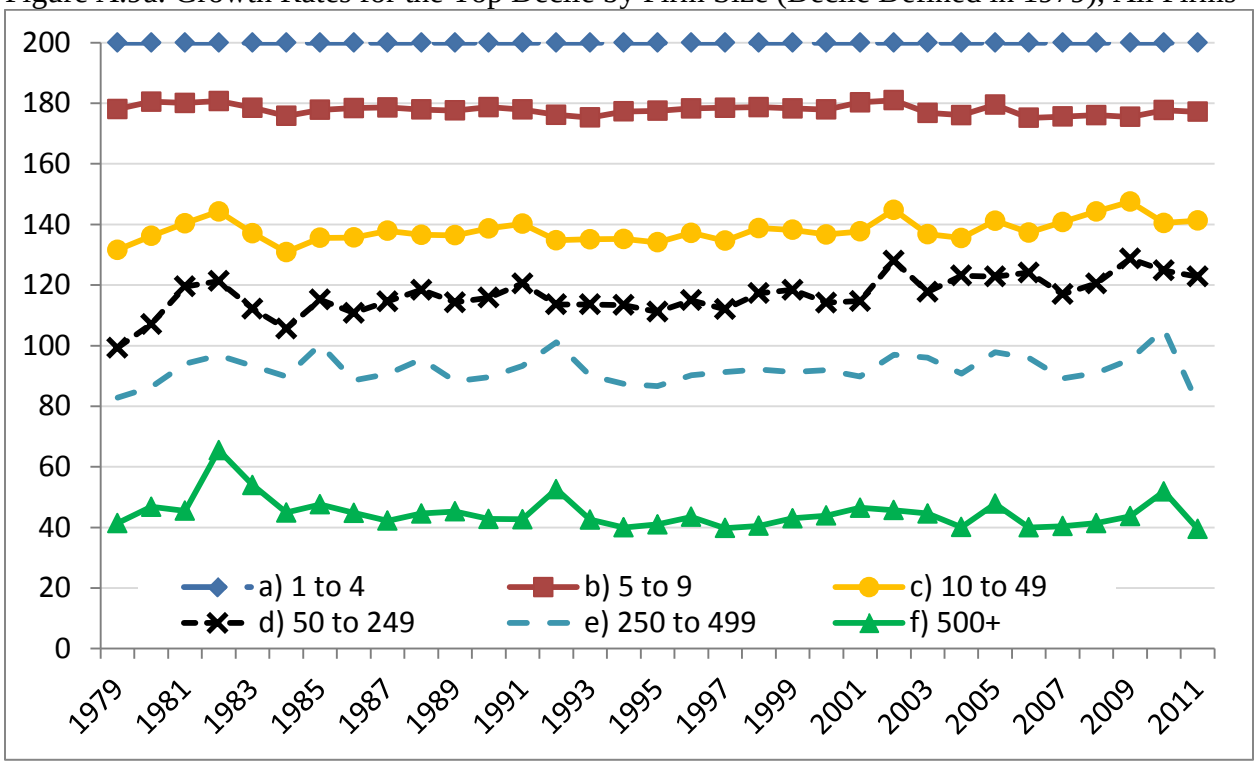
Note: Cohorts are defined by decade of initial public offering. Author calculations from Compustat.

Figure A.8: Within-Firm Volatility for Publicly Traded Firms (Overall and Controlling for Cohort Effects)



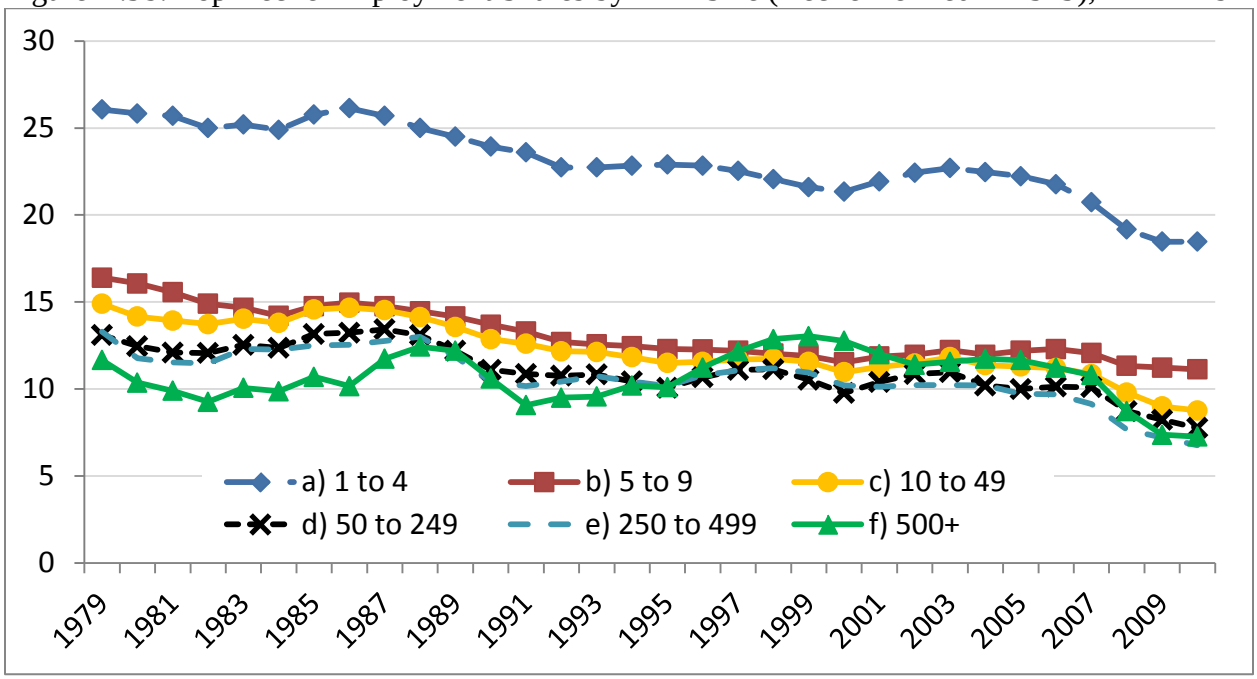
Note: Author calculations from Compustat.

Figure A.9a: Growth Rates for the Top Decile by Firm Size (Decile Defined in 1979), All Firms



Note: Chart depicts employment-weighted average growth rates by size class for firms with growth rates exceeding the 90th percentile (employment-weighted distribution) as of 1979. Author calculations from the Longitudinal Business Database.

Figure A.9b: Top Decile Employment Shares by Firm Size (Decile Defined in 1979), All Firms



Note: Chart depicts the share of employment of each size class that is at firms with growth rates exceeding the 90th percentile (employment-weighted distribution) as of 1979, as 3-year centered moving averages. Author calculations from the Longitudinal Business Database.