Changing Business Dynamism: Volatility of Shocks vs. Responsiveness to Shocks?

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Abstract

The pace of business dynamism as measured by indicators such as job reallocation has declined in the U.S. in recent decades, but this decline has not been monotonic for all sectors. For the High Tech sector, business dynamism as measured by the pace of job reallocation rose through the 1990s but then declined sharply in the post-2000 period. This is in contrast with the Retail Trade sector, which exhibited a sharp decline in dynamism in the 1990s. In this paper we ask whether the observed patterns in the High Tech sector reflect changes in the volatility of idiosyncratic TFP shocks or rather the response of businesses to those shocks. We focus on the High Tech sector since it is an important sector for innovation and productivity growth. Using plant-level data from the High Tech U.S. manufacturing sector, we document rising dispersion in idiosyncratic TFP shocks across plants and little change in the persistence of such shocks. This suggests the patterns of rising and then declining reallocation are not being driven by changes in the volatility of shocks. Instead, we find changes in the marginal effects of idiosyncratic plant-level productivity shocks on growth and survival that mimic the patterns of reallocation in the High Tech sector. During the 1990s, the responsiveness of growth and survival increased in the High Tech sector for young businesses. In contrast, during the 2000s responsiveness declined because of accelerating decline in the responsiveness of both young and mature businesses. These changes in the responsiveness yield substantial changes in the contribution of reallocation to aggregate (industry-level) productivity growth. During the 1990s, the increased responsiveness yields an increase in the contribution of reallocation to productivity growth of as much as half a log point per year. During the post-2000 period, responsiveness declines in an accelerated fashion implying as much as a two log point per year reduction in the contribution of reallocation to industry-level productivity growth.

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A hallmark of market economies, such as the United States, is the continual 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), Davis and Haltiwanger (2014) and Decker et al. (2014)).

One key finding that has emerged from the recent literature is that this decline in business dynamism is largely occurring within cells defined by sectors, geographic regions, and firm size and age classes. One compositional change that accounts for a significant fraction (about 25 percent) of the decline in dynamism is the decline in startups and the accompanying reduction in the share of activity accounted for by young firms. Young firms exhibit more volatility than older firms, so the aging of U.S. firms yields less dynamism. But this is offset in part by the well-known sectoral reallocation away from goods producing industries. The latter have lower rates of dynamism.

While most of the decline in dynamism is within cells, there are striking differences in the nature of the decline across different sectors. In the 1980s and 1990s, the decline in dynamism is dominated by the Retail Trade sector. Retail Trade is also the sector with the largest declines in startups during this period of time. These declines are arguably due to a change in the business model in response to improvements in information and communications technologies and demand factors that favors large, national chains.[1] The evidence suggests that large, national chains are more productive than single unit ("Mom and Pop") firms in the Retail Trade sector. In that respect, the declines in dynamism in the Retail Trade sector may reflect appropriate and welfare-enhancing responses to market signals that have yielded both increased productivity and less business volatility.

If the decline in dynamism and startups observed were productivity enhancing across all sectors this may not be of much concern. However, startups and reallocation display distinctly different patterns in key innovative sectors like the High Tech sector (defined below) suggesting very different underlying mechanisms for the decline. The pace of reallocation in the High Tech sector increased in the 1980s and 1990s but has sharply declined in the post-2000 period. In this paper, after briefly documenting the patterns discussed above, we explore the relationship between productivity and reallocation by focusing only on the High Tech sector. We examine the component of the High Tech sector that is within manufacturing due to data limitations. However, we show that the manufacturing component of the High Tech sector has reallocation dynamics similar to those for the overall High Tech sector suggesting our results are likely to have broader applicability.

[1] There is an extensive literature documenting the shift away from single unit establishment firms ("Mom and Pop" firms) to large national chains (see, for example, Foster et. al. (2006) and Jarmin et. al. (2009)). For evidence, that establishments of large national chains are more productive and more stable see Foster et. al. (2006) and Foster et. al. (2015c).

For the High Tech sector, the main hypotheses that we investigate are motivated by canonical models of firm dynamics such as Jovanovic (1982), Hopenhayn (1992), Hopenhayn and Rogerson (1993) and Ericson and Pakes (1995). These models suggest that the observed pace of firm volatility is driven by the interaction between idiosyncratic (firm- or plant-specific) shocks and the frictions of adjustment (entry, exit, expansion, contraction) for firms. Viewed from this perspective, a change in the pace of indicators of dynamism such as reallocation broadly has two possible sources. One is a change in the intensity of idiosyncratic shocks inducing firm dynamics. The other is a change in the benefits and/or costs associated with firms responding to these shocks.[2] We investigate these issues for the High Tech component of the Manufacturing sector where we can measure establishment-level TFP to capture idiosyncratic shocks along with the observed patterns of growth and survival. We also compare and contrast our findings for the High Tech components of Manufacturing with the remainder of the Manufacturing sector.

We find that the dispersion of idiosyncratic productivity within High Tech manufacturing is rising over time.[3] We also find that the persistence in idiosyncratic TFP exhibits little or no trend over time. Thus, there is little evidence that the time variation in the distribution of productivity shocks can account for the changing pattern of reallocation in the High Tech sector. Instead, we find that the responsiveness to productivity shocks has been changing over time in the High Tech sector. During the 1980s and 1990s we find that plant-level survival and growth became more responsive to

[2] It may be that these two forces interact. For example, a rise in the second moment of shocks can induce changes in responsiveness as in Bloom (2009). We discuss this further below.
[3] Andrews, Criscuolo, and Gal (2015) likewise describe international evidence of rising firm-level productivity dispersion, a finding that is consistent with our results. Our additional finding of declining productivity responsiveness may shed light on that study's questions about technology diffusion.

idiosyncratic TFP differences across plants. But in the post-2000 period, the responsiveness declined substantially. We show that this changing responsiveness to plant-level idiosyncratic productivity differences has important consequences for aggregate productivity. Using a simple accounting decomposition, the increased responsiveness of the 1980s and 1990s yielded as much as a half a log point annual boost in industry-level TFP in the High Tech sector in the second half of the 1990s. The declining responsiveness of the 2000s yielded as much as a two log point drag on annual productivity in industry-level TFP by 2010, a finding that may shed light on the 2000s change in trend productivity growth in the IT sector documented by Fernald (2014).

The paper proceeds as follows. Section II describes the data and basic facts about the declining pace of business dynamism. In section III, we turn to our main focus which is whether the evidence implies a change in the distribution of shocks or a change in the response to those shocks in the High Tech sector. Section IV considers the implications for aggregate (industry-level) productivity. Concluding remarks are in section VII.

II. Business Dynamics: Basic Facts

Most of the findings reported in this paper are based on the Census Bureau's Longitudinal Business Database (LBD) [4] and the public domain statistics on business dynamics that have been generated from the LBD – namely, the Business Dynamics Statistics (BDS).[5] The LBD covers the universe of establishments and firms in the U.S.

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

[5] BDS data are available at http://www.census.gov/ces/dataproducts/bds/.

nonfarm business sector with at least one paid employee. The LBD includes annual observations beginning in 1976, and we use the LBD through 2011 (this version of the data has consistent NAICS codes for the entire period as constructed by Fort (2013)). It provides information on detailed industry, location and employment for every establishment in the private, non-farm sector. Employment observations in the LBD are for the payroll period covering the 12th day of March in each calendar year. We use the public domain summary statistics from the BDS through 2012.

A unique advantage of the LBD is its comprehensive coverage of both firms and establishments. Only in the LBD is firm activity captured up to the level of operational control instead of being based on an arbitrary taxpayer ID.[6] The ability to link establishment and firm information allows firm characteristics such as firm size and firm age to be tracked for each establishment. Firm size measures are constructed by aggregating the establishment information to the firm level using the appropriate firm identifiers. The construction of firm age follows the approach adopted for the 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

[6] 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.

continues operations. We utilize the LBD to construct annual establishment-level and firm-level growth rates. In this paper, we focus on establishment-level growth rates and associated job reallocation to capture indicators of dynamism. Reallocation is a summary measure of cross-sectional dispersion in establishment-level growth rates. In a companion paper (Decker et al. (2015)), we show that the patterns for establishment-level job reallocation are very similar for firm-level job reallocation as well as alternative measures of within-firm and establishment volatility.

Figure 1a depicts the annual pace of establishment-level job reallocation from 1980-2012 from the BDS. The actual series and the Hodrik-Prescott (hereafter HP) filtered trend series are depicted. The secular decline is evident with the HP-filtered series declining by about 25 percent over this period. It is also apparent that there is an acceleration of the trend decline in the post-2000 period given the 17 percent decline in reallocation in this period. Other data sources confirm the long-term trend and post-2000 acceleration. For example, Figure 1b reports quarterly establishment-level reallocation rates from BLS Business Employment Dynamics data (extended back to 1990 by Davis, Faberman and Haltiwanger (2012)). Figure 1b also shows that the trend decline continued through 2014.

Figure 2 shows the trends in job reallocation (using HP trends) for selected sectors. Retail Trade exhibits the sharpest decline in job reallocation rates during the 1980s and 1990s. In contrast, Information and FIRE exhibit increases in the pace of reallocation until about 2000 and then sharply decline thereafter. In a related fashion, Figure 3 shows the share of employment accounted for by young firms for the same sectors. Neither FIRE nor Information exhibits 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 then declines after 2000. Figures 2 and 3 together highlight that not all sectors have exhibited a monotonic decline in indicators of business dynamism and entrepreneurial activity.

The changing patterns of the share of young activity in Figure 3 help account for the changing patterns of reallocation in Figure 2. Figure 4a shows the annualized change in reallocation rates for the same broad NAICS sectors from the business cycle peak in the late 1980s to the business cycle peak in the late 1990s, and Figure 4b shows the decline from the business cycle peak in the late 1990s to the mid 2000s (we use three-year averages in 1987-89, 1997-99, and 2004-06 for this purpose). Also depicted are the annualized changes holding the age composition of businesses constant within each of these sectors. During the 1990s, the sharp decline in reallocation in the Retail Trade sector and the increase in reallocation in the Information sector are evident. The changing age composition helps account for both of these patterns. The declining share of young business activity accounts for 32 percent of the decline in reallocation in Retail Trade, and the rising share of young business activity in Information accounts for 23 percent of the rise in reallocation in that sector. The Services sector exhibited a relatively smaller decline in reallocation rates in the 1990s, but interestingly 100 percent of the 1990s decline is accounted for by the declining share of young business activity in that sector. Turning to the post-2000 period, it is evident that the pace of decline in job reallocation accelerated. During the post-2000 period all broad sectors exhibited a decline (unlike the 1990s). The Information sector exhibits the sharpest decline in the post-2000 period, with 18 percent of the decline accounted for by a decline in young business activity.

The Information sector includes some (but not all) of the sectors that are typically considered the High Tech sectors of the economy. Included in Information 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). We also note that Information includes sectors that are not considered part of the High Tech sector such as Newspaper, Periodical and Book Publishing (NAICS 5111) and Radio and Television Broadcasting (excluding cable) (NAICS 5151). For this purpose, we follow Hecker (2005) and construct a High Tech sector based on the 14 4-digit NAICS sectors with the largest shares of STEM workers. The 14 sectors are listed in Table A.1 in the appendix.[7]

Figure 5 shows the Hodrick-Prescott trends for the Information sector, the High Tech sector so defined, the manufacturing component of the High Tech sector, and the overall Manufacturing 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 was due to a surge in productivity in the IT-producing and IT-using sectors. Moreover, Fernald (2014) finds that there began a trend slowdown in

[7] 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 shortly after 2000 driven by a slowdown in IT-producing and using industries. Interestingly, Figure 5 shows a sharp decline in the pace of job reallocation in the post-2000 period in the High Tech sector.

Figure 6 shows the shares of young firm activity in the Information sector, the High Tech sector, and the High Tech component of manufacturing. The overall High Tech sector and the Information sector exhibit very similar patterns. The High Tech manufacturing component does not exhibit the “dot com” spike in the late 1990s, but still the share rises throughout the 1990s and then falls in the post-2000 period like the overall High Tech sector.

The sectoral patterns suggest that more than one mechanism is at work for the decline in dynamism and that the alternative mechanisms are working over different horizons. During the 1980s and 1990s, the decline in reallocation and young business activity was especially large in the Retail Trade sector. This is consistent with the studies that have shown that there has been a shift in the business model in the Retail Trade sector as “Mom and Pop” businesses were displaced by large, national chains (see Jarmin, Klimek and Miranda (2009) and Foster, Haltiwanger and Krizan (2006)). However, over this same period there was actually a rise in young business activity and a rise in dynamism in the Information sector. In turn, there was a rise in the pace of reallocation 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 and in indicators of business dynamism in the Information and High Tech sectors. In the remainder of this paper, we focus on the High Tech component of the manufacturing sector as this is a sector where we can track the evolution of the distribution of productivity as well as growth dynamics of establishments over a long period of time.

