

The Secular Decline in Business Dynamism in the U.S.

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The pace of business dynamism in the U.S. has declined over recent decades. The decline is evident in a pronounced declining trend in the pace of both gross job creation and gross job destruction and in declining trends in alternative measures of establishment and firm level volatility. An important component of these declining trends is a marked decline in the firm startup rate. A recent finding in the literature is that the changing composition of U.S. businesses cannot account for the decline in dynamism. This is partly because the changing industrial composition of the U.S. economy actually works in the opposite direction. The implication is that much of the decline in dynamism should be viewed as occurring within detailed industry, firm size and firm age categories. To explore the factors underlying this within-cell decline in dynamism, we address two sets of closely related questions in this paper: First, what types of startups have exhibited the largest decline and, relatedly, what types of businesses have exhibited the largest decline in dynamism? Second, is the decline in dynamism accounted for by a decline in the variance of idiosyncratic shocks impacting firms or by a decline in the responsiveness of firms to the shocks?

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A hallmark of market economies, such as the United States, is the reallocation of resources from less-valued or less-productive activities to more-valued or more-productive ones. Business dynamics – the process of business birth, growth, decline and exit – is a critical component of the reallocative process. An optimal pace of business dynamics balances the benefits of productivity and economic growth against the costs associated with reallocation – which can be high for certain groups of firms and individuals. While it is difficult to prescribe what the optimal pace should be, there is accumulating evidence from multiple datasets and a variety of methodologies that the pace of business dynamism in the U.S. has fallen over recent decades and that this downward trend accelerated after 2000 (see Davis et. al. (2007), Haltiwanger, Jarmin and Miranda (2011), Reedy and Litan (2011), Hyatt and Spletzer (2013) and Decker et. al. (2014)).

Recent work (see, e.g., Decker et. al. (2014)) shows that a critical factor in the decreasing pace of business dynamics is a declining business startup rate and the associated decreasing role of dynamic young businesses in the economy. Young businesses exhibit a higher pace of both job creation and destruction, so the declining share of young businesses helps account for the declining pace of measures of business dynamism. As we discuss below, distinguishing between the type of startups and young businesses exhibiting these declines is important and one of the core areas of inquiry of this paper. Other insights come from examining the type of businesses that have exhibited the largest declines.

Why might it be important to distinguish between different types of startups and entrepreneurial activity? Schoar (2010) offers a useful structure for thinking about this question by distinguishing between “subsistence” and “transformational” entrepreneurs. She makes this distinction in the context of firms in emerging economies, but we think this distinction has merit for advanced economies as well. “Subsistence” entrepreneurs are startups or small businesses with little prospects for growth. They were created out of necessity or choice for the entrepreneur to provide productive activity for themselves and perhaps a few others (in many cases, family members). Such businesses have little prospect for innovation or growth. Indeed, the evidence presented in Hurst and Pugsley (2012) suggests that most startups and young businesses in the U.S. were created with

little intent for innovation or growth. Alternatively, “transformational” entrepreneurs are those startups that are engaged in innovative activity that have the potential for high growth. These are the entrepreneurs in models of technological progress where startups are those with the potential to make substantial advances in product or process innovation (e.g., Acemoglu et. al. (2013)). These are models with some form of vintage technology assumption that suggest well-established businesses are less in a position to make major innovations.

Cross sectional evidence of post-entry dynamics of young businesses in the U.S. yields patterns that are consistent with this dichotomy (see Haltiwanger, Jarmin and Miranda (2013) and Decker et. al. (2014)). Most startups in the U.S. either fail or don’t grow. But a small fraction of startups exhibit very high growth. It is the latter businesses that account for a substantial fraction of job creation in the U.S. Acemoglu et al (2013) provide supportive evidence in that they show that amongst firms that are engaged in innovative activity (e.g., R&D expenditures or issuing a patent some time over their life cycle), young businesses have much higher innovation intensity and growth than their more mature counterparts. Additional supportive evidence is found in the relationship between growth and survival and productivity in the micro data. Foster, Haltiwanger and Grim (2013) show that high-productivity businesses are much less likely to exit and have much higher growth rates than low-productivity businesses. Moreover, the marginal effect of productivity on growth and survival is much larger for young businesses.

A reduction in the pace of startups that are subsistence entrepreneurs has very different implications for growth and productivity from a reduction in the pace of transformational entrepreneurs. For example, evidence from Jarmin, Klimek and Miranda (2005) and Foster, Haltiwanger and Krizan (2006) suggests that, over time, it may have become less advantageous to start a “Mom or Pop” retail store. They also show that such “Mom and Pop” stores have high rates of exit and account for a declining share of activity in favor of large, national chains. This by itself yields lower firm volatility and a slower pace of reallocation but without adverse implications for productivity growth. Indeed the evidence in Foster, Haltiwanger and Krizan (2006) suggests that this change in business structure in retail trade has been productivity enhancing as the exiting low productivity “Mom and Pop” stores have been replaced by higher productivity stores

from large, national chains. In contrast, the framework of Acemoglu et. al. (2013) suggests unfavorable implications from a decline in the entry and growth of young innovative businesses. In their framework, older incumbents still invest in innovative activities but they have less capacity to make major innovations. They show that well-intentioned policies that subsidize such older incumbents (e.g., through bailout policies intended to protect the jobs of the large, incumbent firms) will stifle the entry and growth of younger, more innovative firms. They show that such a reduction in young, innovative (i.e., “transformational”) entrepreneurs can have significant adverse consequences for growth and productivity.

We explore these issues by characterizing the type of startups that have exhibited declines in the last several decades. In principle, our objective is to quantify the extent to which the decline has been more in terms of subsistence or transformational entrepreneurs. Identification of these different types of entrepreneurs is obviously a challenge as this classification of firms does not emerge directly from the data. More generally, this conceptual dichotomy is stark while reality may be more nuanced. Entrepreneurs that start what they regard as a niche business for personal reasons may discover they have a product or process with high growth potential.

We investigate these issues by comparing and contrasting differential patterns across sectors (e.g., the patterns in retail trade vs. high tech sectors) as well as the evolution of the full distribution of firm growth rates across firms in different sectors and of different ages. The presence of transformational entrepreneurs is arguably indicated by the high-growth firms discussed above. We investigate the extent to which the decline in dynamism for businesses of different ages is associated with declines in the upper or lower tails of the growth rate distribution.

The second set of questions we investigate is motivated by canonical models of firm dynamics such as Jovanovic (1982), Hopenhayn (1992), Hopenhayn and Rogerson (1993) and Ericson and Pakes (1996). These models suggest that the observed pace of firm volatility is driven by the interaction between the idiosyncratic shocks and the frictions of adjustment (entry, exit, expansion, contraction) for firms. Simply put, these models suggest that a decline in dynamism has two possible sources. One is a decline in the intensity of idiosyncratic shocks inducing firm dynamics. The other is an increase in the frictions associated with the adjustment

of firms. We investigate these issues for the manufacturing sector where we can measure firm-level TFP to capture idiosyncratic shocks along with the observed patterns of growth and survival.

The paper proceeds as follows. Section II describes the data and the measures of firm growth and volatility that we use in our analysis. Section III presents basic facts about the declining pace of business dynamism. Section IV starts by providing analysis of the role the changing composition of businesses has in accounting for the decline in dynamism in the economy. An exploration of the differences in the patterns of declining dynamism across different sectors follows. Section V examines what types of entrepreneurs have declined. In section VI, we turn to whether the evidence implies a change in the distribution of shocks or a change in the response to those shocks. Concluding remarks are in section VII.

II. Business Dynamics Data

Most of the findings reported in this paper are based on the Census Bureau's Longitudinal Business Database (LBD)¹ and the public domain statistics on business dynamics that have been generated from the LBD – namely, the Business Dynamics Statistics (BDS).² 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 currently runs through 2011. 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

¹ 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).

² BDS data are available at <http://www.census.gov/ces/dataproducts/bds/>.

control instead of being based on an arbitrary taxpayer ID.³ 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 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 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 as a legal entity continues operations. 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 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

$$Z_{it} = .5 * (E_{it} + E_{it-1}).$$

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 et al 1996, and Tornqvist, Vartia, and Vartia 1985). We refer to this as

³ A closely related database at the BLS 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.

the DHS growth rate. This critically permits us to construct measures of firm and establishment level volatility 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 organization change, we compute the period $t-1$ to period t net growth rate for a firm as the sum of the appropriately weighted DHS net growth rate of all establishments owned by the firm in period t , including acquisitions, plus the net growth attributed to establishments owned by the firm in period $t-1$ that it has closed before period t . 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.

We use the establishment- and firm-level growth rate measures to compute not only net growth but also job creation and job destruction (and the related job creation from entry and job destruction from exit). At the establishment level, job creation is measured as the employment gains from all new and expanding establishments and job destruction as the employment losses from all contracting and closing establishments. At the firm level, job creation is measured as the employment gains from all expanding and new firms and job destruction as the employment losses from all contracting and exiting firms. By construction, our methods of computing growth imply that firm-level measures of job creation and destruction are lower than establishment-level measures since the latter includes within-firm reallocation of jobs across establishments. For these measures, we follow the approach developed by Davis, Haltiwanger and Schuh (1996) (hereafter DHS).

We focus on measures of business dynamics based on both establishment-level and firm-level volatility. One measure commonly used in the literature 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 employment-weighted 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 $z_{it} = 0.5 * (E_{it} + E_{it-1})$ the size of firm i at time t , and 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

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

where $\bar{\gamma}_{it}^w$ 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 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 also note that we compute this measure at the establishment level in an analogous fashion.

III. The Decline in Business Dynamism

We now describe the basic secular trends in the measures of firm- and establishment-level volatility. Figure 1 presents six different measures: firm- and establishment-level job reallocation, firm and establishment employment weighted standard deviations of growth rates, and within-firm and within-establishment level measures of volatility. All measures exhibit a pronounced secular decline. The cross sectional measures exhibit more high-frequency cyclical variation. Table 1 summarizes the extent of the decline. To abstract from cyclical variation, Table 1 shows the long differences from the average during the 1987-89 period to 2004-06 period in terms of percentage declines. All measures decline by over 10 percent over this period. 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. We exploit the high correlations in what follows by using a variety of different measures. 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.

Figure 2 shows the 90-10 gap in firm growth rates from the employment-weighted distribution of firm-level growth rates. The 90-10 gap for all firms (including entry and exit) as well as for continuing firms is depicted. To facilitate focusing on the trends, the Hodrick-Prescott trend is also included. It is apparent that there is a secular decline in the 90-10 differential for all and continuing firms. 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 in the trend, the second half of the 1990s exhibits a more modest decline, and then there is a sharp decline again in the post 2000 period.

The decline in dispersion in firm-level growth rates for continuing firms implies that the decline in volatility is not simply driven by a decline in firm entry and exit rates. This is a theme we return to later. Figure 3 provides further perspective on this point showing the firm entry and exit rates directly. The firm entry rate (what we also often call the startup rate) exhibits a pronounced secular decline. The firm exit rate does not. Since 2008 the rate of net entry has turned negative.⁴

In the next section we explore the extent to which compositional shifts explain the declines observed in the data. Before doing so, however, it is important to emphasize that the trends discussed in this section 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 job destruction is closely linked to the secular decline in the inflow rate to unemployment (both at the national and sectoral level). Davis, et al. (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. 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 LEHD data on hires, separations, job creation and job destruction.

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 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

⁴ This is a point emphasized by Hathaway and Litan (2014).

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.

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

As is now well documented in the recent literature, underlying these trends are structural shifts that lead to changes in the composition of firms in the economy. In this section, we provide our own brief summary of these findings with our data and methodology. This helps to provide a basis for our subsequent analysis. In this section, we focus most of our attention on the two most important compositional factors – the changing distribution of firm age and the changing sectoral composition of activity.

We begin by examining the role of firm age. The decreasing startup rate shown in Figure 3 naturally leads to a reduction in the number of young firms operating in the economy. As emphasized by Decker et. al. (2014), the share of young firms (age five or less) in the economy and their share of economic activity have experienced significant declines. The share of employment at young firms in the U.S. economy declined from an average of 18.9 percent in the late 1980s to an average of 13.4 percent at the peak before the Great Recession, a 29 percent decline over a 17-year period. Similarly, their contribution to the share of firms and job creation declined by 17 percent and 14 percent, respectively, from a high in the late 1980s of 46.6 percent and 38.7 percent, respectively. The decline in the share of young firms has important implications for the pace of business dynamics. For example, establishments of young (≤ 5 years old) firms have a pace of reallocation that is on average twice as large as the pace of reallocation of more mature (6+) firms. This implies the shift towards older firms will contribute to the decline in measures of business dynamics.

Turning to changes in the sectoral composition, there are well known shifts away from manufacturing activities and toward the retail and service sectors over the last several decades. These three sectors alone account for about 72 percent of employment in 1980 and about 76 percent of employment in 2011, but the composition among the three has changed dramatically. In 1980, manufacturing accounted for 28 percent and

services 24 percent. In 2011, manufacturing accounted for only 11 percent and services 43 percent.⁵

The pace of job reallocation varies systematically by industry. Differences in minimum efficient scale, capital intensity, skill mix, the distribution of technology, demand and cost shocks all vary systematically across industries, and these factors contribute to differences in the pace of job reallocation. Examination of the patterns across broad sectors shows substantial differences. For example, the annual pace of job reallocation in the information sector is 39 percent of employment, compared with 34 percent in the retail sector, 31 percent in the service sector and 23 percent in the manufacturing sector. The shift away from manufacturing to retail, services and the information sector will work in the opposite direction than that of firm age. That is, this structural change should have led to an increase in the pace of business dynamics.

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, 500-1000, 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 whether the firm operates in multiple geographic locations) and 29 different years between 1982 and 2011.⁶ Note that startups are simply those firms with age zero.

⁵See Appendix Figure A.1 for details.

⁶We 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. We note that that these consistent NAICS codes have not yet been incorporated into the BDS, so our illustrative analysis of sectoral composition shifts in Figure 5 is on an SIC basis. But as noted in footnote 7, the broad sector patterns are quite similar on a NAICS basis.

For this purpose, we focus on the establishment-level job flow measures 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 vs. cross sectional measures of volatility. To quantify the extent to which compositional shifts in the characteristics of firms in the U.S. account for the aggregate secular declines in creation and destruction, we use a standard 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:

$$F_{it} - F_{it_0} = \Delta F_{it} = \sum_{c \in i} s_{ct_0} \Delta F_{ct} + \sum_{c \in i} F_{ct_0} \Delta S_{ct} + \sum_{c \in i} \Delta F_{ct} \Delta S_{ct}$$

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 extent to which compositional changes (captured by both the between and 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 4 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 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. (2012) 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 all in all it is not that surprising that size contributes less than business age.