III. Change in Volatility of Shocks or Response to Shocks?

A. Theoretical underpinnings

Canonical models of firm[8] dynamics suggest that a within-sector decline in the pace of reallocation is either due to a change in the volatility of shocks impacting firms or a change in the response to those shocks. A classic reference for our purposes is Hopenhayn and Rogerson (1993). In that paper, firms face idiosyncratic productivity shocks and adjustment frictions for labor. They show that an increase in adjustment frictions reduces the dispersion of firm-level growth rates and reduces aggregate productivity because productivity-enhancing reallocation is reduced.

There is a very large literature on firm dynamics models with adjustment frictions and idiosyncratic shocks. We do not survey this literature here but draw further upon some of the insights and findings to motivate our empirical analysis below. Cooper, Haltiwanger and Willis (2007, 2015) develop theoretical frameworks for estimating the structure of firm-level adjustment frictions of labor from key micro moments on the distribution of firm-level employment growth rates.[9] The key state variables for employment-growth dynamics for firms in these models are the realization of productivity/profitability shocks (inclusive of demand and cost shocks) and the initial level of employment in the period. Firms with high realizations of productivity grow while those with low realizations contract. They show that the dispersion of

[8] We use the term "firms" loosely in this section. Much of the literature focuses on establishment-level dynamics but we use the term "firm" in this section for expositional ease. Our empirical work does focus on establishment-level dynamics for the most part although we exploit firm-level characteristics such as firm age.
[9] Cooper and Haltiwanger (2006) use a similar approach for estimating the structure of firm-level adjustment frictions of capital from key micro moments of the distribution of investment rates.

growth rates will depend on the dispersion of the realizations of productivity and the marginal responses of firms to these realizations that, in turn, depend on the adjustment frictions. Like in Hopenhayn and Rogerson, they find that increases in adjustment frictions induce a reduction in the dispersion of firm-level growth rates. Cooper, Haltiwanger and Willis (2007, see Table 10) also show that in the steady-state a decrease in the dispersion of idiosyncratic shocks yields a decrease in the dispersion of firm-level growth rates.[10] In work highly relevant for the current study, Cairó (2013) uses an increase in the fixed cost of adjusting employment to account for the patterns of declining business dynamism in the U.S. economy.[11]

The recent literature on uncertainty (see, *e.g.*, Bloom (2009) and Bayer and Bachmann (2013)) highlights that in some model setups there may be an inverse relationship between the second moment of idiosyncratic shocks and the inaction range in the adjustment to those shocks. Much of the focus of this recent literature is on the relevance of uncertainty shocks for business cycles (*i.e.*, transitory but persistent increases in the second moment). Our focus is on lower-frequency variation, but this type of interaction between the volatility of idiosyncratic shocks and responsiveness is still potentially relevant for our findings. For example, as this recent literature highlights, with fixed or linear costs of adjustment, an increase in dispersion of shocks will expand the (S,s) range of inaction because of a real options/uncertainty effect. While this increase in the inaction range tends to reduce responsiveness other things equal, the direct effect of the increase in the dispersion of shocks works in the opposite direction (*i.e.*, firms are more

[10] In the analysis for their Table 10, they use a specification that has fixed and linear vacancy posting costs.
[11] She motivates this with interesting evidence that the cost of training of new workers has risen over time.

likely to be hit by larger shocks and adjust more). The typical steady-state finding is that the latter direct volatility effect dominates the former real options/uncertainty effect.[12]

Our empirical approach in the next section is motivated by the insights of these theoretical models. Broadly speaking, these models yield the prediction that firm-level growth in a given period will be an increasing function of the realizations of productivity/profitability shocks conditional on initial endogenous state variables (i.e., initial employment) in each period. This implies that changes in the distribution of firm-level growth rates (e.g., dispersion) can be accounted for by changes in the distribution of productivity/profitability of shocks or changes in the marginal response of firm-level growth to productivity/profitability shock. Changes in the latter may stem from several sources – changes in frictions as in the above cited papers, changes in margins of adjustment, and or structural changes in the economy that change the composition of firms. The latter may also be important for any observed changes in the distribution of productivity/profitability shocks.

Unlike the theoretical literature cited here we do not seek to identify a structural model of adjustment frictions. Given our findings below, we think this is a rich area for future research. Relative to the discussion above, we do not take a stand on the exact form of adjustment costs such as convex vs. non-convex adjustment costs (this topic has been under active investigation in the literature). One potential use of our empirical findings would be as moments to discipline

[12] The overall effect on responsiveness depends both on the effect on adjustment frequency and the effect on adjustment dispersion among units that do adjust. Adjustment dispersion in turn can depend heavily on the nature of the adjustment costs. The Cooper, Haltiwanger and Willis (2007) model has both fixed and linear costs of adjustment, and they find that a reduction in dispersion of shocks yields a reduction in dispersion of firm employment growth rates. Vavra (2014) suggests that the standard steady state finding is that the volatility effect from an increase in dispersion of idiosyncratic shocks dominates the real options or uncertainty effect, a fairly general result extending back to Barro (1972). We take that standard steady state view in the current paper.

such analysis.[13] Our reduced form approach readily permits controlling for many different factors in a panel regression environment and allowing estimates to vary systematically by key firm characteristics such as detailed industry and firm age. In addition, we use this reduced form approach to explore potential explanations for changes in the responsiveness to shocks that we detect.

B. Empirical Analysis

In this section, we investigate these issues for the U.S. manufacturing sector with a focus on the High Tech component of manufacturing. In what follows, we call this the High Tech sector for short even though it is only the manufacturing component of High Tech. It includes the 4-digit sectors in Table A.1 that are in manufacturing. To help provide perspective on our findings for High Tech we also consider the rest of the manufacturing sector which for ease of exposition we call Non Tech. The focus on manufacturing is necessitated by data considerations. The manufacturing sector provides high-quality annual data to construct establishment-level measures of TFP.

For this analysis, we use a consistent and representative plant-level TFP database for all plants in the Annual Survey of Manufactures (ASM) and the Census of Manufactures (CM) from 1981 to 2010.[14] The strength of these data is that we are able to measure plant-level TFP for over 2 million plant-year observations. A limitation of the ASM in non-Census years is that,

[13] Indeed, Cooper and Haltiwanger (2000) used reduced form regressions similar to those we estimate in an indirect inference estimation of structural parameters of adjustment costs (in this case the application was capital adjustment). They also show in the numerical analysis of their structural model that the marginal responsiveness of investment to profit shocks declines with increases in adjustment costs whether from convex or non-convex adjustment costs.

[14] We are building on the data infrastructure developed by Foster, Grim and Haltiwanger (2016) – hereafter FGH. Our empirical specification also is closely related to FGH. The latter examined the changing responsiveness of reallocation to productivity over the cycle. We use the same terms FGH used for this purpose as controls in our analysis.

while it is representative in any given year, it is a rotating sample so its longitudinal properties are inferior to those of the LBD.[15] 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 ASM/CM/LBD we have the subset of establishments from the LBD 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).[16] A second key advantage of integrating the ASM/CM data with the LBD is that it allows us to avoid using the ASM to construct measures of growth and survival. The rotating panel nature of the ASM makes this difficult on many different dimensions. Thus, our empirical approach is to study the relationship between plant-level TFP as measured by the ASM/CM in year t and the growth and survival of plants between t and t+1 as measured in the LBD.[17]

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.[18] The index is given by:

$$lnTFP_{et} = lnQ_{et} - \alpha_K lnK_{et} - \alpha_L lnL_{et} - \alpha_M lnM_{et} \qquad (1)$$

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.

[15] Even the CM is not fully representative of the LBD given that not all establishments receive the Census forms with the questions needed to construct measures of TFP.
[16] The propensity score model uses a logit model to estimate the probability a plant in the LBD (the universe) is in the ASM/CM as a function of detailed industry, firm size and firm age. It allows us to make the cross sectional distribution of plants in any given year be representative of the LBD on these dimensions. Note that these weights are appropriate for making the cross sectional distribution in any given year representative but are not the ideal weights for using samples of ASM/CM that are present in both t and t-1. We discuss this further below.
[17] A closely related empirical strategy would be to estimate the relationship between the innovations to TFP and subsequent growth and survival. The challenge here is that the ASM/CM data does not readily yield an innovation series for all years (see discussion below).
[18] Syverson (2011) provides an excellent summary.

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 deflator 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.[19]

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 detailed industry-by-year average. We use detailed (e.g., 6-digit NAICS) industry effects for this purpose. 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. Given our focus on within-industry-by-year idiosyncratic shocks, this implies we are abstracting from the direct influence of aggregate and industry-specific shocks on firm growth dynamics. We refer to this idiosyncratic TFP measure as the productivity shock. The framework we have in mind is that the idiosyncratic component of TFP is a persistent process, and we model this below as an AR(1) process. The current-period realization of the idiosyncratic component of TFP is the shock, and

[19] Foster et al. (2015a, 2015b) find that the revenue TFP measures using cost shares are highly correlated with revenue TFP measures from estimating the revenue function using proxy methods. Foster et. al. (2015b) show that the revenue residuals from proxy methods are in principle only a function of exogenous variables such as TFPQ and demand shocks.

we also consider innovations to these shocks by estimating the AR(1) process below. It is common in the adjustment cost literature to use the covariance between idiosyncratic shocks so defined and factor adjustments to pin down the structure of adjustment costs.[20]

Our measure of productivity is revenue based. In this respect, we are using a TFPR 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 on a wide scale in the ASM and CM. However, as Foster, Haltiwanger and Syverson (2008) (henceforth FHS) have shown, it is possible to measure establishment-level prices for a limited set of products in Economic Census years (years ending in “2” and “7”). FHS create a physical quantity measure of TFP (which they denote as TFPQ) removing the establishment-level price for establishments producing a set of 11 homogeneous goods (for example, white pan bread). The within-industry correlation between TFPR and TFPQ is high (about 0.75). However, FHS also find 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 and that such demand shocks are positively correlated with TFPR. As such, our measure of establishment-level productivity should be interpreted as reflecting both technical efficiency and demand factors (including product quality factors that may be embedded in prices). For our purposes, a key finding from FHS is that the relationship between growth and survival and TFPQ and demand shocks is quite similar to the relationship between growth and survival and TFPR. It is time variation in the relationship between growth and survival and our revenue-based measure of TFP

[20] Cooper and Haltiwanger (2006) use the covariance between the profitability shock and investment as a key moment. This profitability shock (they denote as A) is modeled as an AR(1) process. As in our analysis they find that the profit shock has substantial persistence but the AR(1) coefficient is far from one. They focus on a balanced panel of large plants so they do not need to deal with the panel rotation issues of the ASM as we discuss below.

that we are exploring. 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.[21]

The first exercise we consider is to explore the evolution of the within-industry dispersion in (log) TFP, where dispersion is quantified as the standard deviation of the within-industry plant-level (log) TFP distribution. This is our measure for the dispersion of idiosyncratic productivity shocks impacting establishments. Figure 7 shows the evolution of the within-industry dispersion in productivity for all manufacturing plants as well as plants in the High Tech and Non Tech components of manufacturing. For this and all the analysis in this section, we use the propensity score weights discussed above. Given our interest in low frequency variation, we report HP trends of this measure of dispersion. Consistent with the literature, there is large dispersion in TFP across plants in the same industry (see, *e.g.*, Syverson (2004, 2011)). The standard deviation of log TFP averages about 36 log points for the all manufacturing and Non Tech manufacturing samples. It averages 40 log points for the plants in the High Tech part of manufacturing. For High Tech, trend dispersion in TFPR rose mildly through 1990s and then more substantially in the post-2000 period. For the remainder of manufacturing, trend dispersion of TFP was relatively constant through the 1990s but rose in the post-2000 period.

The evidence presented earlier suggests that plants of young firms exhibit different paces of reallocation, so we also examine these patterns separately for plants owned by young firms (firm age less than 5) and mature firms. We use the LBD and its firm age measures for each plant to classify plants in the ASM/CM/LBD integrated data for this purpose. These patterns are

[21] See Foster, Haltiwanger and Syverson (2013).

depicted in Figure 8. We find that the levels of within-industry dispersion in productivity are about the same for the young and the old plants in both High Tech and Non Tech. Young and old plants exhibit a positive trend in dispersion in High Tech that roughly mimics the overall. The same holds for Non Tech.