It is apparent that there are offsetting composition effects, with shifts towards less volatile older, larger and multi-unit establishment firms working one way and shifts toward the service and retail 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 considering all of these effects simultaneously, additional considerations become important as well. As we show in the next section, 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 4 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.

Looking Deeper – Patterns for Specific Sectors

Having examined the impact of compositional shifts on economy-wide job flows, it is useful to examine specific sectors in more detail. Figure 5 illustrates the secular

decline in the reallocation rate by NAICS sector using the same long differences as in Figure 4. As before, the difference between the actual rate and the within component is the component of the decline that is accounted for by changes in composition. There is wide variation in the decline across sectors. As a reference we plot the 5.8 percentage point decline in the economy-wide reallocation rate. Businesses in the construction, mining, retail, wholesale, and services sectors on average have experienced relatively large declines. All of these are high reallocation rate sectors. By contrast, businesses in the transportation-communication-utilities, manufacturing, finance, and information sectors have experienced relatively small declines. In this respect, we have observed some convergence in reallocation rates across sectors, with the high reallocation rate sectors experiencing the largest declines. The impact of compositional shifts also differs across sectors. The effects are relatively important in retail, wholesale, and services, where we account for 25.2 percent, 24.5 percent, and 26.9 percent respectively; but less so in manufacturing, finance, and the information sectors, where we account for hardly anything.

The tentative summary of results that would appear to emerge from the analysis so far (and consistent with the recent literature) is that there has been a widespread decline in measures of business dynamism that is largely a within-detailed-cell phenomenon. Some sectors have experienced substantially larger declines than others, and the changing composition of business types accounts for more of the decline in some sectors than others. The finding that retail trade is one of the sectors with the largest declines and that composition effects play a substantial (but hardly the only) role is consistent with the findings in the literature of the shift away from “Mom and Pop” single unit establishment firms to large, national firms in that sector.

It turns out, however, that looking at only the long differences by sector is somewhat misleading. Figure 6 shows the trends in job reallocation (using Hodrick-Prescott trends) for selected sectors. It is striking that the information sector and the FIRE sector exhibit increases in the pace of reallocation until about 2000 and then sharply decline thereafter. In a related fashion, Figure 7 shows the share of employment accounted for by young firms for the same sectors. 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 6 and 7 together highlight that not all sectors have exhibited a monotonic decline in indicators of business dynamism and entrepreneurial activity.⁷

The Information sector includes some (but not all) of the sectors that are high tech. Included are sectors such as software publishing (NAICS 5112) and internet service providers and web search portals (NAICS 5161), but there are other high tech sectors in Manufacturing such as computer hardware and peripherals (NAICS 3341). For this purpose, we follow a study by Hecker (2005) from the BLS on defining high tech sectors based on the 14 sectors with the largest shares of STEM workers. The 14 sectors are listed in Table A.2 in the appendix.⁸

Figure 8 shows the Hodrick-Prescott trends for the information sector, the high tech sector so defined and the manufacturing component of the high tech sector. All exhibit very similar patterns highlighting that there was a rising pace of business dynamism in the high tech part of the economy through 2000, but this has declined sharply 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, Fernald (2014) finds that there has been a trend slowdown in productivity shortly after 2000 driven by a slowdown in IT-producing and using industries. The data in Figure 8 exhibit similar patterns for high tech. There is of course an open question about which direction the causality goes, but it is apparent that the periods of a surge and slowdown in

⁷Figures A.2 and A.3 show the shift-share decompositions for the changes for the periods 1987-89 to 1997-99 and 1997-99 to 2004-04. The first subperiod shows that sectors such as Retail Trade exhibited the largest declines in the job reallocation rate with increases observed for FIRE and Information. For this first period, composition effects (mostly firm age changes) help account for a large fraction of the decline in the retail trade sector. In the second sub-period, the sectors with the largest declines are FIRE and Information. Composition effects account for only a relatively small fraction of these declines (although more for the Information sector consistent with Figure 7 showing the rapid decline in the share of young firm activity in Information after 2000).

⁸ 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.

productivity in the IT-producing and using industries correspond to a surge and slowdown in the pace of business dynamism in the high tech sector. In what follows, we will use this high tech sector to help gauge the patterns of business dynamism in this sector of importance for innovation and productivity growth.

The sectoral analysis offers insights as to whether we have observed a decline in subsistence or transformation entrepreneurs. The answer appears to depend upon sector and time period. During the 1980s and 1990s, the decline in startups and young business activity was especially large in sectors such as retail trade and services. Both sectors also exhibited a sharp decline in business dynamism. This is consistent with the view that over this period there was a substantial decline in “Mom and Pop/Subsistence” entrepreneurs especially in the important sectors of Retail Trade and Services. However, over this same period there was actually a rise in young business activity and a rise in dynamism in the Information and FIRE sectors (and in turn a rise in dynamism in the high tech sector including in the manufacturing component of high tech). But after 2000 there was a sharp decline in young firm activity in the Information sector and a sharp decline in indicators of dynamism in the Information and High Tech sectors. The latter patterns suggest that there may have been a more pervasive decline in transformational entrepreneurs in the post 2000 period. All of this is quite speculative, but we can dig deeper by examining the patterns of firm growth dynamics for high-growth (transformational) firms by firm age and sector. We turn to the latter analysis in the next section.

V. What types of Entrepreneurs Have Declined?

One way to investigate the importance of the distinction between transformational and subsistence entrepreneurs is to examine the full distribution of firm growth rates by firm age and sector. To help motivate this approach, it is useful to review briefly the findings from Haltiwanger, Jarmin and Miranda (2013) and Decker et. al. (2014). They show that young firms exhibit an “up or out” dynamic. 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) 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)). Less well known is that young firms exhibit enormous skewness in growth rates. The 90-50 gap for young firms (less than five years old) is on average about 63 percentage points, while the 50-10 gap is about 46 percentage points. This contrasts with a fairly symmetric growth rate distribution for mature firms, with both a 90-50 gap and a 50-10 gap of about 22 percentage points.. 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. We view these high growth young firms as being one way of identifying “transformational” entrepreneurs.⁹

We now turn to the evolution of the distribution of firm growth rates over time. Figure 9 shows the 90th percentile of firm growth rates for all firms and continuing firms smoothed with Hodrick Prescott trends. Both exhibit a pronounced decline. The decline in the 90th percentile for all is not surprising since all includes entry and exit. The decline in the entry rate alone will yield a decline in the 90th percentile for the all firm distribution, but the continuing firm distribution also exhibits a pronounced decline. Figure 10 shows the evolution of the 90th percentile for young and mature firms again smoothed with Hodrick-Prescott trends. The much higher 90th percentile for young firms than mature firms is quite evident. Interestingly, the 90th percentile for both young and mature firms is relatively stable through 2000 and then declines thereafter, especially for young firms. This implies that the overall decline in the 90th percentile is due to composition effects prior to 2000 as the share of young firms declines. But after 2000 there is a substantial decline in the 90th percentile, especially for young firms.

In terms of the transformational entrepreneurs dichotomy, the evidence in Figure 10 suggests that even before 2000 there has been a decline in the share of young transformational

⁹ One potential limitation of identifying transformational entrepreneurs via high growth is that this is based only on employment growth (and not in terms of sales growth, measures of innovative activity or productivity growth). But recent literature suggests that the high-employment-growth firms are both more innovative and more productive. Acemoglu et. al. (2013) show that among innovative firms that young firms have higher innovation intensity and have high growth. Foster, Grim and Haltiwanger (2014) show that high-productivity young firms have very high employment growth rates. We discuss this issue more in the concluding remarks.

entrepreneurs. This is evident in the decline in the 90th percentile for all continuing firms even with little change in the 90th percentiles for young or mature. One way to view these facts is that the economy was “rolling the dice” less frequently over the 1980s and 1990s with fewer startups and less young firms so that there was less chance of transformational entrepreneurs emerging. Given less young firm activity this contributes to a lower 90th percentile overall. Note that it is conceivable that the decline in young firm activity could have all been subsistence entrepreneurs. But if that were the case we would have expected to actually observe an increase in the 90th percentile for young firms as the share of transformational entrepreneurs among all young entrepreneurs could have been conjectured to have risen. After 2000, we find that not only is the economy rolling the dice less frequently but the likelihood of a young firm being a high-growth firm has declined as is evident through the declining 90th percentile for young firms.

Turning back to the high tech sector, Figure 11 shows that the 90th percentile for high tech firms exhibits a non-monotonic decline. It declined from the late 1970s to the early 1990s, then rose during the 1990s and then fell sharply post 2000. Again interpreting the high-growth firms through the lens of transformational entrepreneurs, we find that this key innovative sector (high tech) has exhibited a decline in the high-growth firms in the post-2000 period.

The decline in high-growth firms translates into declines in skewness of growth rates. This is not mechanical since it could be that the decline in the 90th percentile is matched by an increase in the 10th percentile so that we primarily observed a decline in dispersion and not skewness. But Figures 12.a and 12.b show that there has been a decline in skewness in growth rates (90-50 relative to 50-10 gap) for all firms and for high tech firms (including continuers). In all cases, skewness in growth rates has essentially been eliminated by 2011. Figure 13 shows the change in skewness of growth rates for young and mature continuing firms. There is a noticeable decline in skewness of growth rates in young firms after 2000 coincident with the decline in the 90th percentile for young firms at that time. Apparently, the 10th percentile did not rise concurrently for the young firms. If the decline in young firms were all subsistence entrepreneurs, we would have expected to see a decline in the exit rate (which from Figure 3 we don't see) and perhaps an increase in the 10th percentile (since there would be fewer subsistence firms that either don't grow or fail).

Further Insights from Publicly Traded Firms

Examining dynamics for publicly traded firms provides additional evidence. As documented by Comin and Philippon (2005) and Davis et. al. (2007), publicly traded firms also exhibit rising firm volatility through 2000. Like the high tech sector, though, publicly traded firms also exhibited a decline in measures of volatility in the post-2000 period. Figure 14.a shows that the (Hodrick-Prescott smoothed) 90-10 gap for publicly traded firms rose through about the early 2000s and then has fallen since that time.¹⁰ Figure 14.b shows that high-growth publicly traded firms also increased in the 1990s and then has fallen since about 2000. Figure 14.c shows that the skewness in publicly traded firms growth rates increased in the 1990s and has also fallen since the early 2000s. In all of these figures we also include the high tech sector which also exhibits similar patterns.

How does the rise and fall in volatility for publicly traded firms fit in with the evidence presented earlier? Davis et. al. (2007) showed that the rising volatility for publicly traded firms 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. 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. These patterns are evident in Figures 15 and 16 which shows the employment shares and the volatility of publicly traded firms using the 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 2000.¹¹

¹⁰ Figure A.3 shows that the patterns for within firm volatility for publicly traded firms is similar to the 90-10 gap. Figure A.4 shows within firm volatility for publicly traded firms using the COMPUSTAT data is quite similar to that for the LBD. Figure A.5 shows the within firm volatility using the COMPUSTAT data for employment growth vs. sales growth. A limitation of the latter is that sales (or gross revenue) growth is difficult to compare across industries. For example, some of the volatility using sales growth derives from the energy and financial sectors where revenue is very large at times volatile even if value added growth might not be. It would be preferable to compute volatility measures using value added growth but this is more of a measurement challenge. As an alternative in Figure A.5 we also compute measures of volatility using growth measures at the firm level taking out industry*year effects.

¹¹ The contribution of cohort effects is presented in Figure A.6. Figure A.6 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

IPOs can be thought of as transformational entrepreneurs, and the patterns of the new cohorts of publicly traded firms (i.e., IPOs) mimic what we have seen in terms of high-growth young firms and high-growth firms in the high tech sector. 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. It is true that the 1990s cohort of non-high tech firms also grew rapidly accounting for about 25 percent of non-high tech publicly traded employment in 1999. But the high tech component of the 1990s cohort also exhibits very high volatility relative to the non-high tech cohort (which also exhibits high volatility).

VI. Decline in Volatility of Shocks or Response to Shocks?

Since the decline in volatility is largely a within-cell decline (albeit with different time series patterns across sectors and compositional effects playing a larger role in some time periods and sectors than others), it must be the case that the decline in volatility is either due to a decline in the volatility of shocks impacting firms or a decline in the response to those shocks. In this section, we investigate these issues for the U.S. manufacturing sector. The focus on manufacturing is necessitated by data considerations. The manufacturing sector provides high-quality annual data to construct establishment-level measures of TFP. Manufacturing does not exhibit the largest secular decline, but its decline is still substantial.

For this purpose, we build on the data infrastructure and methodology from Foster, Grim and Haltiwanger (2014) (hereafter FGH). The latter construct a consistent plant-level TFP database for all plants in the Annual Survey of Manufactures (ASM) and the Census of Manufactures (CM). A limitation of the ASM is that while it is representative in any given year it is a rotating sample so its longitudinal properties are inferior to those of the LBD. Following FGH we integrate the ASM/CM TFP data into the LBD. For the LBD we have the outcomes in terms of establishment-level growth for all manufacturing establishments. For the integrated

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 16, which shows a sharp decline in within-cohort volatility for all cohorts but especially the 1980s and 1990s cohorts.

ASM/CM/LBD we have a subset of those establishments for which we can measure TFP. We use propensity score weights to adjust the ASM/CM/LBD sample so that it matches the complete LBD for manufacturing in terms of the detailed industry, size and age distributions (see FGH for details).

The plant-level TFP measure we use is an index similar to that used in Baily, Hulten and Campbell (1992) and a series of papers that built on that work.¹² The index is given by:

$$\ln TFP_{et} = \ln Q_{et} - \alpha_K \ln K_{et} - \alpha_L \ln L_{et} - \alpha_M \ln M_{et} \quad (1)$$

where Q is real output, K is real capital, L is labor input, M is materials, α denotes factor elasticities, the subscript e denotes individual establishments and the subscript t denotes time. Details on measurement of output and inputs are in FGH but we provide a brief overview here. Nominal output is measured as total value of shipments plus the total change in the value of inventories. Output is deflated using an industry-level measure from the NBER-CES Manufacturing Industry Database. Capital is measured separately for structures and equipment using a perpetual inventory method. Labor is measured as total hours of production and non-production workers. Materials are measured separately for physical materials and energy where each is deflated by an industry-level deflator. Outputs and inputs are measured in constant 1997 dollars. Factor elasticities are estimated using industry-level cost shares (of total factor costs). A Divisia index approach is used for the latter so that industry-level cost shares are permitted to vary over time.

Given the large differences in output and input measures across industries (for example, steel versus food), our TFP measures need to control for industry differences in any comparison over industries. We do this by creating measures of (log) TFP that are deviations from the industry-by-year average. We refer to this as TFP in the remainder of the paper, but it should be interpreted as the deviation of establishment-level TFP from the industry-by-year average.