To help understand the implications of this rising within-industry dispersion of productivity, it is also useful to examine the patterns of persistence in plant-level TFP. Much of the literature on plant-level productivity has found that plant-level productivity shocks exhibit considerable persistence but are far from a unit root process. In terms of implications of productivity shocks for plant-level dynamics, the adjustment cost literature (*e.g.*, Cooper and Haltiwanger (2006) and Cooper, Haltiwanger and Willis (2007)) shows that the implied patterns of plant-level growth dynamics depend on the persistence of the idiosyncratic shocks. This is intuitive since in the face of adjustment costs plants are more likely to respond to persistent shocks.

Our data infrastructure is not ideally suited for estimating persistence since this requires relying on the longitudinal nature of the ASM/CM, which is less robust than the longitudinal properties of the LBD. That is, estimating productivity persistence parameters requires pairwise continuing plants in t-1 and t to be measured in the ASM/CM. The panel rotation of the ASM as well as Census years make this a challenge. That is, in the first years of a new ASM panel and in Census years we have a much smaller and less representative set of continuing plants than other years if we rely on linked ASM/CM data for longitudinal outcomes (for our main analysis we use the LBD for longitudinal outcomes, and we have a representative sample each year in the cross section). For this exercise we exclude those years.[22] With these caveats in mind, Figure 9a shows the estimates from a simple AR(1) model of TFP applied to continuing plants. The estimates are presented separately for High Tech and Non Tech. We only depict averages by decades given that we have to exclude specific years as noted above. The estimates are in the 0.6 to 0.7 range. Moreover, the estimates are reasonably stable over time. For High Tech, there is a slight decrease in persistence in plant-level TFP in the 1990s, but it rebounds in the post-2000 period.

For the set of years where we can estimate the AR(1) process, we can also recover the distribution of innovations to plant-level TFP for continuing plants. Since this is for selected years we report averages of standard deviation of innovations to TFP by decades as we did with persistence. We find patterns that mimic the pattern of dispersion in TFP. That is, the dispersion of innovations for High Tech rises mildly in the 1990s and then rises more substantially in the post-2000 period.

The findings presented thus far suggest that the changing patterns of reallocation are not driven by changing patterns in the dispersion of TFP or the persistence in TFP. Consider plants in High Tech manufacturing. Figure 6 shows a pattern of rising reallocation during the 1990s and then sharply falling reallocation in the post-2000 period. For dispersion and persistence of TFP to account for these patterns we would expect dispersion and/or persistence to mimic these patterns. The patterns we present suggest that, if anything, we should see a rising pace of reallocation in the High Tech and Non Tech in the post-2000 period, which is exactly the time we have seen a decline in the pace of reallocation.

[22] Even for other years, our propensity score weights are not ideally suited for making the sample of continuers representative. In principle, we can develop separate propensity score weights for this restricted sample of continuing plants. Doing so is more of a challenge, but we plan to investigate this in future drafts of the paper.

We now turn to investigating whether there is a change in the responsiveness of growth and survival to idiosyncratic differences in TFP across plants.[23] For this purpose, we rely on the integrated ASM/CM/LBD. The ASM/CM (along with propensity score weights) provides a representative cross sectional distribution of plant-level TFP. The LBD provides the ability to measure growth and survival from t to t+1 without relying on the ASM/CM data.

We use Davis, Haltiwanger and Schuh (1996) (hereafter DHS) growth rates so that when we compute growth rates between *t* and *t*+1 for all incumbents in year *t* we can be inclusive of plant exit ($g_{e,t+1} = (E_{et+1} - E_{et})/(0.5 * (E_{et+1} + E_{et}))$. Equation (2) shows our basic specification:[24]

$$g_{e,t+1} = \lambda_{t+1} + \beta_y * TFP_{et} * Young_t + \delta_{1y} * TFP_{et} * Young_t * Trend_t$$
$$+\delta_{2y} * TFP_{et} * Young_t * TrendSQ_t + \beta_o * TFP_{et} * Mature_t$$
$$+\delta_{1o} * TFP_{et} * Mature_t * Trend_t + \delta_{2o} * TFP_{et} * Mature_t * TrendSQ_t + X'_{et}\Theta + \varepsilon_{e,t+1} \quad (2)$$

where $g_{e,t+1}$ is the DHS employment growth rate for establishment *e* between time t and 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, *TrendSQ* is a quadratic trend, $Young_t$ is a dummy equal to 1 if the plant is young in year t, $Mature_t$ is a dummy equal to 1 if the plant is mature in year t and X_{et} is a set of controls discussed further below. Note that trend terms are not entered as main effects since there is a full set of year effects. The latter capture general trends as well as national cyclical effects. We estimate equation (2) using our propensity score weights. All of the terms involving TFP are fully saturated with young and mature dummies, as the evidence in the

[23] Our approach is closely related to 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. The specification we use relating growth and survival to TFP is common in the literature (see Syverson (2011)).

prior sections suggest that the dispersion of plant-level growth dynamics differs systematically across plants owned by young and more mature firms.

While this is a reduced form specification, it is broadly consistent with the specifications of selection and growth dynamics from the literature we discussed above.[25] 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.*, 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.

Our interest is in investigating whether the response to idiosyncratic productivity shocks has changed over time. We explore this in a simple fashion via the interaction between the linear and quadratic trends and TFP. We have in unreported results considered alternative ways to capture a changing trend (*e.g.*, interacting a linear trend with decade dummies), and results are robust to considering such alternatives.

We estimate specification (2) for 1981-2010 with the following controls as captured by X_{et}. For the latter we include the young firm dummy, establishment size, firm size, state effects and a state-level business cycle indicator (the change in state-level unemployment rate).[26] We

[25] The use of annual data is a limitation relative to the recent literature on estimating structural adjustment costs for employment dynamics. In interpreting the timing of the annual data, it is useful to note that TFP reflects TFP in the calendar year t, and growth from t to t+1 represents the growth from March of year t to March of t+1. Estimating this with innovations would also be of interest but our ability to have (i) a representative sample of innovations and (ii) innovation series for all years is limited. Also, we only have plant-level innovations for continuing plants. Our current specification has a representative distribution of all incumbents in t including those plants that just entered in t.

[26] 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.

interact the state-level cyclical indicator with plant-level TFP following FGH. The cyclical variables are all interacted with the young and old dummies. Since we are interested in the changing response and the Great Recession is at the end of our sample, we do not want our estimates of the changing trend responses (the main coefficients of interest) to be driven by the changes in the response to TFP over the cycle.

The first column of Table 1 shows the estimates for the plants in High Tech while the second column shows the estimates for the plants in Non Tech. We only report the main effects for TFP by firm age group and the interactions with the trend terms. Given the many interaction effects, it is easier to interpret the variation across age groups and time by sector graphically which we show in Figure 10. However, we note that all of the effects of interest for the High Tech sector in column 1 of Table 1 are statistically significant at the five percent level. For the Non Tech sector, four of the six coefficients in column 2 of Table 1 are statistically significant at the 10 percent level.

Figure 10 shows the pattern of the marginal effect of TFP on plant-level growth for young and mature plants by decade. To compute these statistics, we set the cyclical indicator (the state level change in unemployment) to zero so the effects reflect controlling for the cycle but are evaluated at a neutral cyclical state. The top and bottom panels of Figure 10 show the patterns for High Tech plants and Non Tech plants, respectively. For High Tech plants, we find that young plants are much more responsive than mature plants to idiosyncratic differences in TFP. Taken together with earlier findings, the high pace of reallocation of young plants is not driven by a high variance of TFP but rather by a high responsiveness to TFP differences. This is consistent with a learning model where young plants are especially responsive to TFP as they learn where to find themselves in the productivity distribution.

Our main focus is the variation in the responsiveness over time. First, consider High Tech. The difference in responsiveness between young and mature plants implies that overall responsiveness will change given changes in the age composition. For example, the increase in the share of activity accounted for by young businesses in High Tech during the 1990s implies an increase in overall responsiveness, while the decrease during the post-2000 period implies a decrease in overall responsiveness. We also find interesting patterns within age groups. For young plants, responsiveness increases from the 1980s to the 1990s and then declines in the post-2000 period. For mature plants, responsiveness decreases throughout the time sample but accelerates during the post-2000 period.

The lower panel of Figure 10 shows the analogous patterns for Non Tech. Here again we find that young plants are more responsive to TFP than mature plants. For Non Tech there has been a decline in the share of young business activity throughout the period (this pattern mimics the overall manufacturing pattern in Figure 3) implying a decline in overall responsiveness due to composition effects. Within age groups, we find a decline throughout the period with an acceleration of the decline in the post-2000 period.

Putting the pieces together, the patterns imply an overall increase and then decline in responsiveness of growth to TFP for plants in High Tech. This is driven by a number of factors: (i) the higher responsiveness of young plants and the shifting age composition; (ii) the increase and then decrease in the responsiveness of young plants; and (iii) the acceleration of the decline in responsiveness for both young and old plants in the post-2000 period.

There may be interactions between the effects we have detected. The rising dispersion of TFP (and its innovations) in the post-2000 period may be contributing to declining responsiveness through expansion of inaction bands. But this cannot account for all of the declining responsiveness since rising dispersion of TFP typically should yield an increase in the pace of reallocation and we find the opposite in the post-2000 period. In addition, the 1990s exhibited a mild increase in productivity dispersion accompanied by an increase in responsiveness for young plants (and rising reallocation).

Another potential source of interaction is the role of selection in influencing the observed dispersion in TFP. In unreported results, we find that part of our declining responsiveness in the post-2000 period is due to a declining responsiveness of exit to productivity shocks. The reduced covariance between survival and productivity can contribute to rising dispersion since low productivity plants are more likely to survive. But again the patterns over time suggest this cannot be a dominant part of the story. During the 1990s, we find increased responsiveness of exit but mild increases in dispersion in productivity.

IV. Implications for Aggregate (Industry-Level) Productivity

How important are the changes in responsiveness for aggregate fluctuations in productivity? Much of the literature on the aggregate relationship between productivity and reallocation revolves around the extent to which resources are shifted away from less productive to more productive establishments (see Syverson (2011) for a recent survey). Our micro analysis is very much about such shifts, a fact which we now exploit in a simple counterfactual exercise to provide some perspective on the aggregate implications of the findings above. In each year we first compute the following base year index using the actual data:

$$P_t = \sum_i \theta_{it} P_{it} \qquad (3)$$

where θ_{it} is the employment weight for plant *i* in period *t* and P_{it} is plant-level productivity (deviated from the industry-year mean).[27] Then we use the model to generate a counterfactual index given by:

$$P_{t+1}^{C} = \sum_i \theta_{it+1}^{C} P_{it} \tag{4}$$

where θ_{it+1}^{C} is the predicted employment share for plant *i* in period *t* based upon the estimated model, that is, based on the assumption that plants respond to productivity shocks by growing or shrinking according to model parameters. We compute the predicted employment share using base-year employment levels and the predicted growth rates in employment from the estimated model.[28] We measure the gains from reallocation as $P_{t+1}^{C} - P_t$. We can compute the gains from reallocation under different scenarios. First, we can construct the gains from reallocation using the full model including all of the estimated trend effects. Second, we can construct the gains from reallocation that would have occurred in the absence of the trend effects. We take the difference between these two cases as the changes in the contribution of reallocation due to changing trend responses. We compute this diff-in-diff counterfactual calculation for each year.

The results of this counterfactual exercise are depicted in Figure 11. For High Tech plants, the increasing responsiveness over the 1980s and 1990s yields an implied counterfactual increase in the contribution of reallocation that peaks at about half a log point per year in the 1990s. The sharp decline in responsiveness during the post-2000 period implies a declining contribution of reallocation of as much as 2 log points per year by 2010. The magnitude of this effect is very large. Some caution needs to be used in interpreting the magnitude at the end

[27] FGH show that the index of industry level productivity in (4) yields fluctuations in industry level productivity that mimic the patterns of productivity from aggregated statistics. Since our plant-level TFP also reflects demand/quality effects this index of industry-level productivity should be interpreted appropriately. But as noted FGH find that the industry indices from (2) correspond fairly closely with industry indices from aggregate statistics using traditional growth accounting methods.

[28] For this purpose we use the same approach as in Figures 10. We set the cyclical effects to zero by setting the state-level change in unemployment to zero.

points and certainly extrapolating out-of-sample since the pattern in Figure 11 is driven by fitting a quadratic trend. But we regard our findings as implying that the decline in the contribution of reallocation to productivity may be quite substantial.

It is interesting that the changing responsiveness starts to be a drag on productivity in 2003, about the time that Fernald (2014) finds a trend break in productivity growth in the IT sector. For Non Tech plants, the changing responsiveness has relatively little impact until the post-2000 period. But by 2005 the acceleration of the decline in responsiveness in this part of manufacturing yields as much as a half of a log point drag on productivity per year.

Given that we use the actual distribution in TFP in each year for these counterfactuals, the changing patterns of dispersion we have shown are also potentially contributing factors. However, since we are examining a diff-in-diff, the changing pattern of dispersion influences both the counterfactual with and without the changing trend response. We also note that some caution should be used in interpreting our counterfactual results as yielding patterns that mimic actual aggregate (industry-level) productivity growth. This is because there may be changes in the within-plant productivity components of aggregate (industry-level) manufacturing that we have not estimated in this context.[29]

V. **Concluding Remarks**

While there has been a decline in business dynamism in the overall U.S. economy for the last few decades, the nature and character of this decline has changed substantially over time. During the 1980s and 1990s, the decline was dominated by the Retail Trade sector. During this period, there has been a well-documented shift away from Mom and Pop retail businesses to

[29] Investigating within-plant productivity changes is challenging because the ASM/CM data is not ideally suited for quantifying within-plant productivity changes. However, as discussed above, it may be that a representative sample of continuers can be constructed for certain years. We plan to explore this in future drafts.

large, national chains. Since the evidence also shows that the productivity of large, national chains is substantially greater than that of Mom and Pop businesses, this decline in dynamism in Retail Trade arguably reflects benign changes in the business model so that the typical Retail Trade establishment has become both more productive and more stable over time.

In the post-2000 period, however, there has been an acceleration of the overall decline in indicators of business dynamism that has been led by declines in key innovative sectors like the High Tech sector. In the 1990s, the High Tech sector exhibited increases in the pace of reallocation and indicators of entrepreneurship. Post 2000, this is the sector with the largest declines in these indicators. The current paper focuses on this sector to address basic questions about the evolution of the pace of reallocation. Canonical models of firm dynamics imply that a decline in dynamism should be from one of two sources: either a change in the volatility of shocks or a change in the responsiveness to shocks. We investigate the role of these alternative sources for the High Tech component of manufacturing. The latter exhibits patterns of reallocation that mimic those of the overall High Tech sector.

We find that the within-industry dispersion of TFP rose modestly in the 1980s and 1990s and more sharply in the post 2000 period. In addition, the persistence of the idiosyncratic component of TFP has not exhibited much variation over time. These findings suggest that it is not changes in the shock processes that account for the changing patterns of reallocation in the High Tech manufacturing sector. The patterns of reallocation are of rising reallocation in the 1990s and then sharply declining reallocation in the post-2000 period.

Instead, we find evidence of changing responsiveness of plant-level growth and survival to idiosyncratic differences in TFP in the High Tech sector. This change in responsiveness is accounted for by a number of complementary factors. First, we find that young plants are more responsive to idiosyncratic differences in TFP than are more mature plants. The rising share of activity accounted for by young plants in the 1990s and then the decline in the post-2000 period in High Tech helps account for a changing pace of reallocation. Second, we find that young plants first exhibit an increasing responsiveness of growth and survival to TFP through the 1990s and then a decline that accelerates in the post-2000 period. Third, mature plants exhibit a decline in responsiveness to TFP that accelerates in the post-2000 period.

The changing pattern of responsiveness of plant-level growth and survival to TFP has implications for aggregate (industry-level) productivity growth. We find that increased responsiveness of growth and survival to idiosyncratic differences in TFP in High Tech during the 1990s yielded an increase in the contribution of reallocation to industry-level productivity growth of as much as half a log point per year. In turn, we find that that the acceleration of the decline in responsiveness of plant-level growth to idiosyncratic TFP differences in High Tech yields a decline in the contribution of reallocation to industry-level productivity growth of as much as two log points per year.

The open question raised by our analysis is what has been driving these changes in the responsiveness of plant-level growth and survival to idiosyncratic differences in TFP. Part of our answer is that the changing age composition of businesses plays a role since young businesses are more responsive to TFP shocks. But this in turn raises the question as to why there have been changes in the composition of young businesses over time. For the High Tech sector, this remains an open question. Second, we find that amongst young plants in High Tech there is a change in the responsiveness of growth and survival to plant-level TFP. There is also a change in the responsiveness of more mature plants that accelerates during the post-2000 period.

The factors that underlie these changes are not yet understood. Given the potential productivity consequences, understanding those factors should be a high priority for future research.

While the current paper does not yet investigate these factors, it is useful in concluding to outline candidate factors. One candidate could be policy frictions that reduce incentives for labor adjustment, such as unlawful discharge regulations or occupational licensing.[30] In the High Tech manufacturing sector, another possible cause of declining productivity responsiveness during the post 2000s is the transition from "general-purpose" to "special-purpose" equipment manufacturing in the U.S as highlighted by Byrne (2015).[31] Businesses manufacturing these special-purpose products may be less responsive to productivity due to demand constraints or uncompetitive environments that reduce adjustment imperatives.

The evidence we have presented describes the response of employment growth to productivity shocks, but within-establishment employment growth is not firms' only means of adjustment. Firms may increasingly adjust to shocks through investment in physical or intangible capital given the ongoing substitution towards capital and away from labor in the economy. Globalization may be playing a role since increased exposure to foreign trade facilitates adjustment by scaling international operations. We plan to explore these and related hypotheses in future work.

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[30] Davis and Haltiwanger (2014) review relevant studies and provide suggestive evidence.

[31] We thank Christopher Foote for this insight.

References

Andrews, Dan, Chiara Criscuolo, and Peter N. Gal. 2015. "Frontier Firms, Technology Diffusion and Public Policy: Micro Evidence from OECD Countries." OECD: *The Future of Productivity: Main Background Papers.*

Bachmann, Rüdiger and Christian Bayer. 2013. "Wait-and-See Business Cycles." *Journal of Monetary Economics* 60(6): 704-19.

Baily, Martin Neil, Charles Hulten, and David Campbell. 1992. "Productivity Dynamics in Manufacturing Plants." In *Brookings Papers on Economic Activity: Microeconomics*, ed. Clifford Winston and Martin Neil Baily. Washington, DC: Brookings Institution Press.

Barro, Robert J. 1972. "A Theory of Monopolistic Price Adjustment." *The Review of Economic Studies* 39(1): 17-26.

Becker, Randy A., John Haltiwanger, Ron S. Jarmin, Shawn D. Klimek, and Daniel J. Wilson. 2006. "Micro and Macro Data Integration: The Case of Capital." Chap. 12 in *Studies in Income and Wealth* edited by Dale W. Jorgenson, J. Steven Landefeld, and William D. Nordhaus, vol. 66, *A New Architecture for the U.S. National Accounts*, pp. 541-609. Chicago, IL: National Bureau of Economic Research, University of Chicago Press.

Bloom, Nicholas. 2009. "The Impact of Uncertainty Shocks." *Econometrica*, 623-85.

Byrne, David M. 2015. "Domestic Electronics Manufacturing: Medical, Military, and Aerospace Equipment and What We Don't Know about High-Tech Productivity," FEDS Notes 2015-06-02. Board of Governors of the Federal Reserve System.

Cairó, Isabel. 2013. “The Slowdown in Business Employment Dynamics: The Role of Changing Skill Demands.” *Mimeo.* At http://www.econ.upf.edu/eng/graduates /gpem/jm/cairo.html.

Cooper, Russell and John Haltiwanger. 2000. “On the Nature of Capital Adjustment Costs.” NBER Working Paper No. 7925.

Cooper, Russell and John Haltiwanger. 2006. “On the Nature of Capital Adjustment Costs.” *Review of Economic Studies* 73(3); 611-33.

Cooper, Russell, John Haltiwanger, and Jonathan Willis. 2007. “Search Frictions: Matching Aggregate and Establishment Observations.” *Journal of Monetary Economics* 54 Supplement 1: 56-78.

Cooper, Russell, John Haltiwanger, and Jonathan Willis. 2015. “Dynamics of labor demand: Evidence from plant-level observations and aggregate implications,” *Research in Economics,* 69: 39-50.

Davis, Steven J. and John Haltiwanger. 2014. “Labor Market Fluidity and Economic Performance.” NBER Working Paper 20479 (published in the 2014 Federal Reserve Bank of Kansas City Jackson Hole Conference Symposium).

Davis, Steven J., R. Jason Faberman, and John Haltiwanger. 2012. “Labor Market Flows in the Cross Section and Over Time.” *Journal of Monetary Economics* 59(1): 1-18.

Davis, Steven J., John Haltiwanger, Ron Jarmin, and Javier Miranda. 2007. "Volatility and Dispersion in Business Growth Rates: Publicly Traded versus Privately Held Firms." Chap. 2 in *NBER Macroeconomics Annual 2006* edited by Daron

Acemoglu, Kenneth Rogoff, and Michael Woodford, vol. 21, pp. 107-80. Cambridge, MA: MIT Press.

Davis, Steven J., John C. Haltiwanger, and Scott Schuh. 1996. *Job Creation and Destruction.* Cambridge, MA: MIT Press.

Decker, Ryan, John Haltiwanger, Ron Jarmin and Javier Miranda. 2014. "The Role of Entrepreneurship in US Job Creation and Economic Dynamism" *Journal of Economic Perspectives* 28(3) 3-24.

Decker, Ryan A., John Haltiwanger, Ron S. Jarmin, and Javier Miranda. 2015. "Where Has All the Skewness Gone? The Decline in High-Growth (Young) Firms in the U.S." *European Economic Review* (forthcoming).

Ericson, Richard, and Ariel Pakes. 1995. "Markov-Perfect Industry Dynamics: A Framework for Empirical Work." *Review of Economic Studies* 62(1): 53–82.

Fernald, John. 2014. "Productivity and Potential Output Before, During, and After the Great Recession." Chap. 1 in *NBER Macroeconomics Annual 2014* edited by Jonathan A. Parker and Michael Woodford, vol. 29, pp. 1-51. Cambridge, MA: MIT Press.

Fort, Teresa. 2013. "NAICS 2002 Code Assignments to the Longitudinal Business Database." Mimeo, Center for Economic Studies.

Foster, Lucia, Cheryl Grim, and John Haltiwanger. 2016. "Reallocation in the Great Recession: Cleansing or Not?" *Journal of Labor Economics.*

Foster, Lucia, Cheryl Grim, John Haltiwanger, and Zoltan Wolf. 2015a. "From Devilish Details to Insights: Micro and Macro Productivity," mimeo.

Foster, Lucia, Cheryl Grim, John Haltiwanger and Zoltan Wolf. 2015b. "Firm-Level Dispersion in Productivity: Is the Devil in the Details" mimeo.

Foster, Lucia, John Haltiwanger, Shawn Klimek, C.J. Krizan and Scott Ohlmacher. 2015c. "The Evolution of National Chains: How we got here", Center for Economic Studies Working Paper No. CES-WP-15-10.

Foster, Lucia, John Haltiwanger, and C.J. Krizan. 2006. "Market Selection, Reallocation and Restructuring in the U.S. Retail Trade Sector in the 1990s." *The Review of Economics and Statistics* 88(4): 748-58.

Foster, Lucia, John Haltiwanger, and Chad Syverson, 2008. "Reallocation, Firm Turnover, and Efficiency: Selection on Productivity or Profitability?" *American Economic Review*, 98(1): 394-425.

Foster, Lucia, John Haltiwanger, and Chad Syverson. 2014. "The Slow Growth of New Plants: Learning about Demand?" Forthcoming, *Economica.*

Haltiwanger, John, Ian Hathaway, and Javier Miranda. 2014. "Declining Business Dynamism in the U.S. High-Technology Sector." The Kauffman Foundation.

Haltiwanger, John, Jarmin, Ron, and Javier Miranda. 2009. "Business Dynamics Statistics: An Overview." Kauffman Foundation: Other Research. At http://www.kauffman.org/uploadedFiles/BDS_handout_011209.pdf.

Haltiwanger, John, Ron Jarmin, and Javier Miranda. 2011. "Historically Large Decline in Job Creation from Startups and Existing Firms in the 2008-09 Recession." Business Dynamics Statistics Briefing No. 5, The Kauffman Foundation.

Haltiwanger, John, Ron S. Jarmin, and Javier Miranda. 2013. "Who Creates Jobs? Small vs. Large vs. Young." *Review of Economics and Statistics* 95(2): 347-61.

Hecker, Daniel. 2005. “High-technology employment: a NAICS-based update,” *Monthly Labor Review* (U.S. Dept. of Labor and U.S. Bureau of Labor Statistics), Volume 128, Number 7, July 2005: 58.

Hugo A. Hopenhayn. 1992. “Entry, Exit, and firm Dynamics in Long Run Equilibrium.” *Econometrica*, Vol. 60(5): 1127-50

Hopenhayn, Hugo and Richard Rogerson. 1993. “Job Turnover and Policy Evaluation: A General Equilibrium Analysis.” *Journal of Political Economy* 101(5): 915-38.