Our measure of productivity is a revenue-based measure of productivity. This means differences in establishment-level prices are embedded in our measure of productivity. Unfortunately, the Census Bureau does not collect establishment-level prices. However, as Foster, Haltiwanger and Syverson (2008) (henceforth FHS) have shown, it is possible to back-out the establishment-level price effects for a limited set of products in Economic Census years

¹² Syverson (2011) provides an excellent summary.

(years ending in “2” and “7”). FHS create a physical quantity measure of TFP removing the establishment-level price for establishments producing a set of 11 homogeneous goods (for example, white pan bread). The within-industry correlation between revenue and physical productivity measures in FHS is high (about 0.75). However, FHS also find there is an inverse relationship between physical productivity and prices consistent with establishments facing a differentiated product environment. In addition, FHS find establishment-level prices are positively related to establishment-level demand shocks. As such, our measure of establishment-level productivity should be interpreted as reflecting both technical efficiency and demand factors. More recent work by FHS suggests demand conditions vary substantially by establishment age – and as such the variation in our measure of TFP across establishments of different ages may reflect demand factors more than differences in technical efficiency.¹³ However, we only capture the demand factors as they translate into establishment-level prices.

We undertake two types of exercises. First, we examine the evolution of the within-industry dispersion in (log) TFP. This is a proxy for the intensity of idiosyncratic shocks impacting establishments. Figure 17 shows the evolution of the within-industry 90-10 gap in productivity and the standard deviation of (log) TFP. Consistent with the literature (see, e.g., Syverson (2004,2011)) there is large dispersion in TFP across plants in the same industry. The standard deviation exceeds 30 log points in all periods and the 90-10 gap exceeds 70 log points. Moreover, the evidence suggests that this dispersion is, if anything, rising over time. One concern might be that this measured dispersion is capturing permanent differences across plants. However, estimation of a simple AR1 for continuing establishments shows that while plant-level productivity is persistent the first order autocorrelation coefficient is far below one (we estimate it to be about 0.65). Moreover, most of the variance in the TFP shown in Figure 17 is accounted for by the variance of the innovations to TFP.¹⁴ We also find no evidence that the AR1 coefficient has been changing much over time. We interpret Figure 17 as implying that there is no evidence that there has been a decline in the dispersion of the idiosyncratic shocks.

We look at the response of establishments to realizations of TFP on both the extensive

¹³ See Foster, Haltiwanger and Syverson (2013).

¹⁴ In estimating the AR1 specification, we exclude ASM first panel years and Census years since it is those years for which we don't have a representative sample of plants with measured TFP in year t and $t-1$. It is for this reason we prefer to use the TFP measure rather than the innovations in the analysis that follows. But we explore the impact of the innovations to TFP and the changing response to such innovation in appendix Table A.2.

and intensive margins through empirical specifications relating growth and survival to productivity.¹⁵ We consider two samples when looking at establishment growth. First, we look at growth for all incumbent establishments; those that exist in period t . Second, we consider only establishments that are continuers from t to $t+1$. The use of the DHS growth rate facilitates using both the “all establishments” sample and the “continuing establishments” sample. Recall, with the DHS growth rate, we have a bounded dependent variable and, when using all establishments, we have observations at the lower bound of -2. Likewise, in the exit equation, we use a linear probability specification with the left hand side variable equal to one if the establishment exits and zero otherwise. Equation (2) shows our basic specification:

$$Y_{e,t+1} = \lambda_{t+1} + \beta * TFP_{et} + \delta * TFP_{et} * Trend_{t+1} + X'_{et}\Theta + \varepsilon_{e,t+1} \quad (2)$$

where Y is a set of outcomes for establishment e at time $t+1$, TFP is total factor productivity for establishment e at time t deviated from industry-by-year means, $Trend$ is a simple linear time trend, and X_{et} is a set of controls discussed further below. Note that $Trend$ is not entered in as a main effect by itself since there is a full set of time effects. The latter capture general trends as well as cyclical effects. There are three outcomes (all measured from t to $t+1$): “Overall Growth” (continuers+exit), “Exit,” and “Conditional Growth” (conditional on survival - i.e., continuers only). In considering the specification, timing is important. We explore the determinants of growth and survival from t to $t+1$ based on the realized productivity of the establishment in period t .

While this is a reduced form specification, it is broadly consistent with the specifications of selection and growth dynamics from the literature. There is already much evidence that high-productivity establishments are more likely to survive and grow (see, e.g., Syverson, 2011). Put differently, standard models of exit in the literature relate the decision to exit between t and $t+1$ to the realization of TFP in period t along with other controls (e.g., controlling for the endogenous state variables such as size which is part of our X_{et} as described below. In a similar fashion, adjustment cost models of employment growth relate the growth in employment from period t to $t+1$ to the realization of TFP in period t along with period t size.

¹⁵ Our approach is closely related and builds on the specifications in FGH. The latter was interested in how the response to TFP changes over the cycle. We are interested in the secular trends in the response.

Our interest is in investigating whether the response to idiosyncratic productivity realizations has changed over time. We are exploring this in a simple fashion via the interaction between *Trend* and TFP. We estimate this specification for 1981-2010 with the following controls as captured by X_{et} . For the latter we include establishment size, firm size, state effects and a state-level business cycle indicator (the change in state-level unemployment rate).¹⁶ We interact the state-level cyclical indicator with plant-level TFP following FGH. Since we are interested in the changing response and the Great Recession is at the end of our sample, we don't want our estimate of δ (the main coefficient of interest) to be driven by the changes in the response to TFP over the cycle.

Table 2 shows the estimates for the main specification for all three outcomes. The first row of the table confirms what many others have found – establishments with high realizations of TFP in period t are more likely to grow and less likely to exit. Of more interest is the second row. We find that there is evidence of declining response of both growth and survival to realizations of TFP over time. The trend effects are highly statistically significant; we provide perspective on the quantitative significance below. Before turning to the latter, we explore some additional specifications in Tables 3 and 4. In Table 3, we permit the responses to realizations of TFP to differ by firm age (that is, by the age of the parent firm). We find that establishments of young firms are much more responsive to TFP realizations than more mature plants and that the trend decline in response is substantially larger for plants of young firms. In Table 4, we investigate whether there is evidence of an accelerated decline in trend response post 2000 since earlier evidence suggests an acceleration of the decline in measures of business dynamism after 2000. We find evidence that there has been an acceleration of the declining response post 2000, particularly for establishments of young firms.

How quantitatively important are the estimated effects? To address this question we consider two related counterfactual exercises based on the estimated model. For this purpose, we focus on the estimates in Table 2 for overall growth. In each year in the actual data, we observe the plant size distribution in terms of employment and the plant realizations of TFP. In considering the latter, it is important to emphasize that by this we mean the realization of TFP

¹⁶ For firm size effects, we use firm size classes in period t . For establishment size effects, we have considered both establishment size classes and log employment at the establishment level in period t . We obtain very similar results for both cases, and in the paper we use log employment at the establishment level.

within the detailed industry-by-year cell so we are exploiting where plants fall within their industry-by-year distribution in any given year. Using the estimated model, we can compute predicted DHS growth rates for all these plants from t to $t+1$. For this purpose, we use only the TFP, establishment size and cyclical effects, effectively holding the other controls constant (e.g., geographic distribution). Using the predicted growth rates we first compare the distribution of establishment-level growth rates from t to $t+1$ in the actual data vs. the predicted distribution. We report this exercise in Figure 18 using the interquartile range of establishment-level growth rates. The actual 75-25 gap exhibits some cyclical variation (rising during recessions) but a downward trend. For the predicted distributions we consider two cases. The first is where we include the trend effect and the second is with the trend effect set to zero. It is apparent that the dispersion in TFP (and size) across establishments is only able to account for a fraction of the dispersion in establishment-level growth rates. However, it is also apparent that the downward trend in the response to TFP yields a non-trivial quantitative effect. For example, abstracting from the cyclical variation by using the 1987-89 to 2004-06 change, the actual dispersion in establishment-level growth rates declines by 19 percent while the predicted dispersion declines by 20 percent. We note that even without the trend there is some decline in predicted dispersion, presumably reflecting changes in the distribution of establishment size over time. Moreover, we note that the predicted model only captures a small fraction of the actual cyclical changes in dispersion in establishment-level growth rates.

The second counterfactual exercise follows in the spirit of the accounting decompositions of productivity growth in Foster, Haltiwanger and Krizan (2001) and Foster, Haltiwanger and Syverson (2008). We consider counterfactual changes in the employment-weighted average productivity across plants. Since our measure of productivity is within industry and year this can be considered a counterfactual of the change in the within-industry employment-weighted average productivity. The counterfactual is constructed as follows. First, for each year we construct the actual employment-weighted average productivity using the actual employment and actual TFP in the data.¹⁷ Second, we compute the counterfactual predicted

¹⁷ One limitation is that the index of industry productivity growth underlying this counterfactual is based on the change between t and $t+1$ of employment-weighted log TFP. A preferable index would be an output- or composite input-weighted index. We have investigated and found that the employment-weighted index is highly correlated (0.8) with an output-weighted index. Another concern is that the output- or input-weighted index differs from

employment-weighted average using the model to predict the change in employment weights. For this purpose, we use the two predicted counterfactuals used in Figure 18. The difference between the predicted employment-weighted average productivity and the actual is an estimate of how much the employment-weighted average is being generated from the predicted changes in employment weights. We have two different counterfactuals – one with the trend effect and one without . To generate the predicted effect of the decline we compute the difference between these two estimates of the productivity gain from changing employment weights. In that respect, it is a diff-in-diff estimate of the impact of the declining response. Figure 19 shows the resulting diff-in-diff counterfactual prediction. Compared to the early 1980s, the declining trend response yields a prediction of almost 1 log point annual reduction in average employment-weighted productivity by the end of the sample

The findings in this section imply that the decline in measures of dynamism in the manufacturing sector is not due to a decline in the realizations of idiosyncratic productivity shocks but rather a decline in the response to such shocks.¹⁸ Moreover, the evidence suggests that this potentially yields a decline in within industry productivity growth since the reallocation of employment from low- to high-productivity businesses has slowed down. We say potentially in spite of the strong predictions from Figure 19 as those results should be viewed as a result holding other factors constant. While the results imply a reduced response of growth and survival to realizations of TFP, it matters why there has been a reduced response. Even if it is due to an increase in adjustment frictions, the increase might be due to changes in the organization of businesses that are productivity enhancing. For example, Cairo (2013) offers evidence that the training requirements of jobs have increased due to both the changing occupational mix of jobs and increases in training requirements within jobs. She develops a model where increased training requirements reduce the pace of job reallocation in the economy. She models this change in training requirements as an increase in adjustment costs, so that it is

standard industry-level productivity growth indices. We have found that the output- and employment-weighted indices are highly correlated with the latter (again about 0.8).

¹⁸In Appendix Figure A.7 and Table A.3 we explore the same questions for high tech manufacturing. Figure A.7 shows a rising trend in idiosyncratic productivity realizations in high tech manufacturing. Table A.3 shows that young plants in these sectors exhibited a rising response to productivity realizations through 2000 and a falling response thereafter. Older plants exhibited a declining response throughout. In terms of the main questions of this section, for high tech manufacturing we find evidence suggesting that it is changing response rather than changing shocks that accounts for the change in volatility.

consistent with the findings in this section. However, she argues that the increased training requirements may be due to a change in technology and the skill mix needed in responses to such changes. As such, there may be within-plant changes in productivity induced by these changes that offset the declines in productivity growth in Figure 19. Still Figure 19 implies that the decline in response has important implications for the contribution of reallocation to productivity growth over time.

VII. Concluding Remarks

There has been a pervasive decline in indicators of business dynamism over the last several decades. One important factor is the decline in business startups and the associated decline in the share of business activity accounted for by young businesses. However, changes in the firm age distribution can only account for a fraction of the overall decline in dynamism. In addition, changing industrial composition works in the opposite direction of the changing age distribution. The industrial structure has changed away from sectors with relatively low dynamism (manufacturing) to sectors with high rates of dynamism (services and retail trade). The implication is that most of the decline is within industry/firm age cells.

We investigate two sets of questions. First, what types of startups have declined, and in a closely related way, what types of businesses have exhibited the largest decline? Our evidence suggests that prior to 2000 the decline in “Mom and Pop” or “subsistence” entrepreneurs plays an important role. This is evident in the especially large decline in startups and measures of dynamism in the retail trade and service sectors. Interestingly, in the information and related high tech sectors, there was a rise in dynamism and young business activity through 2000. However, after 2000 the decline in business dynamism accelerated, and the underlying factors appear to have changed as well. After 2000, the information and high tech sectors exhibited sharp declines in measures of dynamism and entrepreneurial activity. In addition, it is after 2000 that we observe a decline in high growth businesses. We observe that through a decline in high-growth young businesses as well as high-growth businesses in the high tech sector. The decline in high-growth businesses is also accompanied by a decline in the rightward skewness of growth rates of businesses – again most notably for young businesses and for high tech businesses. The rightward skewness of the growth rates of young businesses and in high tech businesses is evidence that some young businesses and high tech businesses take off and disproportionately

account for growth. Recent research shows that such skewness underlies why historically startups make a long-lasting contribution to job creation. Strikingly, skewness of growth rates has largely been eliminated for all businesses and for high tech businesses by 2011. Moreover, skewness of growth rates for young businesses falls substantially after 2000. These post-2000 patterns suggest that the decline in dynamism in the post-2000 period involves a greater role for the decline in transformational entrepreneurs.

The second set of questions investigates whether the decline in within-industry dynamism is due to a decline in the volatility of idiosyncratic shocks impacting businesses or a decline in the response to such shocks. While our evidence for this analysis is confined to the manufacturing sector, our evidence shows that the decline in within-industry dynamism is all due to a decline in the response to shocks. Moreover, we show that this has potentially adverse effects on industry-level productivity growth since there has been a slowdown in the pace at which resources are being reallocated from low- to high-productivity businesses. We note that our findings don't identify the source of the decline in the response to shocks. The decline might be induced by a change in technology or business organization that has offsetting positive effects on productivity.

Our analysis makes progress on the nature and source of the declines in dynamism but there are many open questions for future research. One of the limitations of our analysis is that virtually all of our measures of business dynamism are based on the volatility of firm-level employment growth rates. It could be that our findings reflect changes in the dynamics of employment growth relative to other margins of adjustment for firms. For example, it might be that, historically, businesses with high draws of productivity rapidly expanded employment. However, more recently innovative businesses may be growing through adding machines or by expanding internationally. If so, our results are still of critical importance for job growth, but the interpretation and driving forces may be quite different. In future research, we plan to investigate these and other related issues.

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Table 1: Percentage Declines in Measures of Volatility

	Job Reallocation	Std Deviation	Within Volatility
Firms	-11.2	-10.0	-10.9
Establishments	-16.1	-11.2	-10.3

Table 2. Changing Responsiveness of Plant-Level Growth from t to t+1 to (log) TFP in t

	Overall Growth Rate (Continuers + Exitters)	Exit	Conditional Growth Rate (Continuers Only)
TFP	0.1878*** (0.0024)	-0.0629*** (0.0010)	0.0698*** (0.0014)
TFP*Trend	-0.0021*** (0.0001)	0.0002*** (0.00006)	-0.0020*** (0.00009)

* p < 0.10, ** p < 0.05, *** p < 0.01. Note all specifications have over 2 million observations. Controls include year effects, size effects, state effects, cyclical indicators at the state level interacted with TFP. This holds for all the regressions below.

Table 3. Changing Responsiveness of Plant-Level Growth from t to t+1 to (log) TFP in t

Overall Growth Rate

	All	Young	Mature
TFP	0.1878*** (0.0024)	0.3176*** (0.0056)	0.1518*** (0.0027)
TFP*Trend	-0.0021*** (0.0001)	-0.0057*** (0.0003)	-0.0009*** (0.0002)

See notes above. Note that the Young and Mature coefficients are estimated from a pooled specification with both young and mature that permits all of the TFP terms to be interacted with age indicator and the age indicators are in the set of additional controls as well.

Table 4. Changing Responsiveness of Plant-Level Growth from t to t+1 to (log) TFP in t

Overall Growth Rate

	All	Young	Mature
TFP	0.1818*** (0.0030)	0.2850*** (0.0070)	0.1537*** (0.0033)
TFP*Trend	-0.0011*** (0.0003)	-0.0016*** (0.0006)	-0.0012*** (0.0003)
TFP*Trend*Post2000	-0.0008*** (0.0002)	-0.0036*** (0.0005)	0.0002 (0.0002)

See notes above. Note that the Young and Mature coefficients are estimated from a pooled specification with both young and mature that permits all of the TFP terms to be interacted with age indicator and the age indicators are in the set of additional controls as well.

Figure 1: Alternative Measures of Business Dynamism

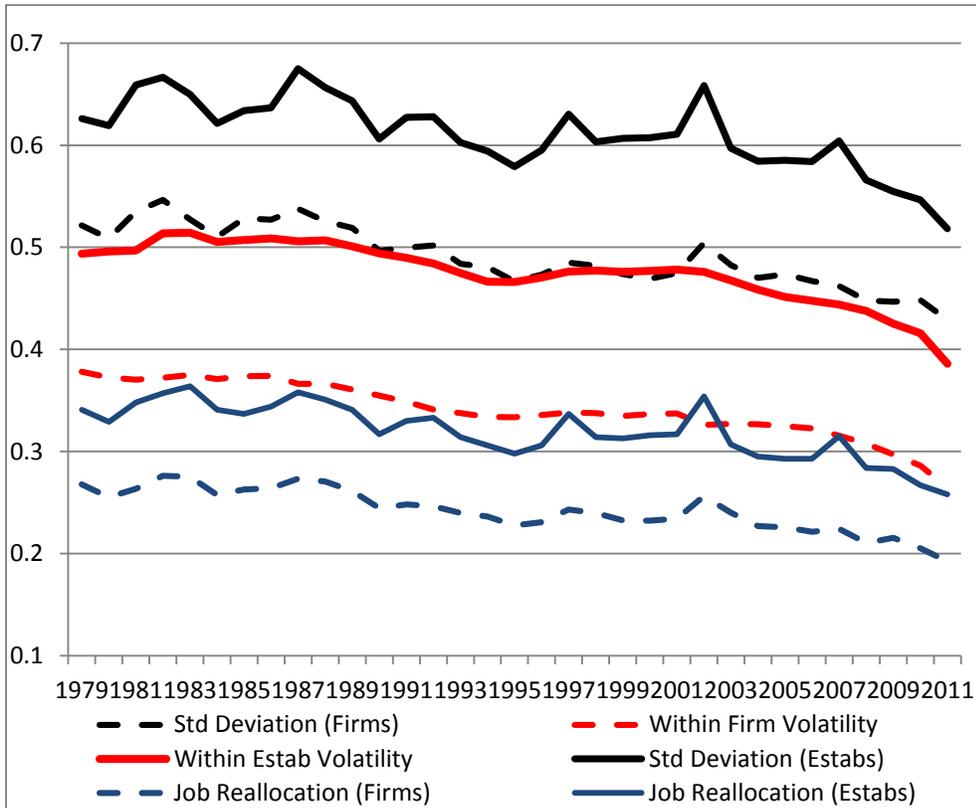


Figure 2: 90-10 Gap in Firm Growth Rates (Employment-Weighted Distribution)

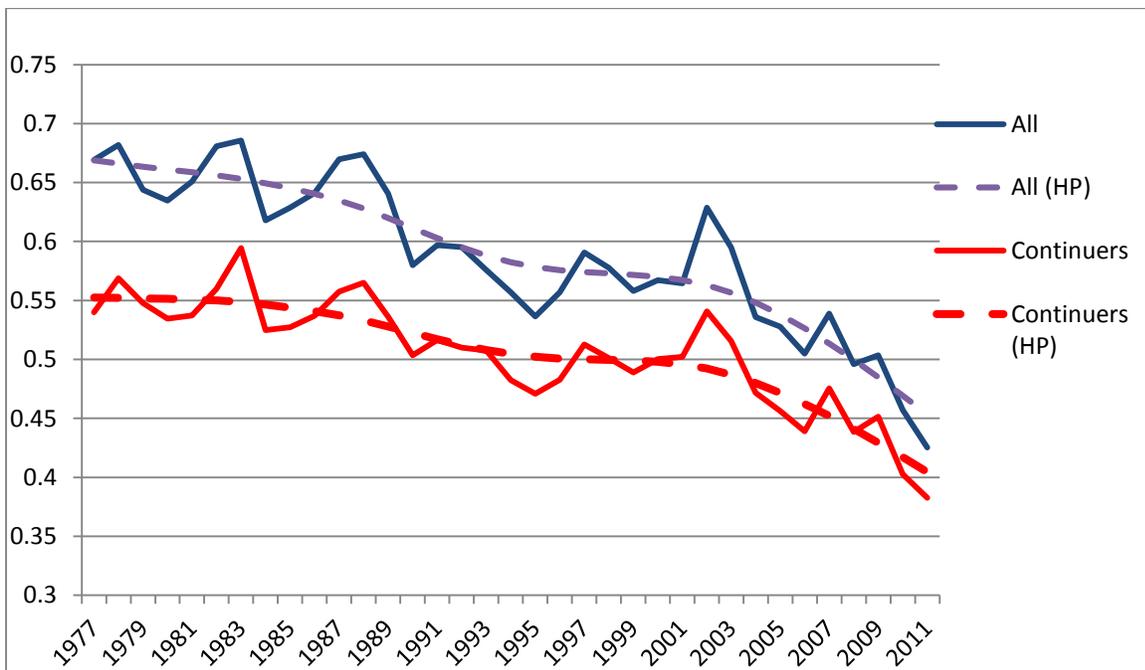


Figure 3: Annual Firm Entry and Exit Rates

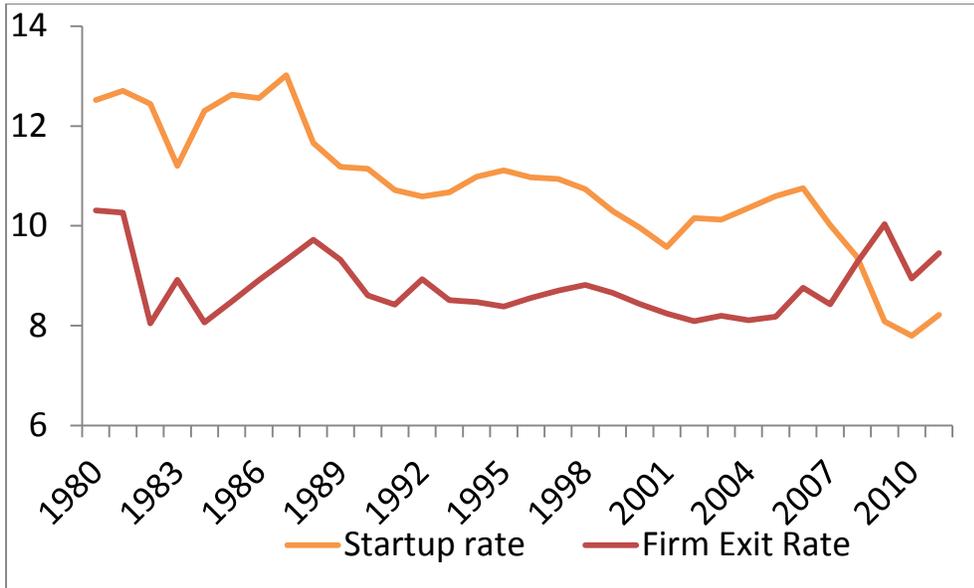


Figure 4: Percent of Decline in Job Flows Accounted for by Composition Effects, Private Sector, 1987-89 to 2004-06

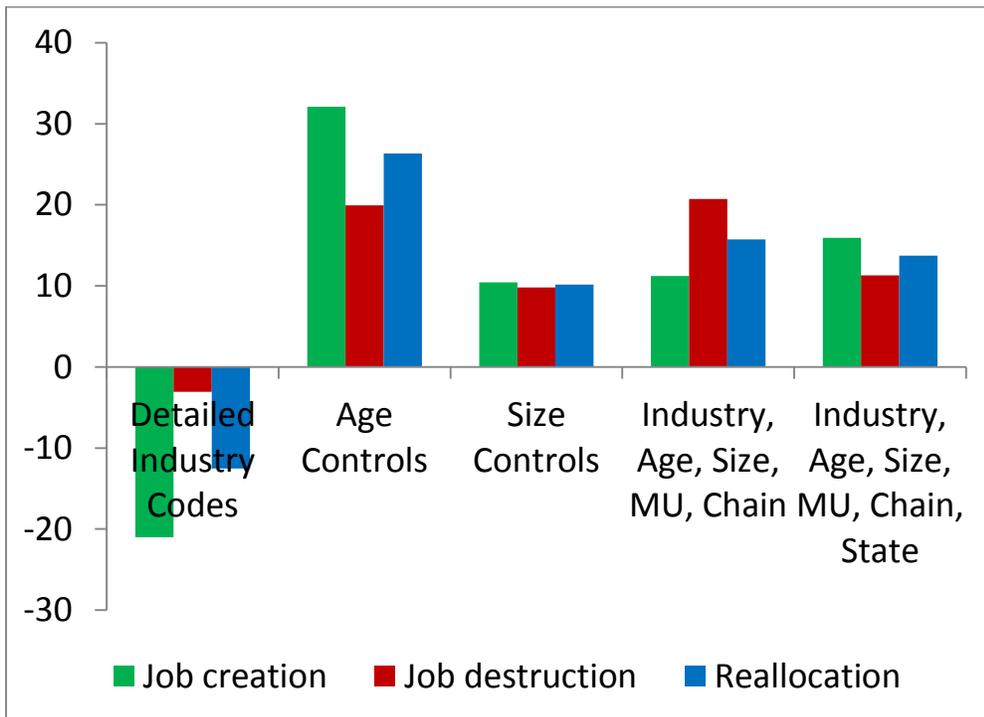
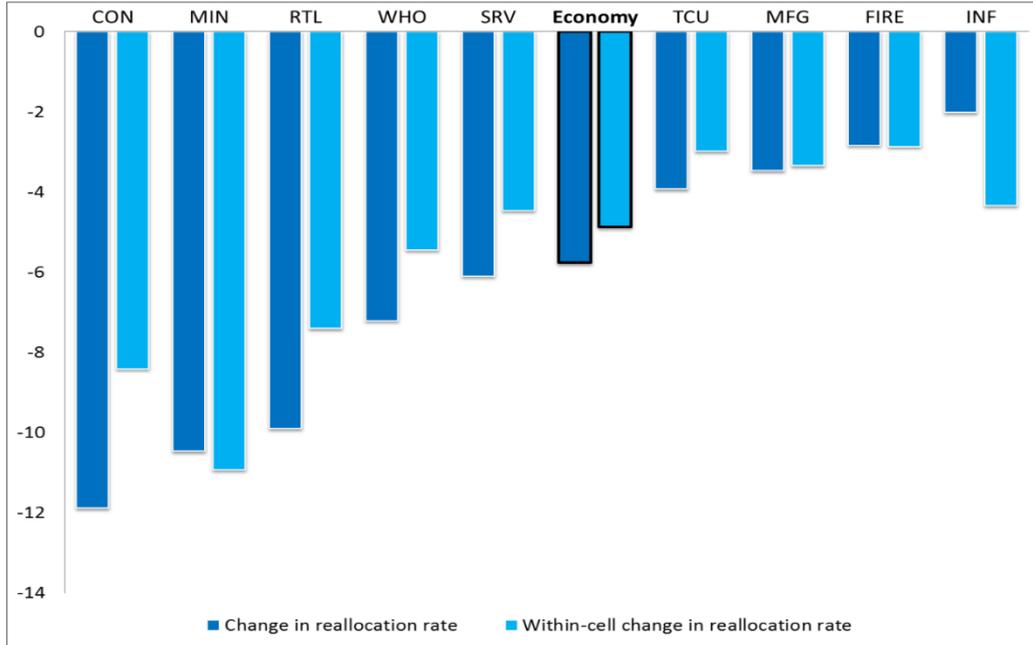


Figure 5: Change in reallocation rate and fraction accounted for by Within-cell Reallocation Rate, 1987/09-2004/06



Notes: Author calculations from the U.S. Census Bureau's Longitudinal Business Database. Sector definitions use consistent NAICS definitions. See text for details of the decomposition used to generate the within cell change. The within cell change is based on controlling for 4-digit NAICS, firm age, firm size, multi-unit and chain status in a fully interacted manner.