Hyatt, Henry R. and James Spletzer. 2013. “The Recent Decline in Employment Dynamics.” *IZA Journal of Labor Economics* 2(3): 1-21.

Jarmin, Ron S., Shawn Klimek, and Javier Miranda. 2009. "The Role of Retail Chains: National, Regional and Industry Results." Chap. 6 in *Studies in Income and Wealth* edited by Timothy J. Dunne, J. Bradford Jensen, and Mark J. Roberts, vol. 68, *Producer Dynamics: New Evidence from Micro Data*, pp. 237-62. Chicago, IL: National Bureau of Economic Research, University of Chicago Press.

Jarmin, Ron S., and Javier Miranda. 2002. "The Longitudinal Business Database." CES Working Paper no. 02-17. Washington, D.C.: Center for Economic Studies, U.S. Census Bureau.

Jovanovic, Boyan. 1982. “Selection and the evolution of industry.” *Econometrica*, 50(3): 649–70.

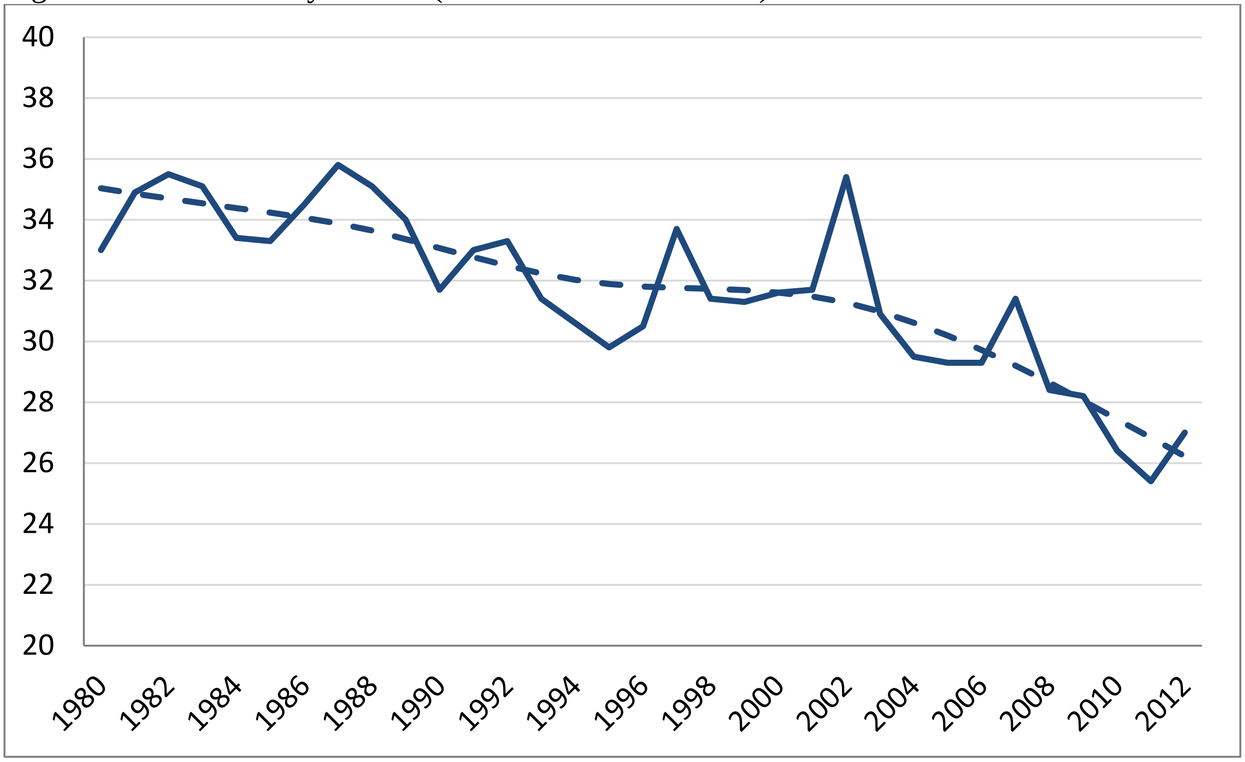
Reedy, E.J. and Robert E. Litan. 2011. “Starting Smaller; Staying Smaller: America's Slow Leak in Job Creation.” Kauffman Foundation Research Series: Firm Foundation and Economic Growth. At http://www.kauffman.org/research-and-policy/starting-smaller-staying-smaller-americas-slow-leak-in-job-creation.aspx.

Syverson, Chad. 2004. “Product Substitutability and Productivity Dispersion.” *Review of Economics and Statistics* 86(2): 534-50.

Syverson, Chad. 2011. “What Determines Productivity?” *Journal of Economic Literature* 49(2): 326-65.

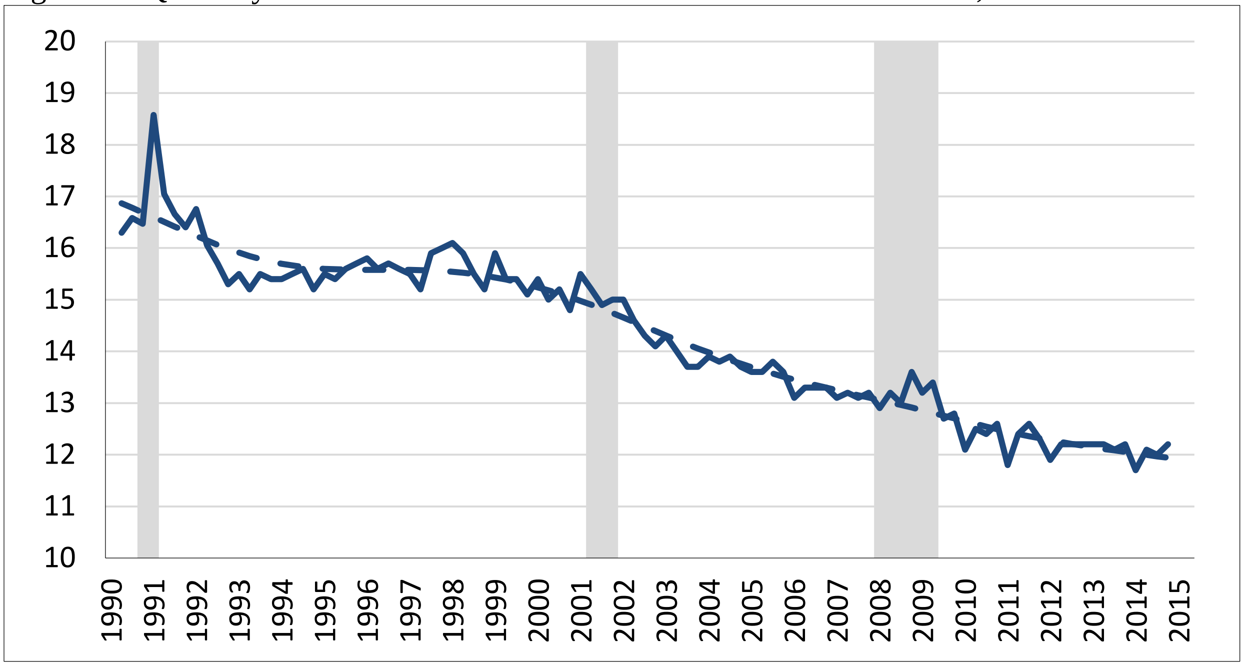
Vavra, Joseph. 2014. “Inflation Dynamics and Time-Varying Volatility: New Evidence and SS Interpretation.” *Quarterly Journal of Economics* 129(1): 215-58.

Figure 1a: Decline in Dynamism (Annual Job Reallocation)



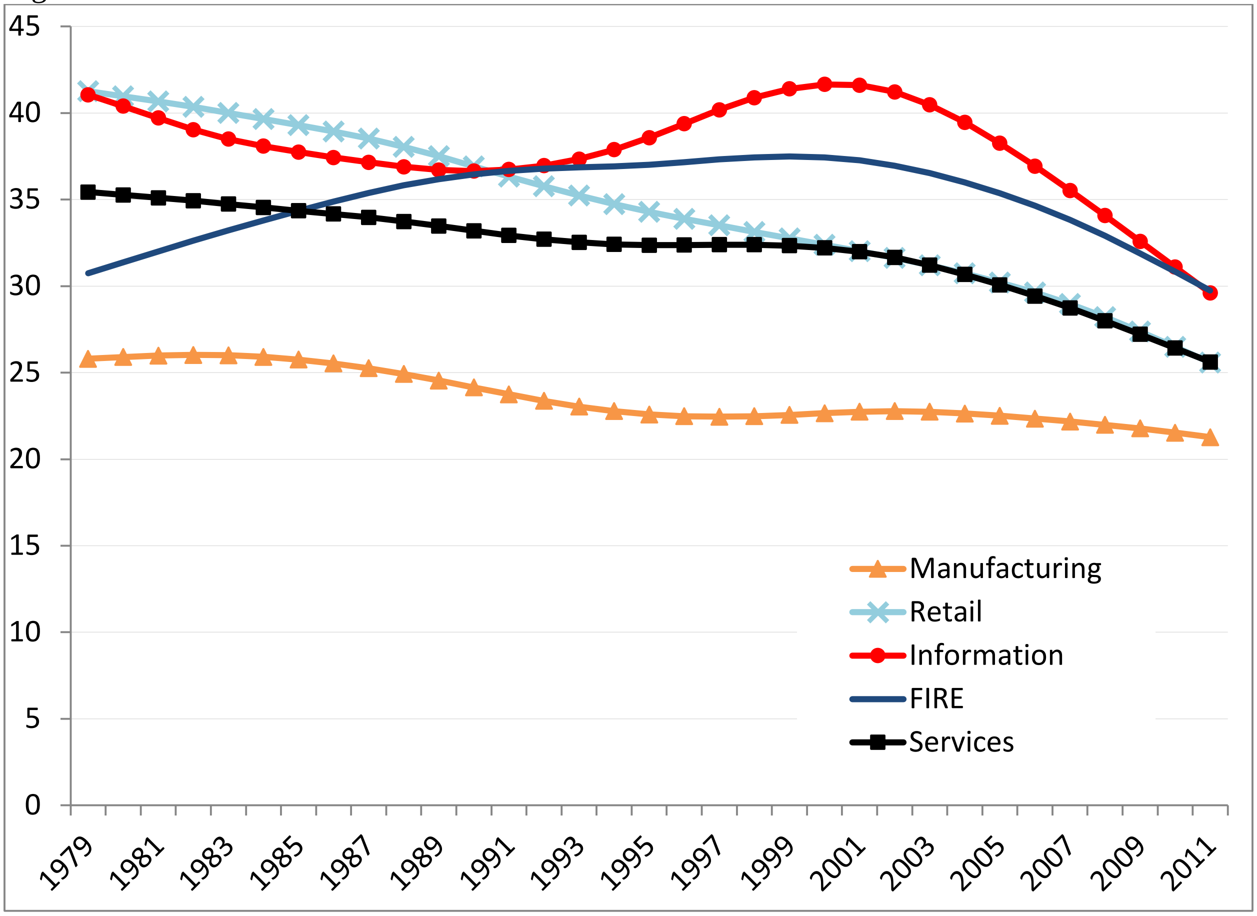
Note: Y axis does not start at zero. Dashed line indicates HP trend with parameter set to 100. Author calculations from Business Dynamics Statistics.