Figure 6. Reallocation Rates (HP trends) by Selected Sectors

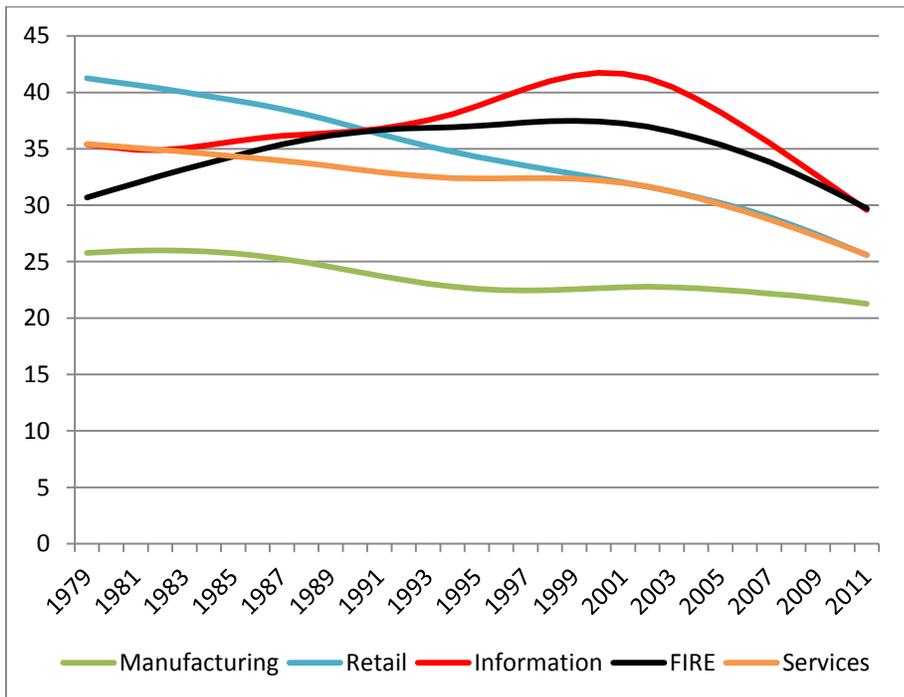
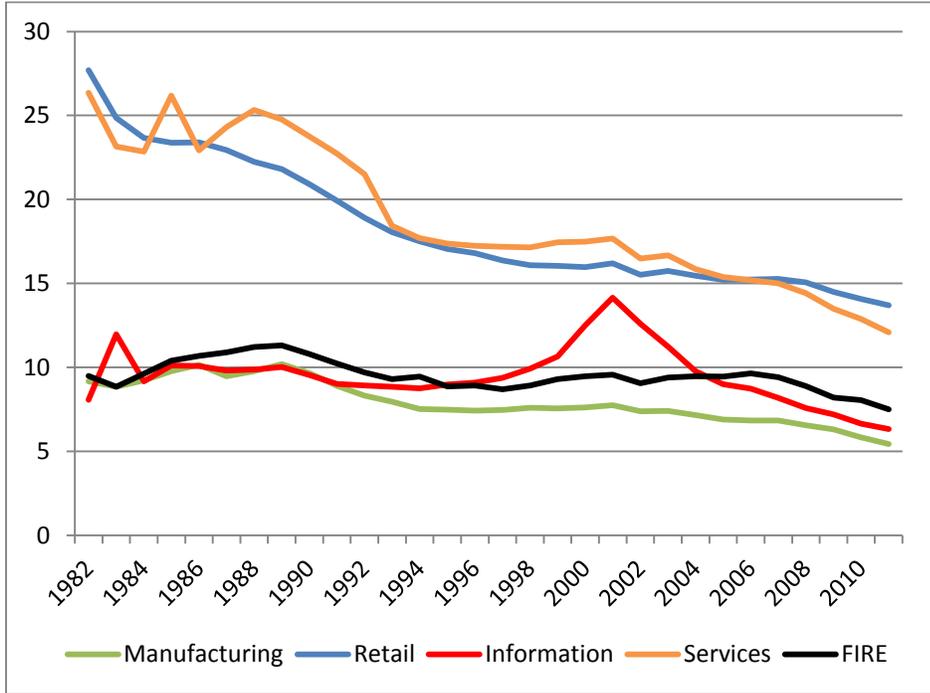


Figure 7: Share of employment from young firms (firm age five or less) for selected sectors



Notes: Author calculations from the U.S. Census Bureau's Business Dynamics Statistics. Sector definitions are on a NAICS. Employment shares in each period based on the average of employment in period t-1 and t (the denominator of the DHS growth rate).

Figure 8. Job Reallocation Rates (HP trends) for Information and High Tech Sectors

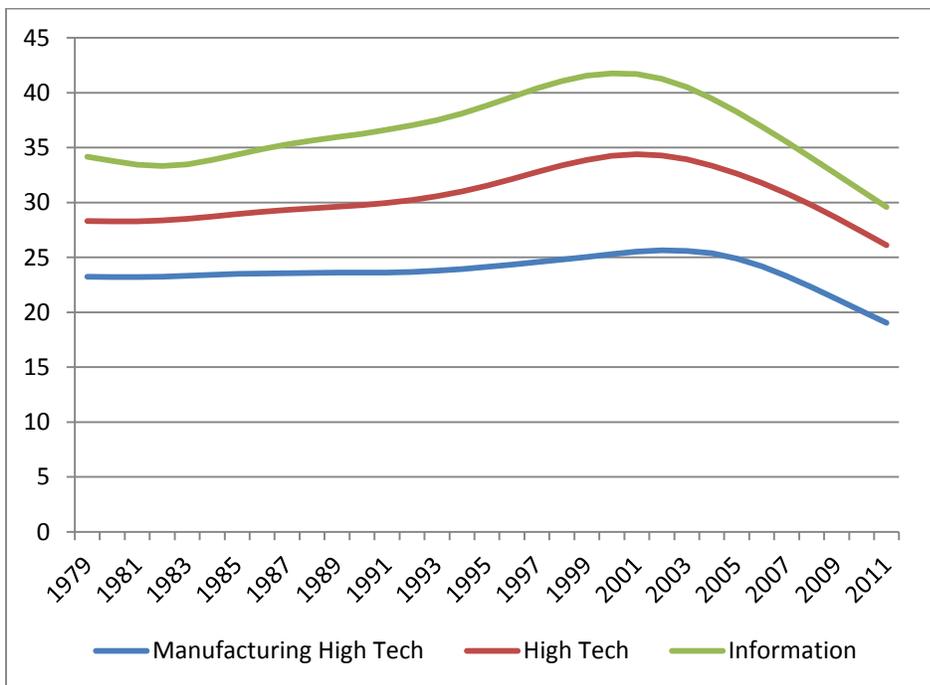


Figure 9. High-Growth Firms (90th Percentile from Employment Weighted Distribution)

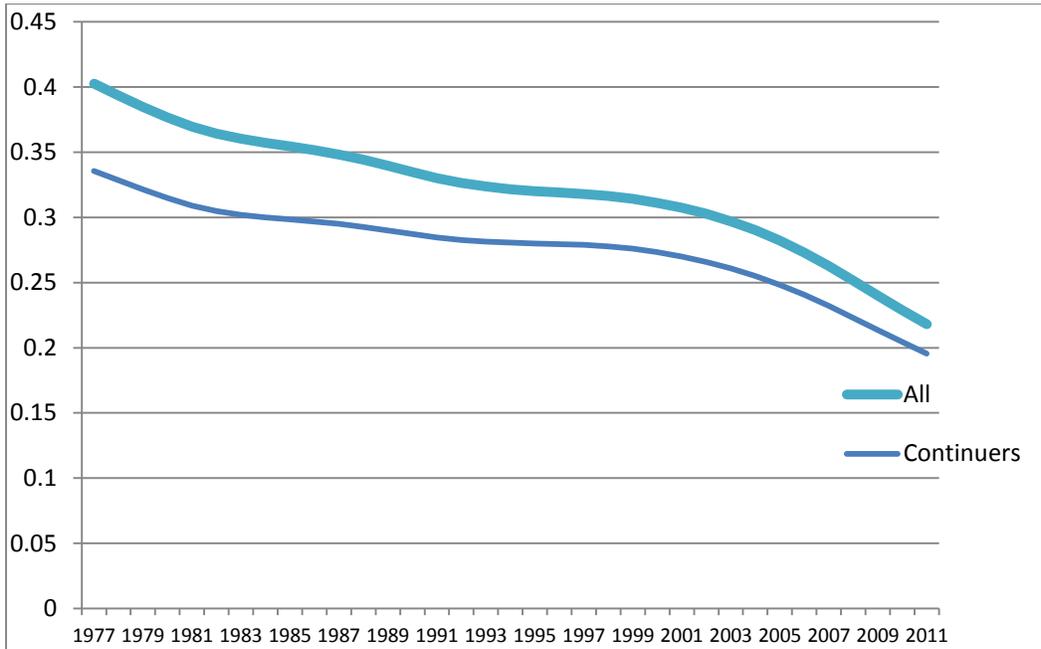


Figure 10. High Growth Firms by Firm Age (90th Percentile of Employment-weighted distributions), Continuing Firms

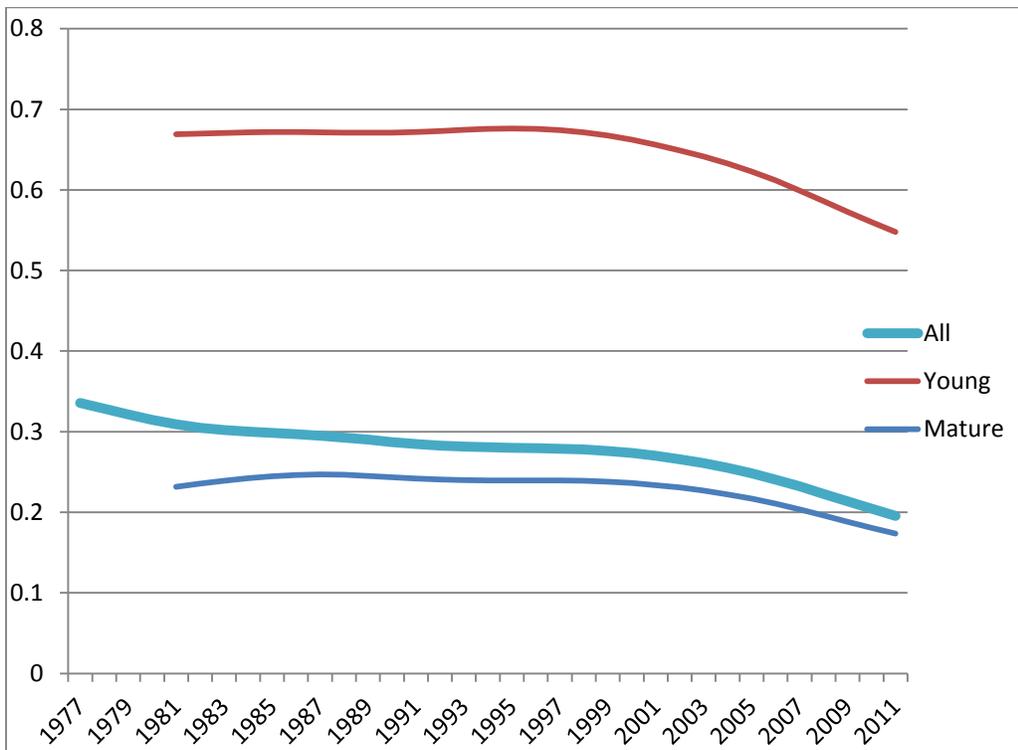


Figure 11. High Growth High Tech Firms vs. All Firms (90th Percentile of Employment Weighted Distributions)

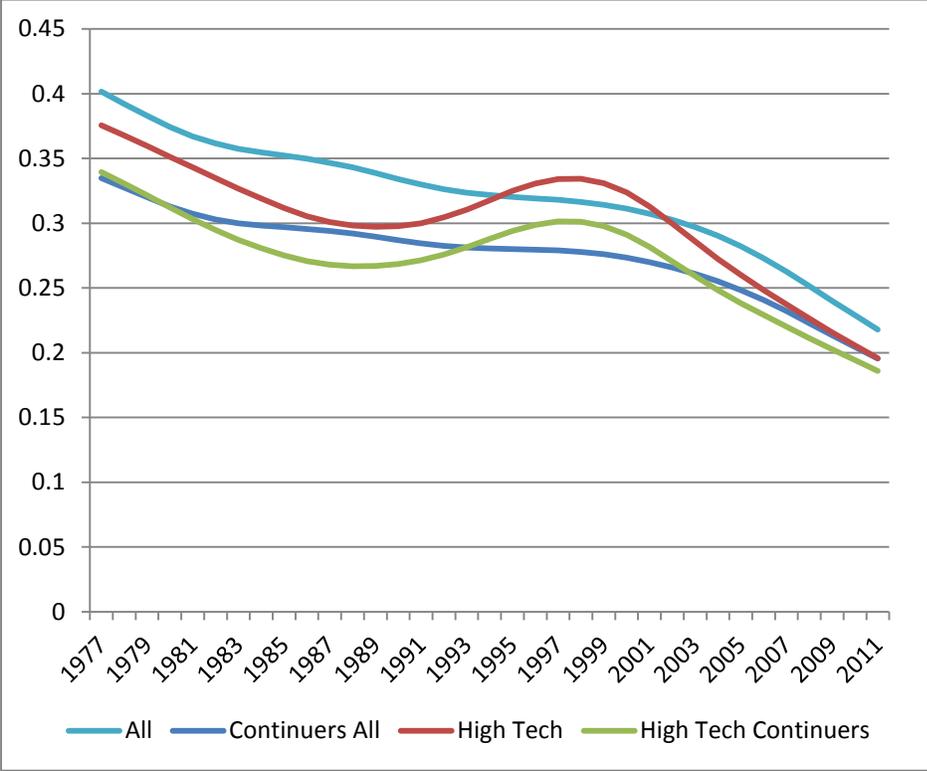


Figure 12a. 90-50 vs. 50-10 Gaps for All and Continuing Private Sector Firms

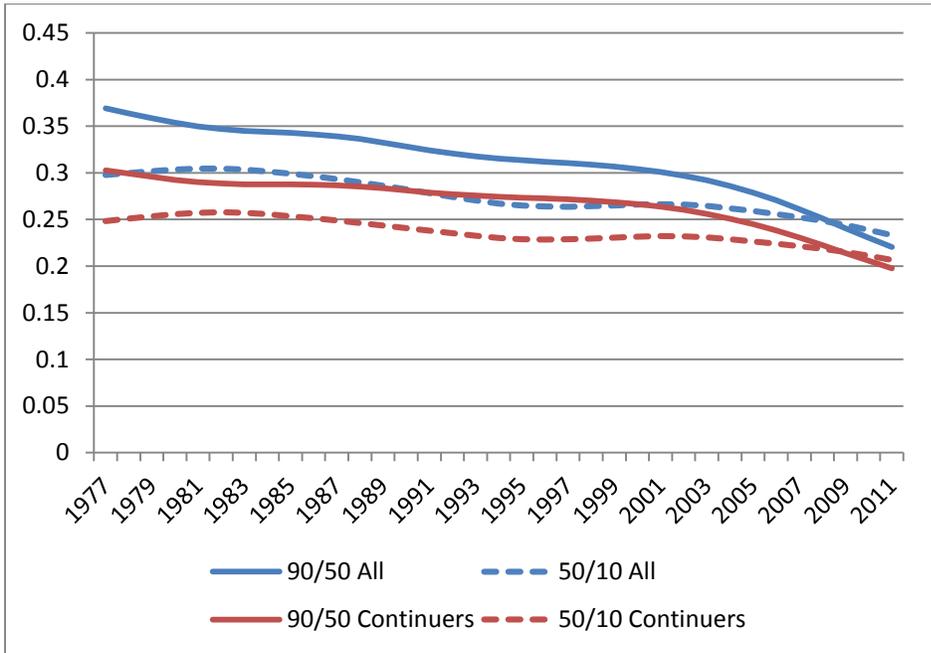


Figure 12b. 90-50 vs. 50-10 Gaps for High Tech (All and Continuing Firms)