Figure 1b: Quarterly Job Reallocation for the U.S. Private Non-Farm Sector, 1990:2-2014:4



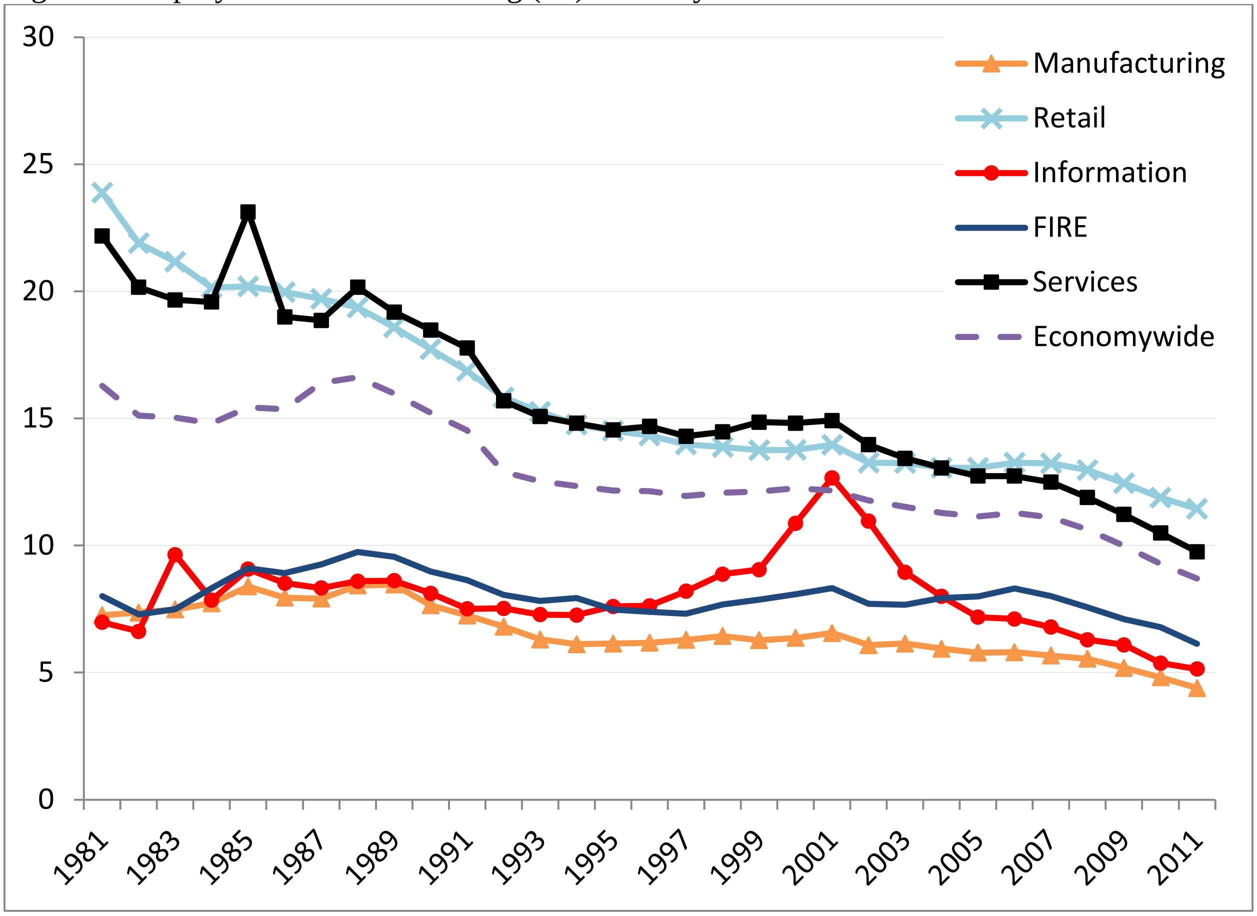
Note: Y axis does not start at zero. Gray bars indicate NBER recession dates. Dashed line indicates HP trend with parameter set to 1600. Source: BLS Business Employment Dynamics extended back to 1990:2 by Davis, Faberman and Haltiwanger (2012).

Figure 2: Sectoral Trends in Reallocation



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

Figure 3: Employment shares for Young (<5) Firms by Broad Sector



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

Figure 4a: Annual Change in Reallocation Rate from 1987/99 to 1997/99 by Sector: Actual and Holding Age Composition Constant

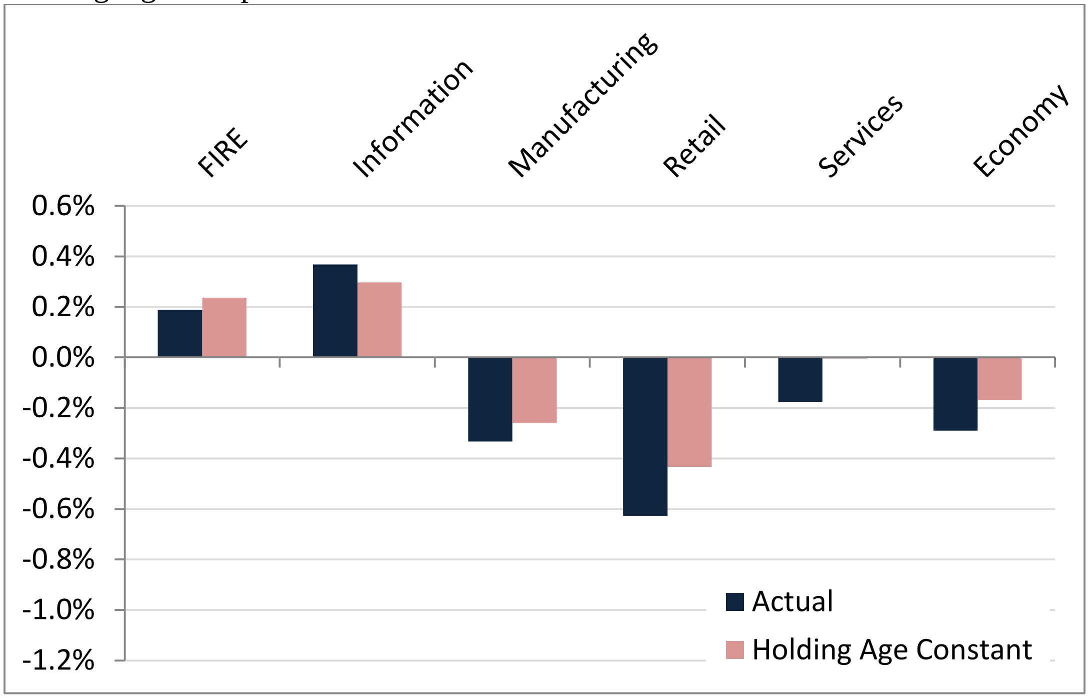
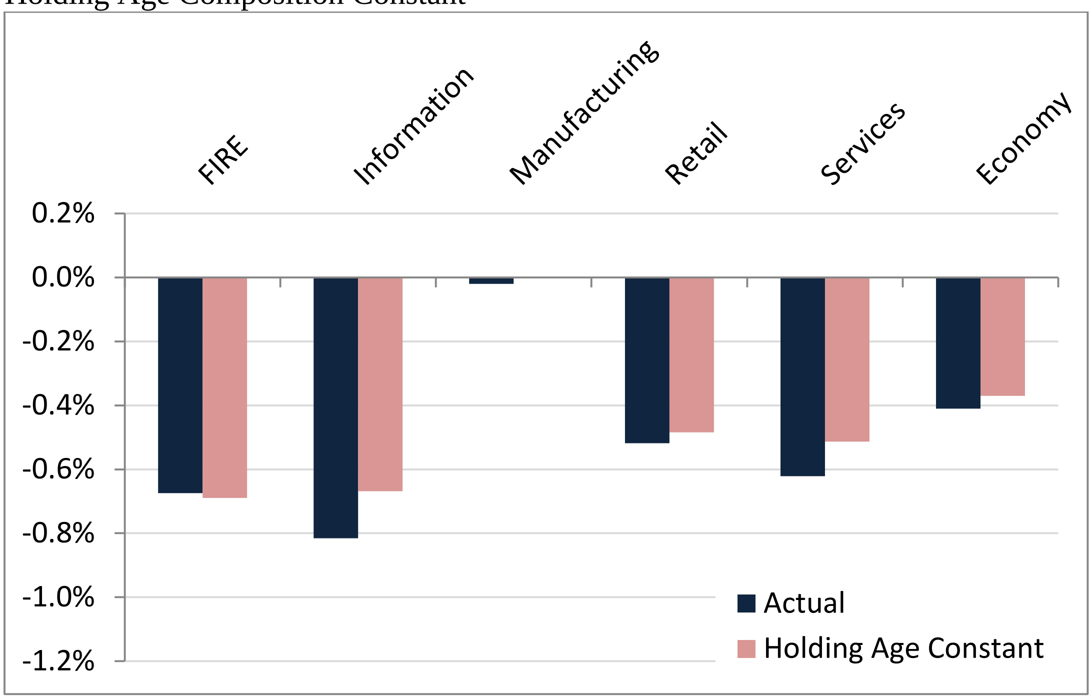
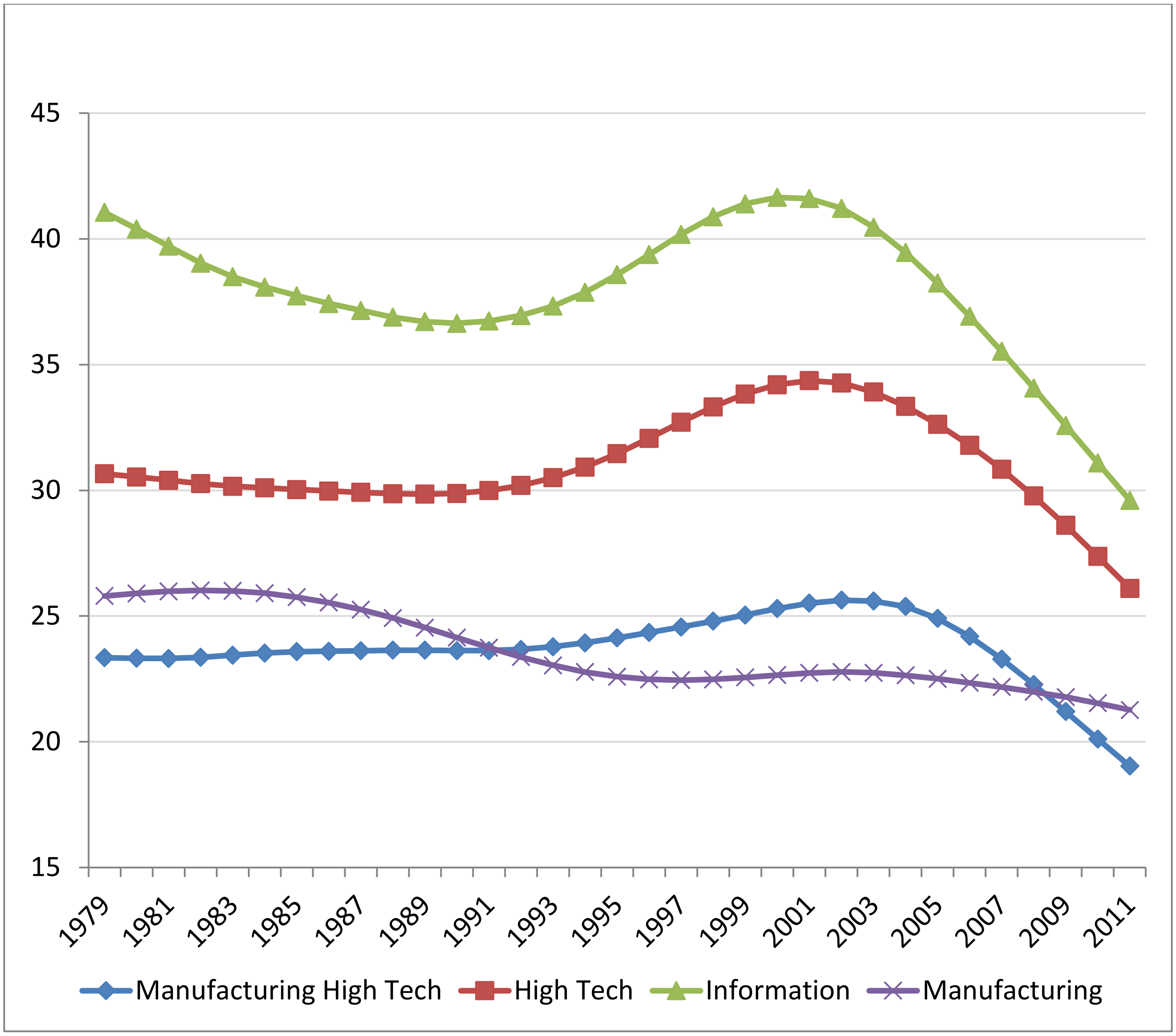


Figure 4b: Annual Change in Reallocation Rate from 1997/99 to 2004/06 by Sector: Actual and Holding Age Composition Constant