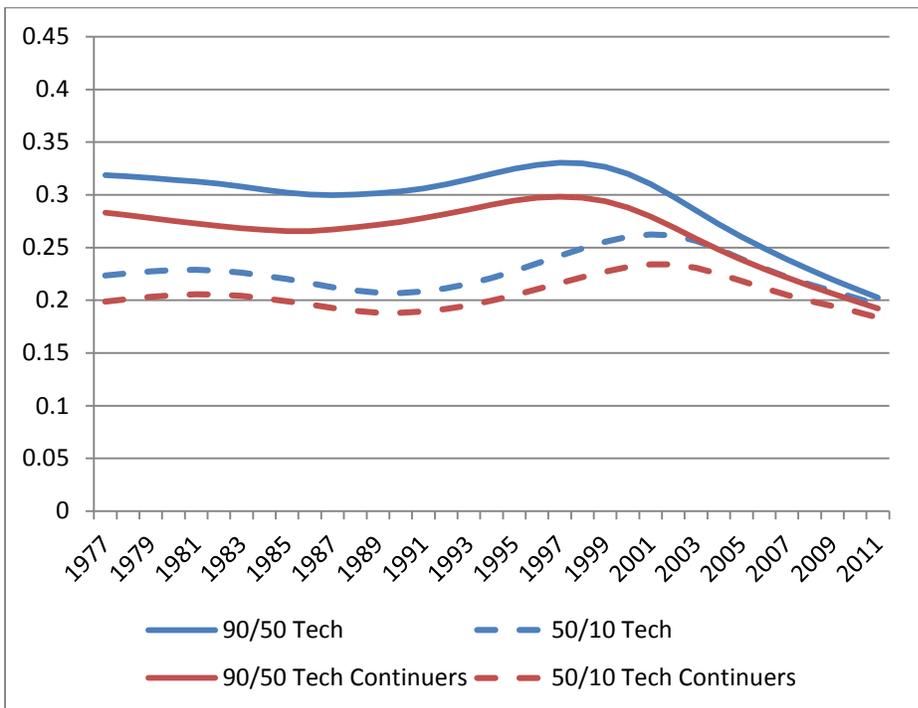


Figure 13. 90-50 vs. 50-10 Gaps for Young and Mature Firms

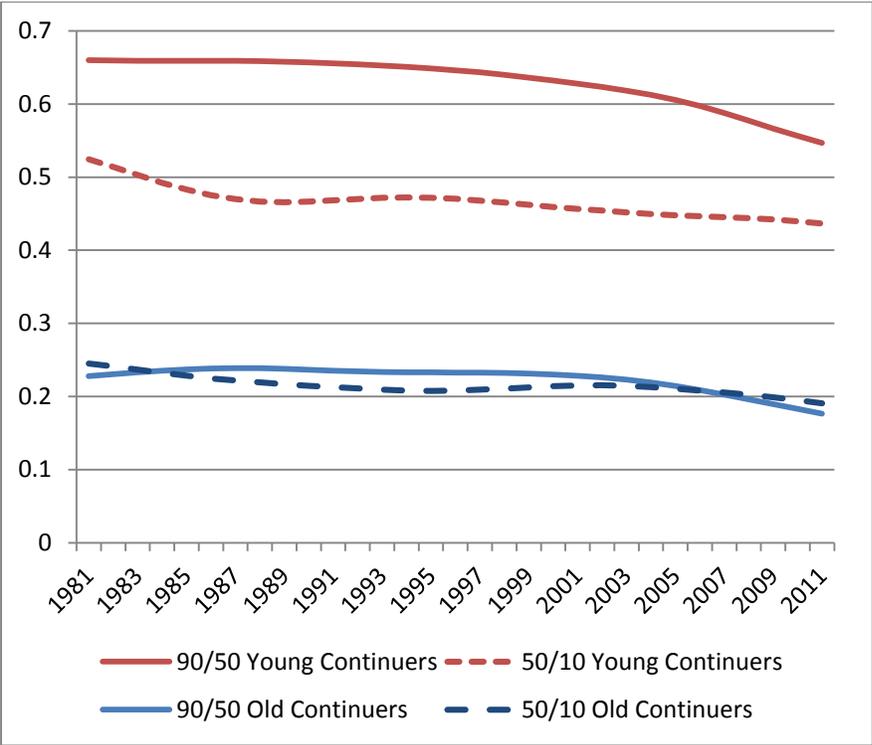


Figure 14a. 90-10 Gaps for High Tech and Publicly Traded Firms

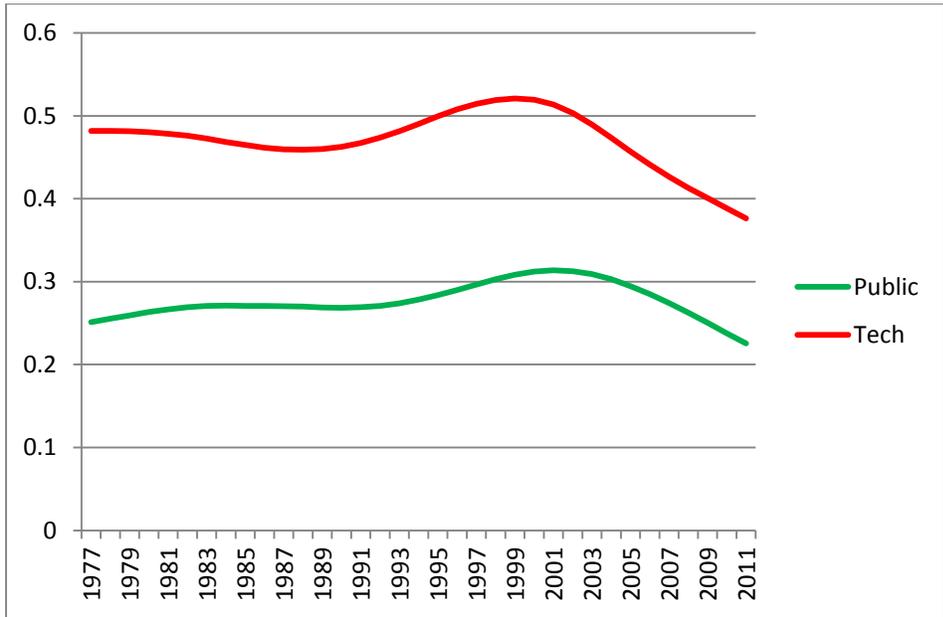


Figure 14b. High Growth High Tech and High-Growth Publicly Traded Firms (90th Percentile)

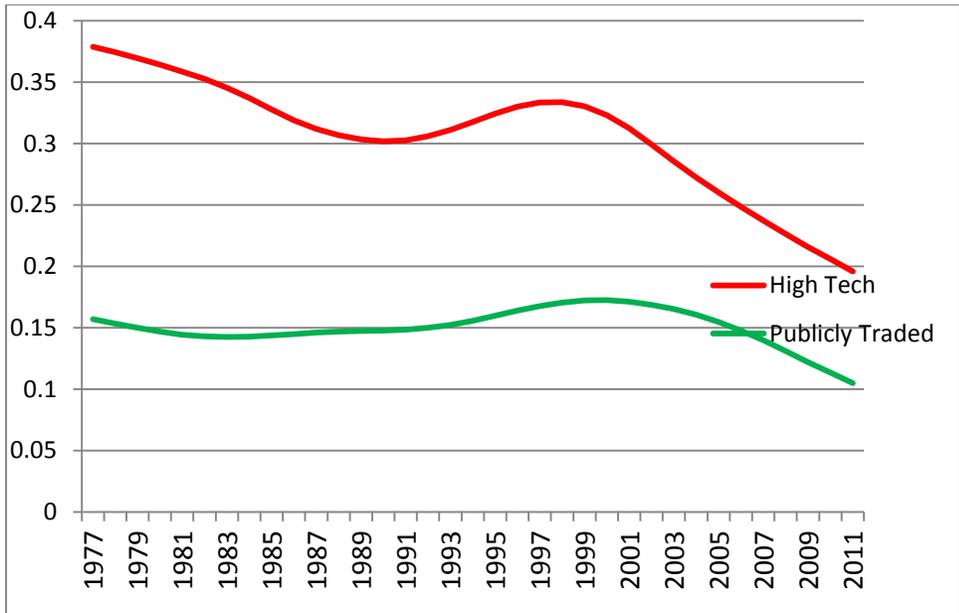


Figure 14.c. 90-50 vs. 50-10 Gaps for High Tech and Publicly Traded

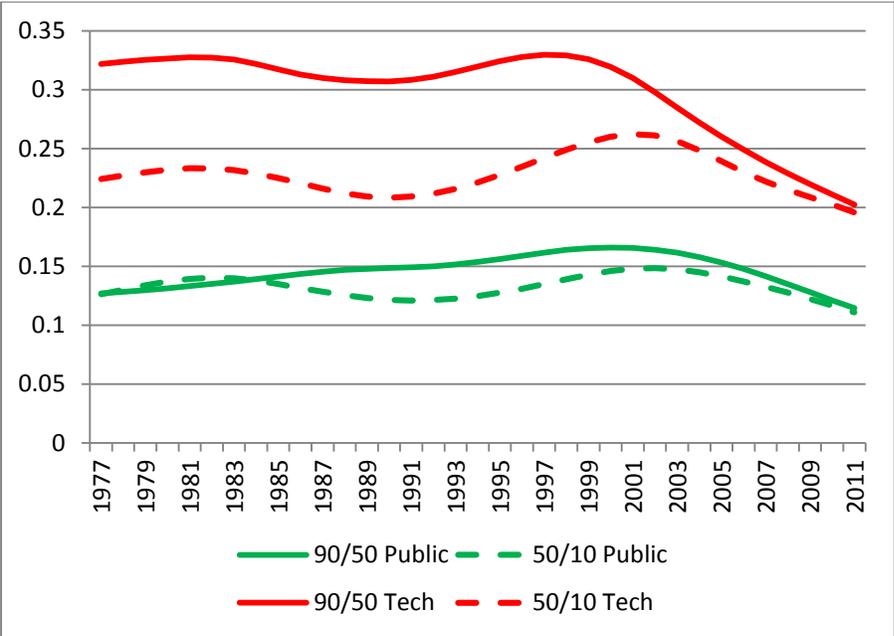


Figure 15. Employment Shares by Cohorts of Publicly Traded Firms

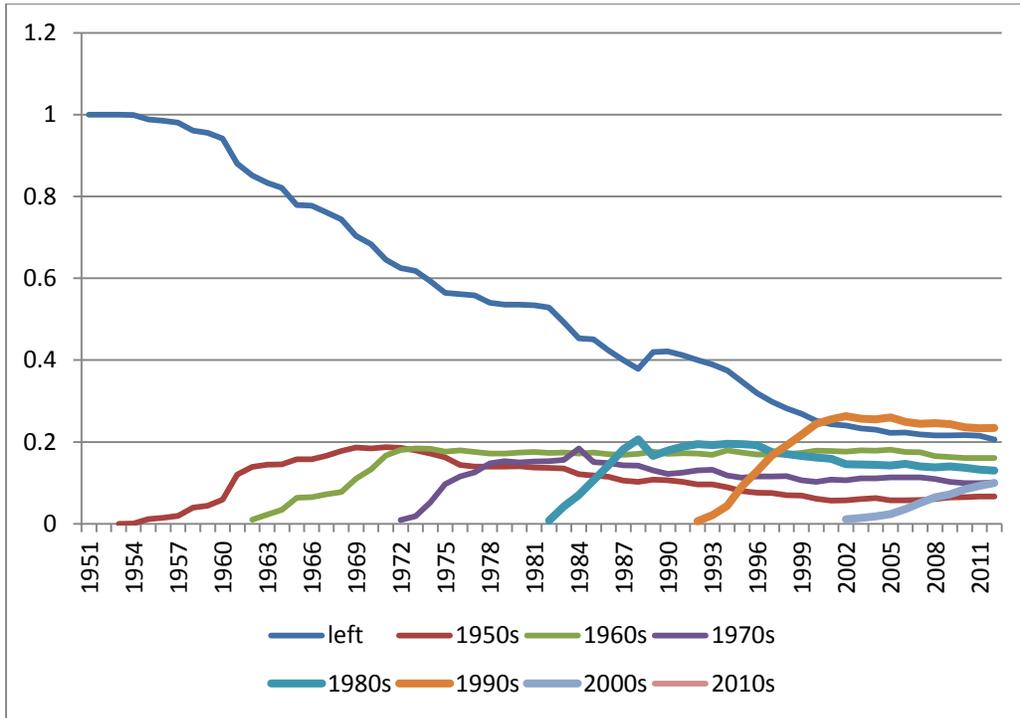


Figure 16. Within-Firm Volatility of Publicly Traded Firms by Cohorts

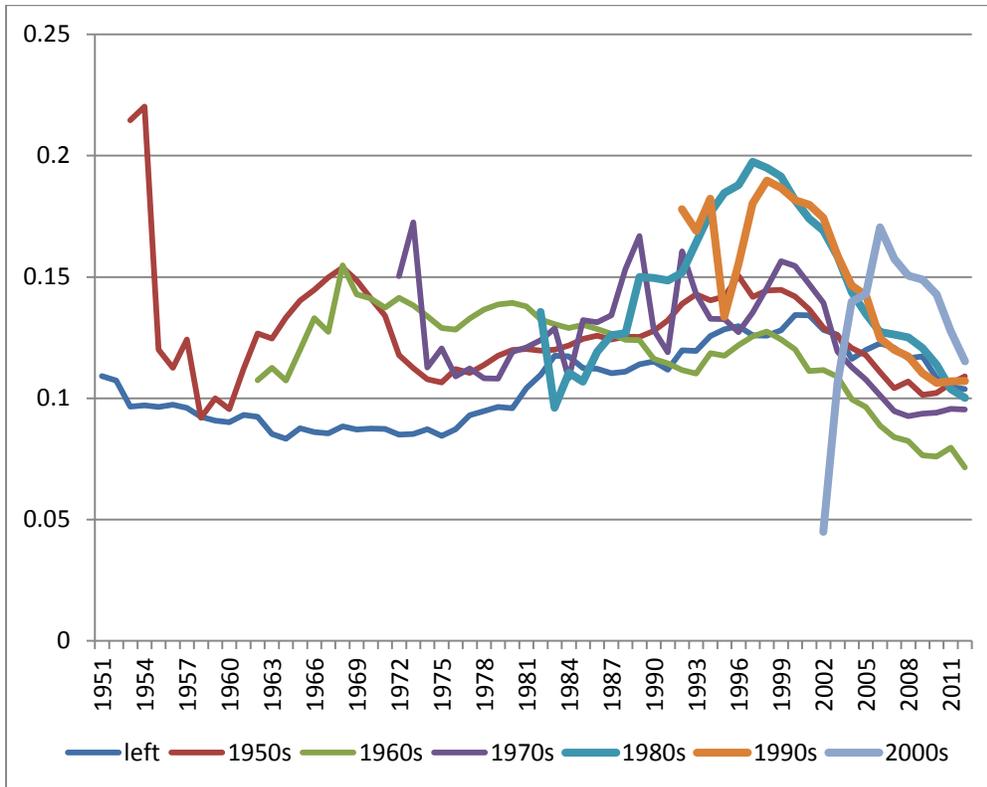


Figure 17. Dispersion of Within-Industry TFP in Manufacturing (3 year Moving Average)

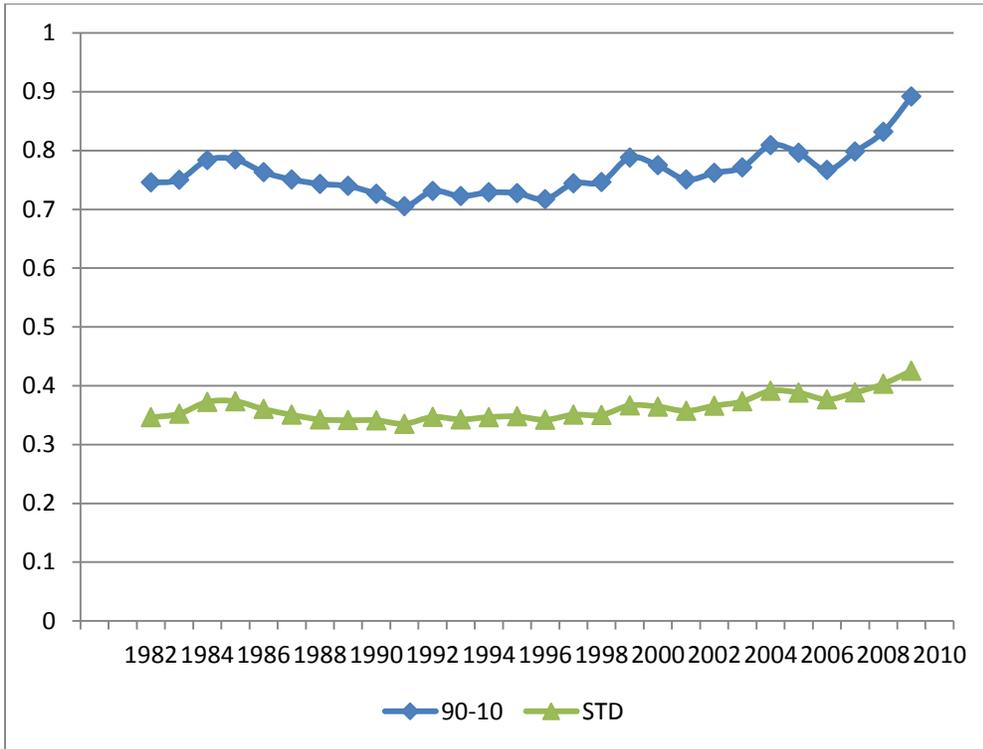


Figure 18. Actual vs. Counterfactual Dispersion in Establishment-Level Growth Rates (3-year MA)

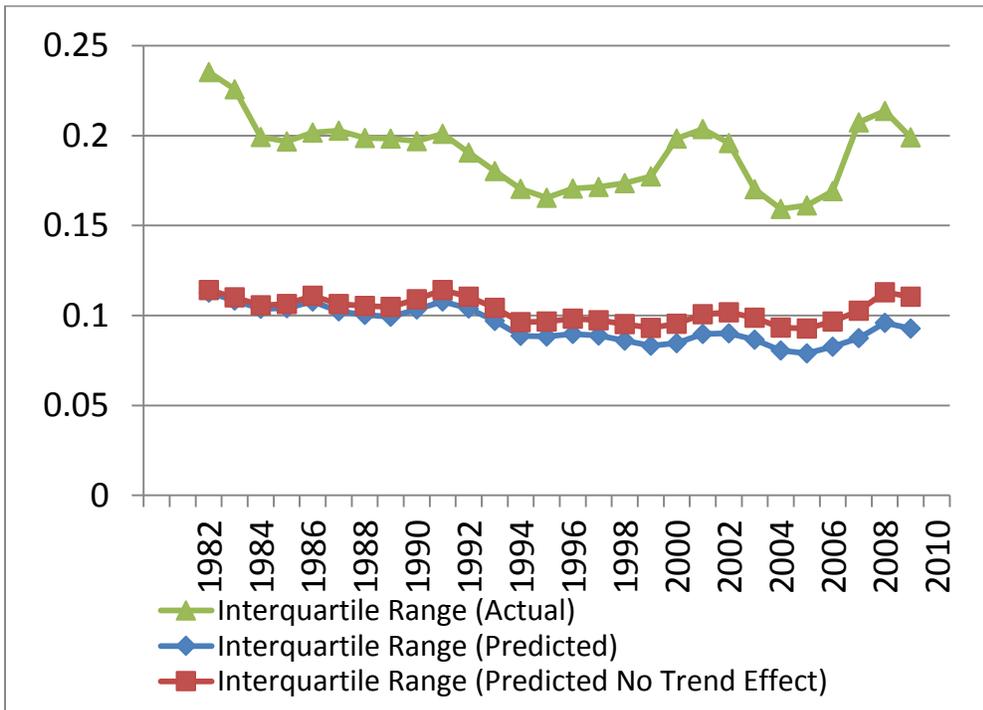
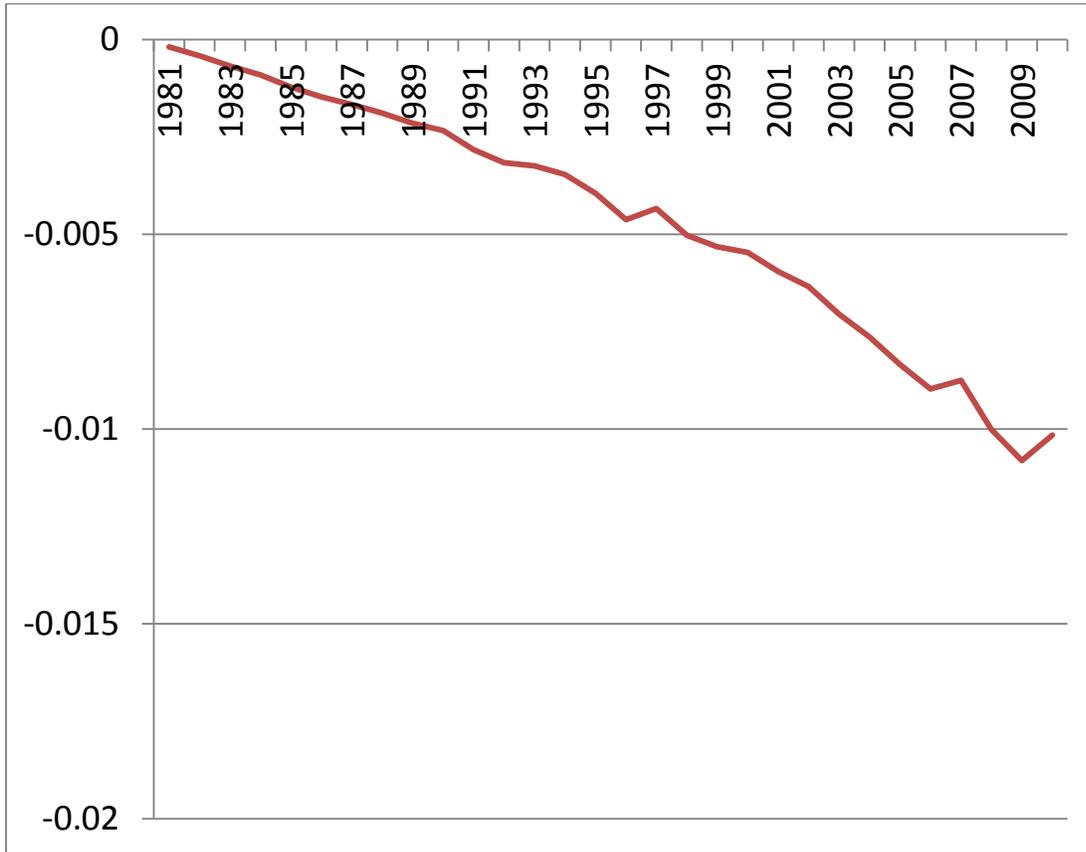


Figure 19. Diff-in-Diff Counterfactual Reduction in Productivity Growth Due to Declining Trend Response



Appendix Tables and Figures

Table A.1: High-Technology Industries

NAICS Code	Industry
<i>Information and Communications Technology (ICT) High-Tech</i>	
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
<i>Miscellaneous High-Tech</i>	
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)

Table A.2. Changing Responsiveness of Plant-Level Growth from t to t+1 to TFP Innovations in t

	Overall Growth Rate (Continuers + Exitters)	Exit	Conditional Growth Rate (Continuers Only)
TFP Innovations	0.2131*** (0.0051)	-0.0715*** (0.0021)	0.0848*** (0.0032)
TFP Innovations*Trend	-0.0019*** (0.0003)	0.0001 (0.0001)	-0.0021*** (0.0002)

* p < 0.10, ** p < 0.05, *** p < 0.01. Note this specifications excludes years where the set of plants with lagged values is non-representative (e.g., first panel years of ASM and CM years). Still about 800,000 observations. Controls include year effects, size effects, state effects, cyclical indicators at the state level interacted with TFP innovations. TFP innovations are based on estimating an AR1 specification for plant-level TFP for plants that are in period t and t-1. The innovation is the component of current period (t) TFP not accounted for by lagged TFP.

Table A.3. Changing Responsiveness of Plant-Level Growth from t to t+1 to (log) TFP in t (High Tech MFG)

Overall Growth Rate

	All	Young	Mature
TFP	0.1964*** (0.0124)	0.2941*** (0.0305)	0.1683*** (0.0136)
TFP*Trend	-0.0021* (0.0011)	0.0077*** (0.0028)	-0.0032*** (0.0012)
TFP*Trend*Post2000	-0.0011 (0.008)	-0.0105*** (0.0020)	0.0002 (0.0009)

See notes above. Note that the Young and Mature coefficients are estimated from a pooled specification with both young and mature that permits all of the TFP terms to be interacted with age indicator and the age indicators are in the set of additional controls as well.

Figure A.1: Share of Employment by Broad (NAICS) Sectors

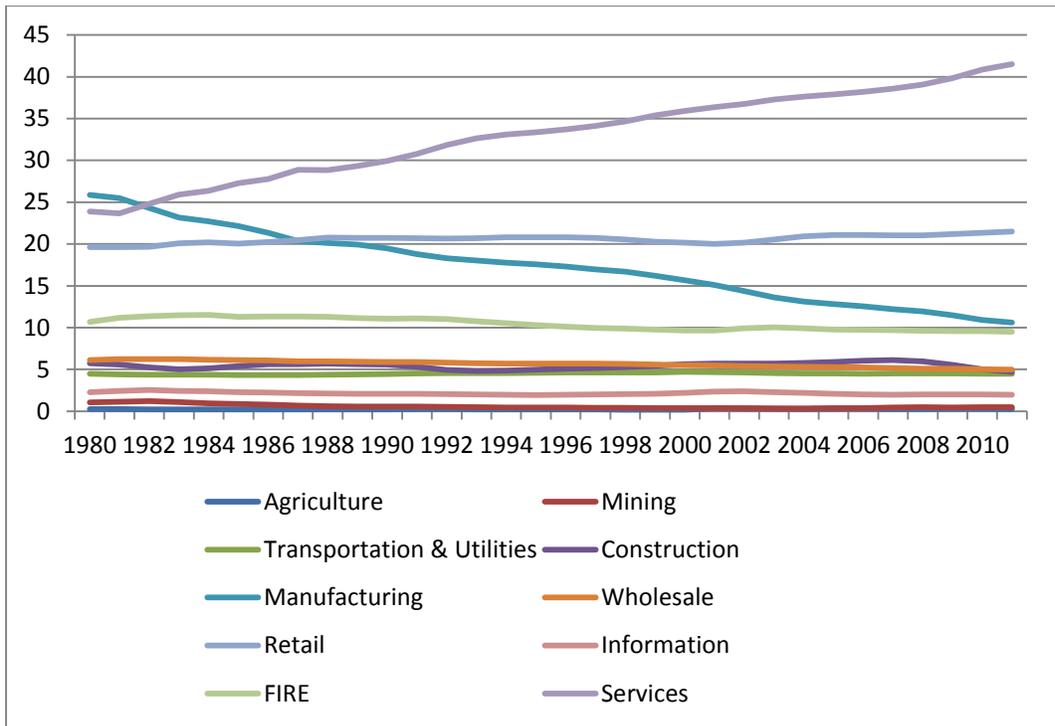


Figure A.2. Change in Reallocation Rate and Within Cell Change n Reallocation Rate for Selected Sectors, 1987-89 to 1997-999

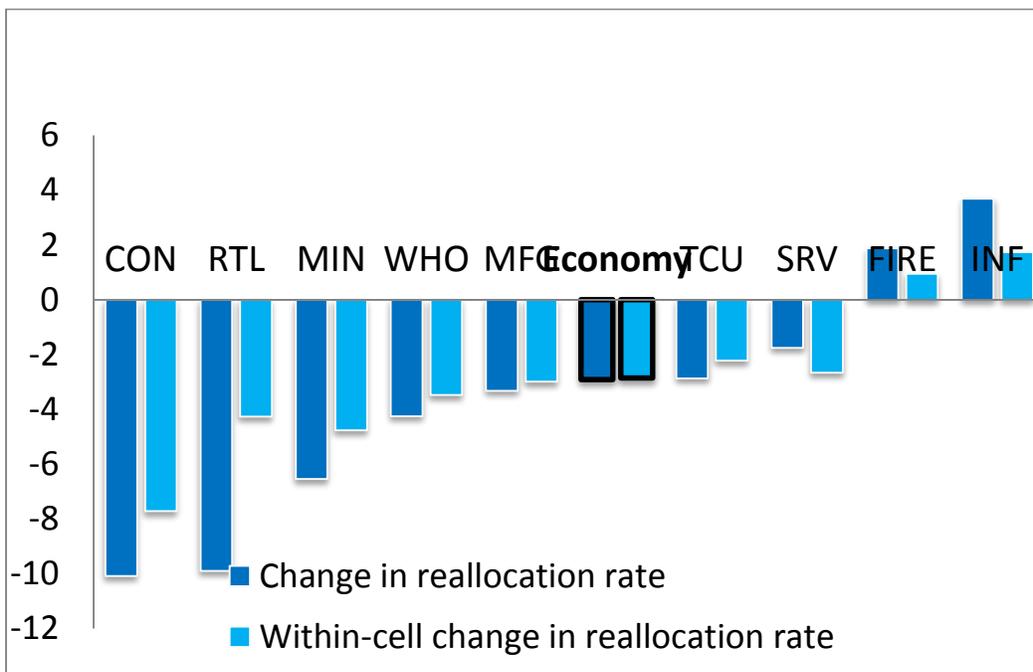


Figure A.3. Change in Reallocation Rate and Within-Cell Change in Reallocation Rate for Selected Sectors, 1997-99 to 2004-06