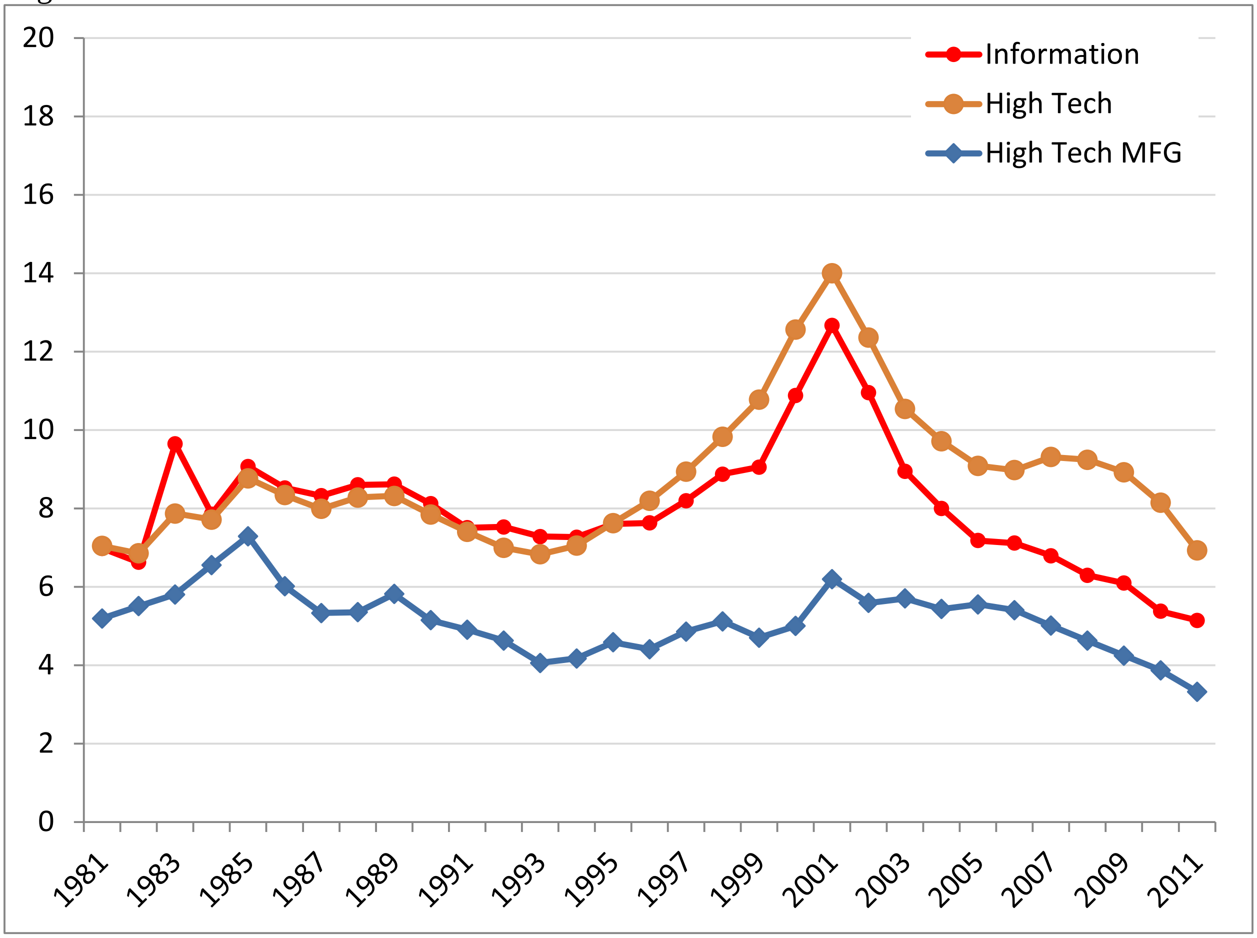
Note: Sectors are defined on a consistent NAICS basis. Author calculations from the Longitudinal Business Database.

Figure 5: High Tech, Information, High Tech Manufacturing and Manufacturing Reallocation Trends



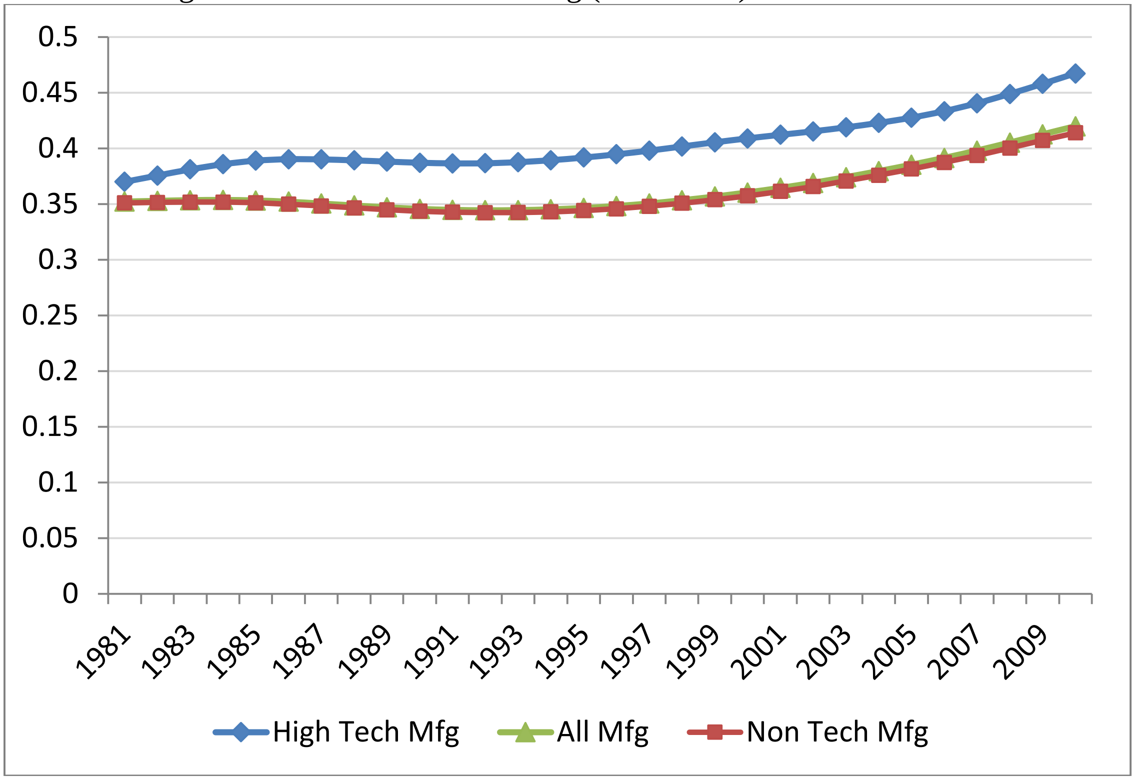
Note: Y axis does not start at zero. High Tech is defined as in Hecker (2005). Information and Manufacturing sectors are defined on a consistent NAICS basis. Author calculations from the Longitudinal Business Database.

Figure 6: Employment shares for Young Firms for Information, High Tech and Manufacturing High Tech



Note: Young firms have age less than 5. High Tech is defined as in Hecker (2005). Information and Manufacturing sectors are defined on a consistent NAICS basis. Author calculations from the Longitudinal Business Database.

Figure 7: Within-Industry TFP Dispersion (Std Deviation) in Total Manufacturing, High Tech Manufacturing and Non Tech Manufacturing (HP Trends)



Note: The standard deviation is the based on within-detailed industry log TFP. High Tech is defined as in Hecker (2005). Manufacturing is defined on a consistent NAICS basis. Author calculations from the Longitudinal Business Database, the Annual Survey of Manufacturers, and the Census of Manufacturers. Hodrick Prescott Trends depicted.

Figure 8a: Within-Industry TFP Dispersion (Std Dev) for High Tech: Young vs. Mature

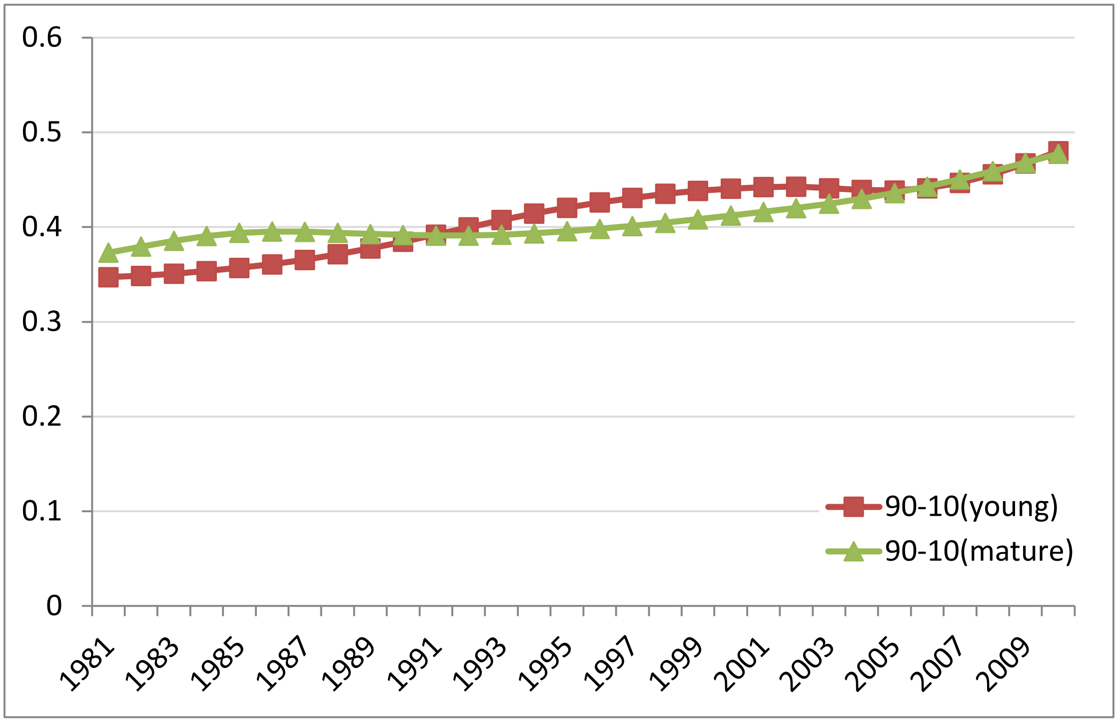
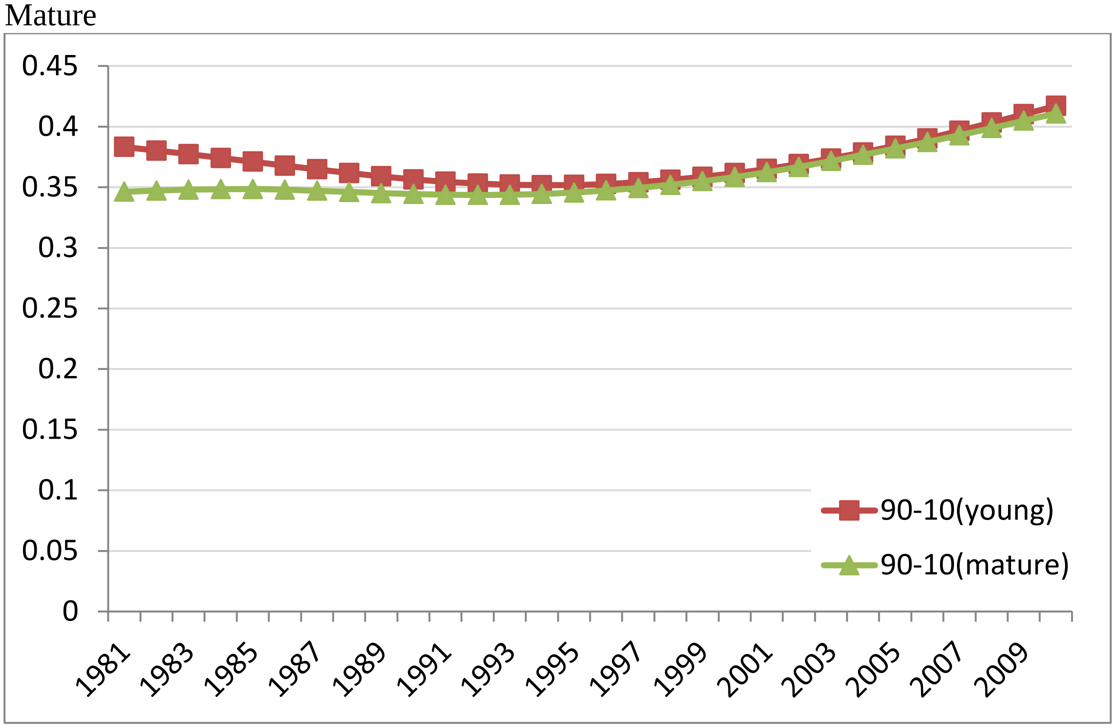
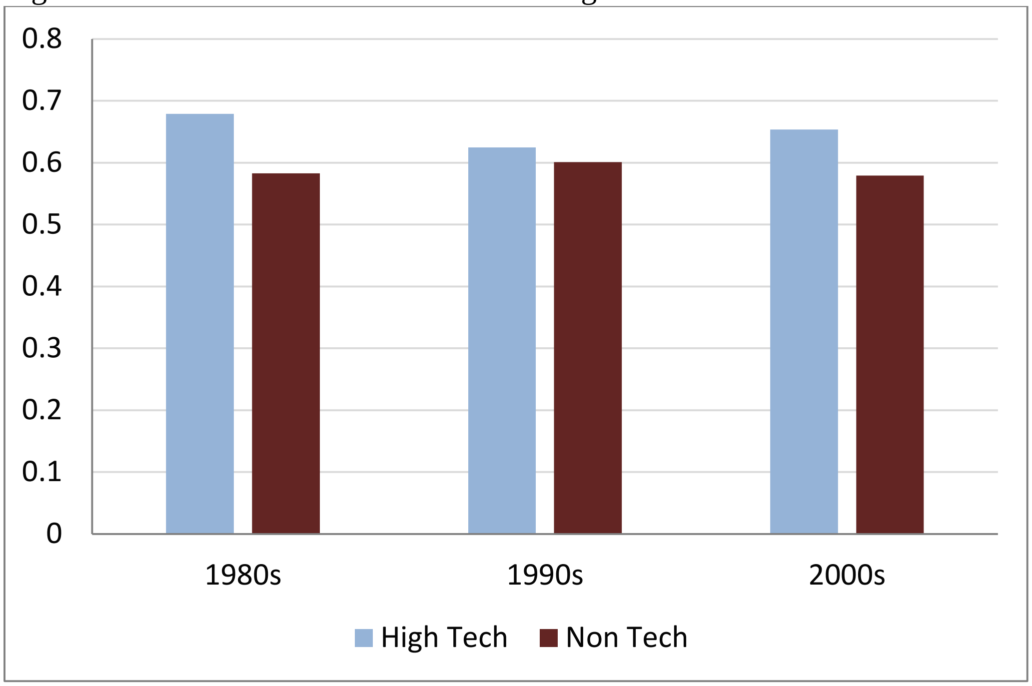


Figure 8b: Within-Industry TFP Dispersion (Std Dev) in Non Tech Manufacturing: Young vs. Mature



Note: Young firms have age less than 5. The standard deviation is the based on within-detailed industry log TFP.   High Tech is defined as in Hecker (2005). Author calculations from the Longitudinal Business Database, the Annual Survey of Manufacturers, and the Census of Manufacturers. HP Trends Depicted.