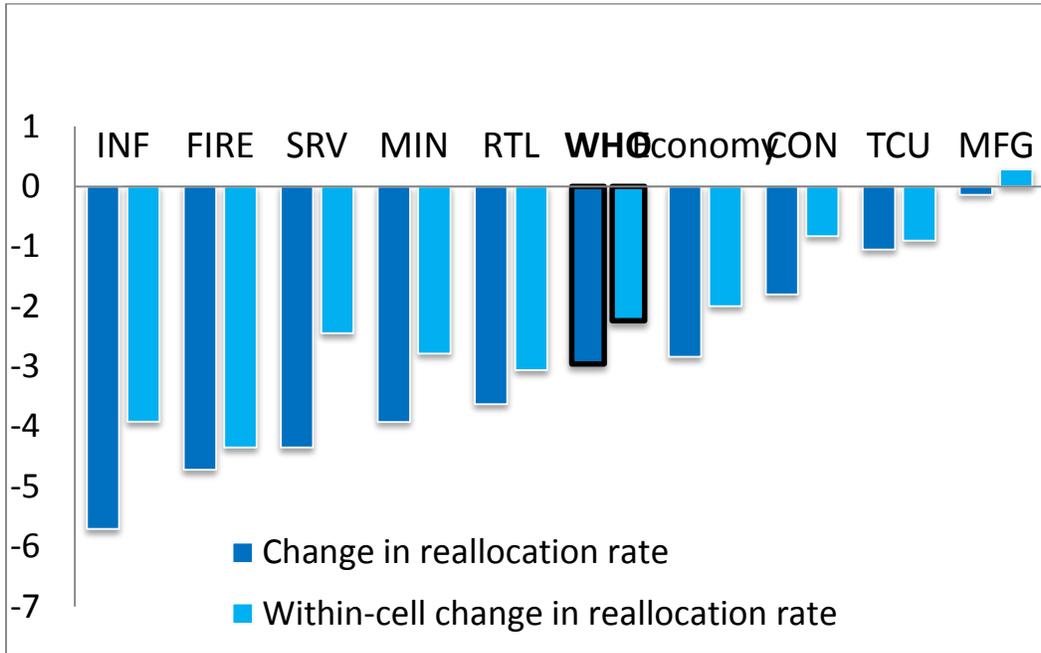


Figure A.4. 90-50 vs. 50-10 for Selected Sectors

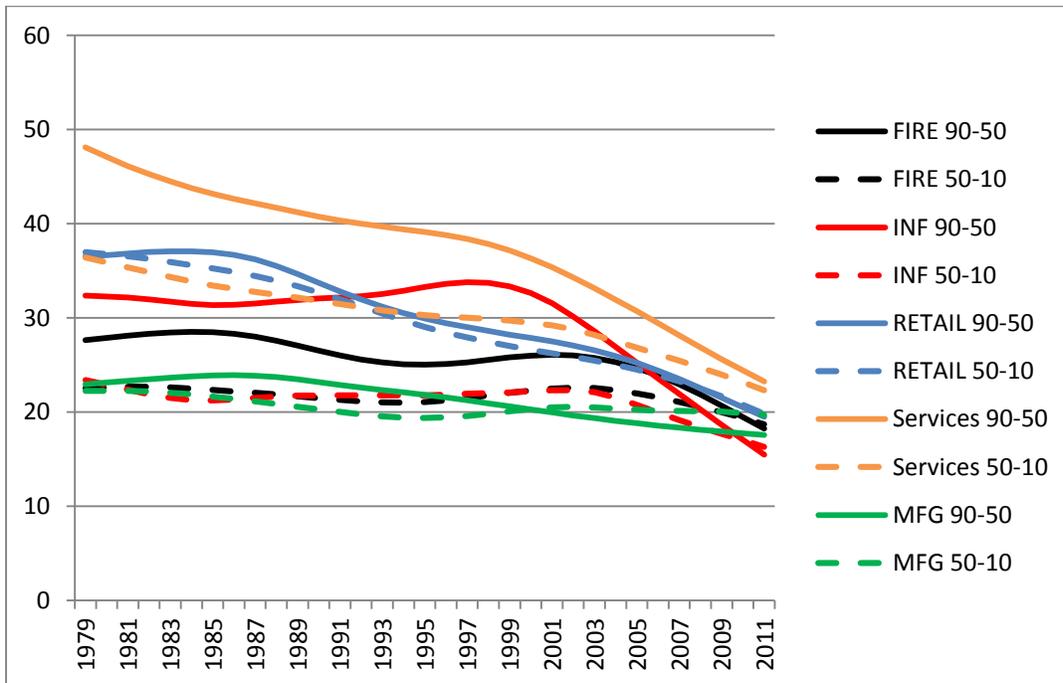


Figure A.3 Within-Firm Volatility for All, Publicly Traded and Privately Held Firms

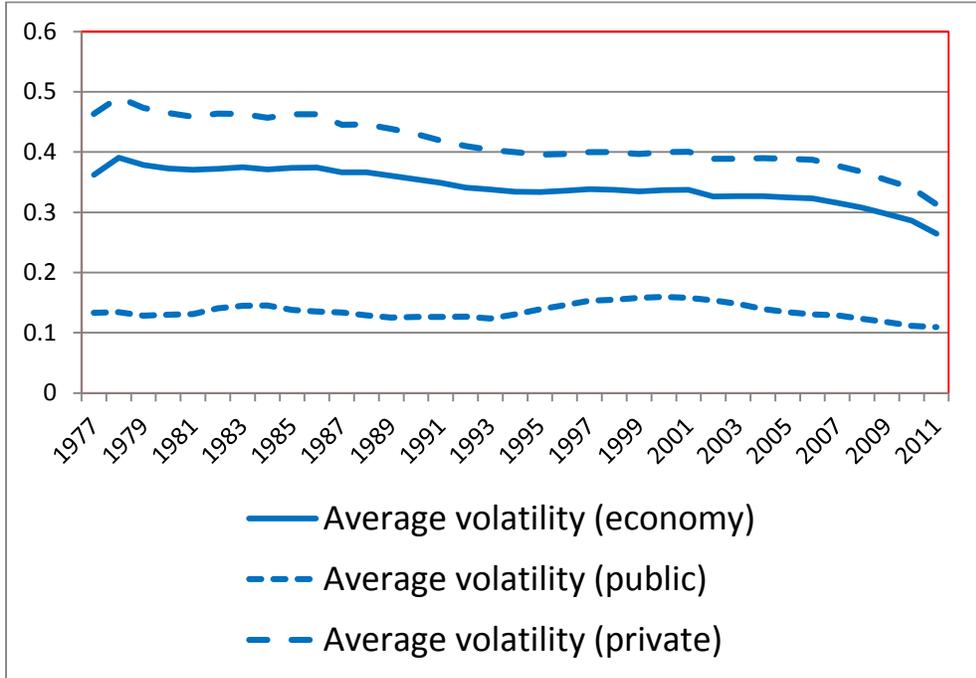


Figure A.4 Within-Firm Volatility for Publicly Traded Firms for COMPUSTAT and LBD (Employment-Growth Based)

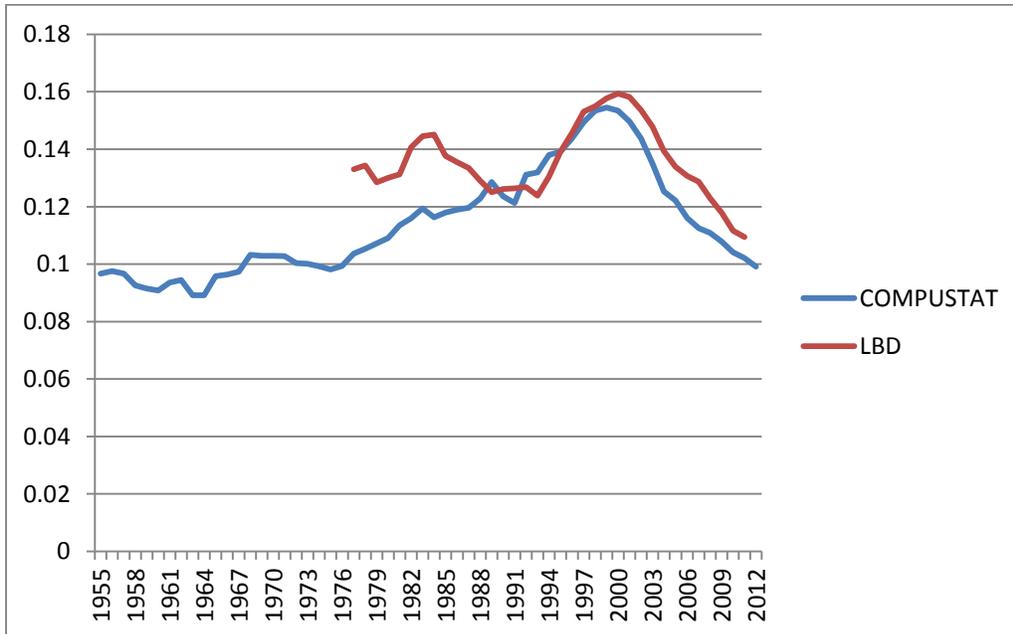


Figure A.5 Within Firm Volatility for Employment and Sales Growth (With and Without Industry Fixed Effects)

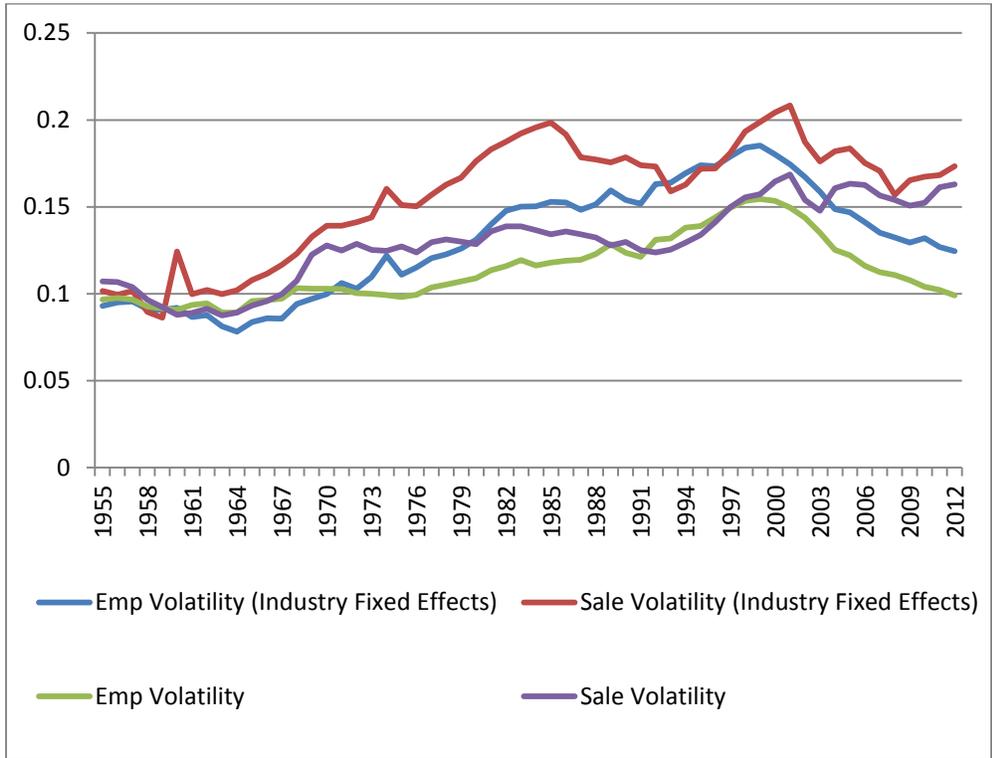


Figure A.6. Within-Firm Volatility for Publicly Traded Firms (Overall and Controlling for Cohort Effects).

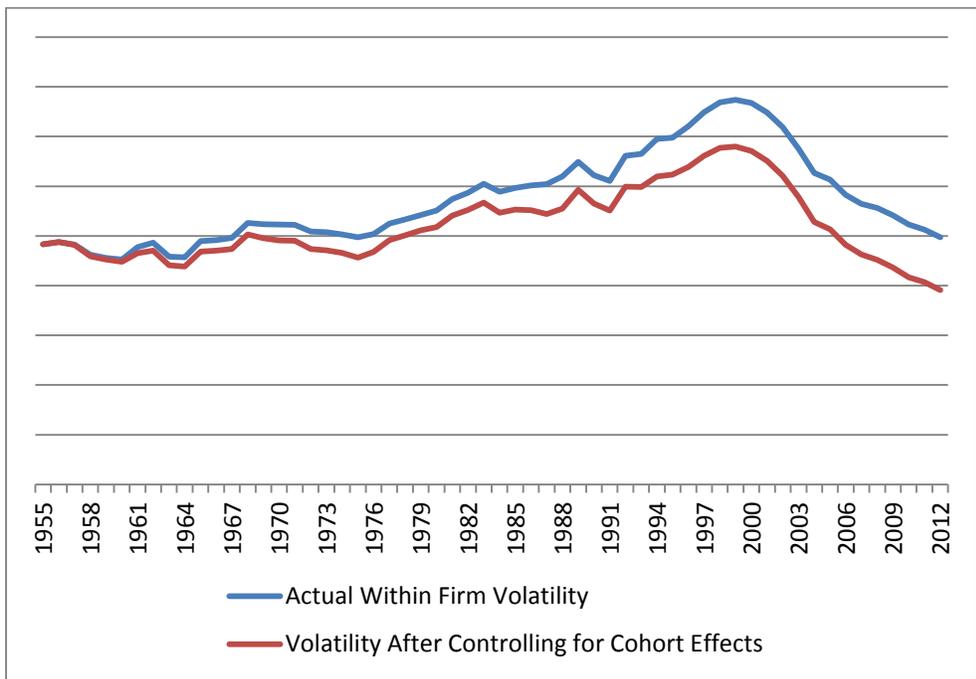


Figure A.7. Within-Industry Dispersion in TFP in High Tech Manufacturing (3 year MA)