Figure 9a: Persistence of TFP for Plants: High Tech vs. Non Tech



Note: High Tech is defined as in Hecker (2005). Author calculations from the Longitudinal Business Database, the Annual Survey of Manufacturers, and the Census of Manufacturers.

Figure 9b: Standard Deviations of Innovations to TFP for Plants: High Tech vs Non Tech

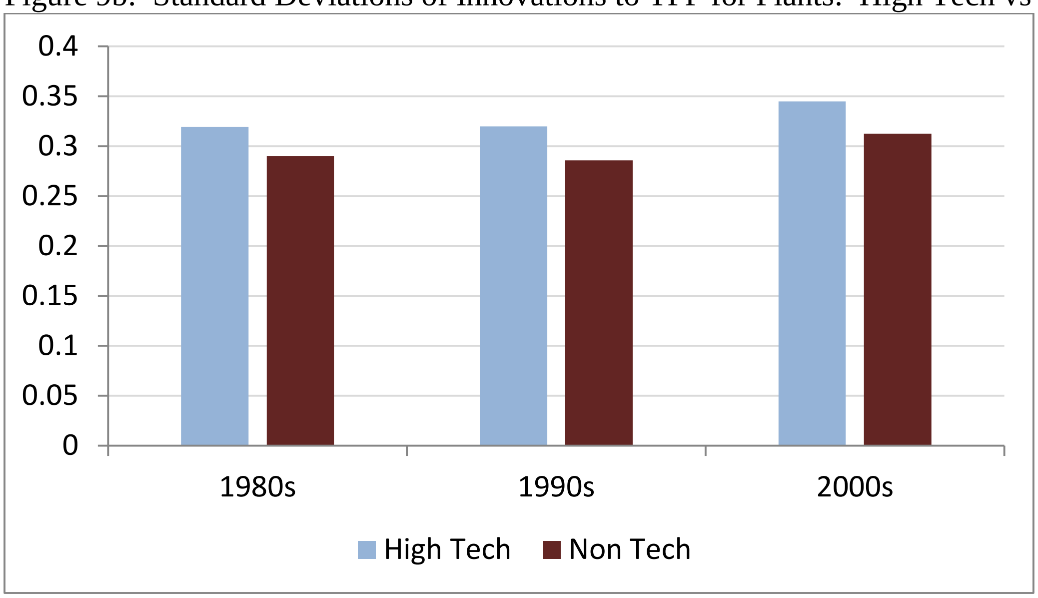
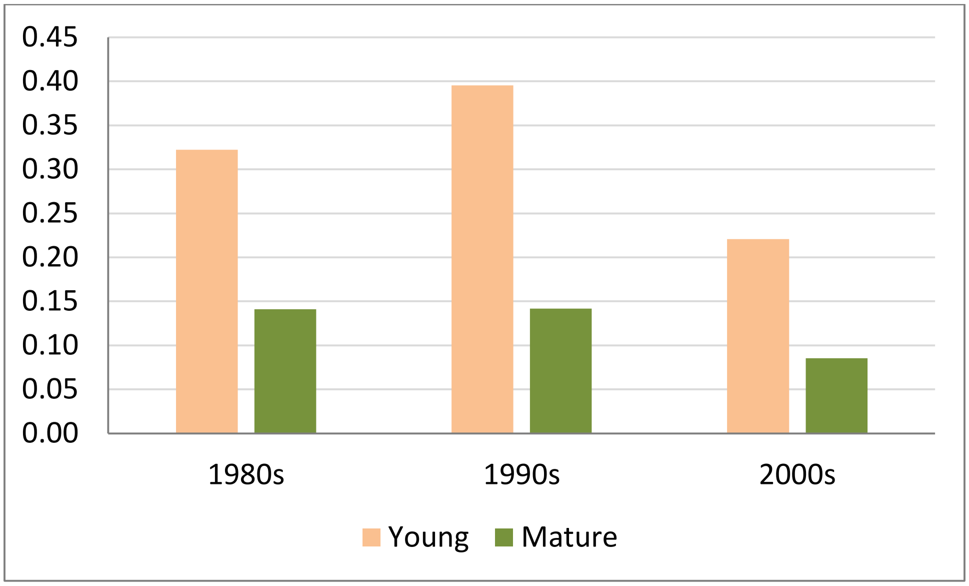
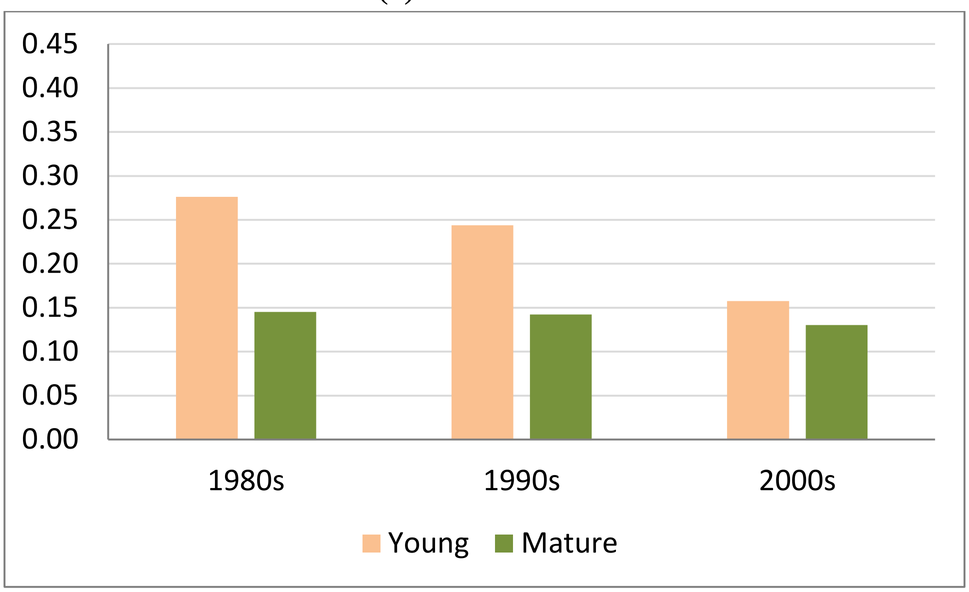


Figure 10: Marginal Effect of TFP on Plant-Level Net Growth: Young vs. Mature

(a) High Tech Plants

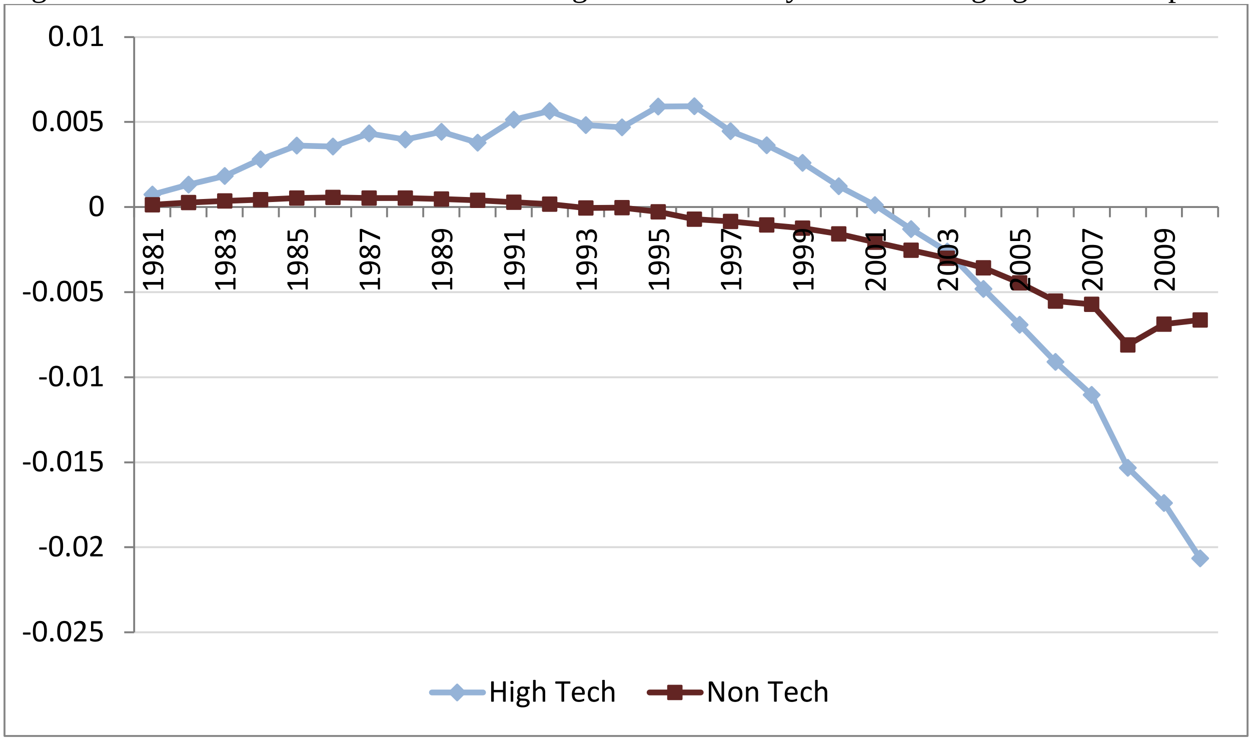


(b) Non Tech Plants



Note: Young firms have age less than 5. High Tech is defined as in Hecker (2005). Author calculations from the Longitudinal Business Database, the Annual Survey of Manufacturers, and the Census of Manufacturers.

Figure 11: Diff-in-Diff Counterfactual Change in Productivity Due to Changing Trend Response



Note: High Tech is defined as in Hecker (2005). Author calculations from the Longitudinal Business Database, the Annual Survey of Manufacturers, and the Census of Manufacturers.

Table 1: Estimated Impact of Lagged Productivity on Plant-Level Growth (Using DHS Growth Rate Including Exiting Plants)

	High Tech	Non Tech
TFP*Young	0.2025***	0.2767***
	(0.0390)	(0.0090)
TFP*Young*Trend	0.0317***	0.0014
	(0.0061)	(0.0014)
TFP*Young*TrendSQ	-0.0012***	-0.00024***
	(0.0002)	(0.00005)
TFP*Mature	0.1228***	0.1439***
	(0.0174)	(0.0043)
TFP*Mature*Trend	0.0054**	0.0005
	(0.0026)	(0.0007)
TFP*Mature*TrendSQ	-0.0003***	-0.00004*
	(0.0001)	(0.00002)

Notes: Standard Errors in Parentheses. Tech Sample is more than 120000 plant-year observations from 1981-2010. Non Tech Sample has more than 2 million observations. Young firms have age less than 5. Unreported are estimates of controls including year effects, state effects, firm age dummies, firm size dummies, log plant level employment in period t, state cyclical indicators (change in state level unemployment rate), state cyclical indicators interacted with TFP. All variables that use TFP including all interactions are fully interacted with firm age dummies. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.1: High-Technology Industries

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

Source: Bureau of Labor Statistics, Hecker (2005)