# 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 U.S. High Tech 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 for young businesses in the High Tech sector. 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.

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 and more stable 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.

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[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). We discuss this evidence further below.

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

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[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. A simple accounting decomposition shows that 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. Section V explores possible

mechanisms underlying the changing responsiveness patterns to productivity shocks in

the High Tech sector. Concluding remarks are in section VI.

## 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

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[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).

Statistics (BDS).[5] 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 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)). Specifically, 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)

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

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. 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 are alternative measures of within-firm and establishment volatility.

Figure 1a depicts the annual pace of establishment-level job reallocation from 1980 to2012 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 four-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 highlighted by Fernald (2014) , much of the surge in productivity growth in the overall

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[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.

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 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), Foster, Haltiwanger and Krizan (2006), and Foster et. al. (2015c)). These studies show that the share of sales and employment from single unit establishment firms fell from about 50 to 35 percent from 1977 to 2007. Almost all of this is accounted for by a rapid rise in the share of sales and employment accounted for by large, national chains. These studies also find establishments in large, national chains are more productive and more stable than single unit establishment firms. The

productivity gap (measured by labor productivity) between an establishment of a large, national chain and single unit establishments within the same industry is about 30 log points. The employment-weighted annual exit rate of single unit establishment firms is about 8 percent per year, while large national chains exit at a rate of less than 1 percent per year. As argued in these studies, these changes in the business model in retail trade were likely facilitated by advances in information technology and globalization that have permitted large, national chains to build large and efficient supply chains and distribution networks.

If all sectors had the patterns of retail trade, the decline in entrepreneurship and business dynamism might largely be interpreted as being driven by benign factors. 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 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)

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[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 focuses 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.

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 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

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[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.
[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.

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 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

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[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.

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, 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

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[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.

[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

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.

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

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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.

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 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-

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[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.

[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.

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).[21] 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 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.[22]

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-

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[21] 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. Moreover, they find that those revenue residuals are very highly correlated with the TFPR measures that emerge using cost shares.

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

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 (the lines overlap in the chart).  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 the 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

depicted in Figure 8.  We find that the levels of within-industry dispersion in productivity are

about the same for plants of young and the old firms in both High Tech and Non Tech.  Plants of

young and old firms 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. For this exercise we exclude those years.[23] 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

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[23] 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.

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.

We now turn to investigating whether there is a change in the responsiveness of growth and survival to idiosyncratic differences in TFP across plants.[24] 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

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[24] 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)).

specification:[25]

$$g_{e,t+1} = \lambda_{t+1} + \beta_y * TFP_{et} * Young_t + \delta_{1y} * TFP_{et} * Young_t * Trend_t$$

$$+\delta_{2y} * TFP_{et} * Young_t * TrendSQ_t + \beta_o * TFP_{et} * Mature_t$$

$$+\delta_{1o} * TFP_{et} * Mature_t * Trend_t + \delta_{2o} * TFP_{et} * Mature_t * TrendSQ_t + X'_{et}\Theta + \varepsilon_{e,t+1}$$

(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.  By young, we mean the plant is

owned by a firm that is less than five years old.[26]  By mature, we mean the plant is owned by a

firm that is 5 or more years old.  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 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.[27]  There is already

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[26] This is one of many instances where our analysis focuses on establishment-level dynamics taking into account the characteristics of the parent firm.   In all of our analysis, when we refer to a young plant we are referring to the age of the parent firm.

[27] 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

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).[28] We interact the state-level cyclical indicator with plant-level TFP following FGH. The cyclical variables are all interacted with the young and mature 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

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current specification has a representative distribution of all incumbents in t including those plants that just entered in t.

[28] 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.

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 plants in young and mature firms 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 plants in young firms, responsiveness increases from the 1980s to the 1990s and then declines in the post-2000 period. For plants in mature firms, 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 plants in young firms are more responsive to TFP than plants in mature firms. 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 plants in young firms and the shifting age composition; (ii) the increase and then decrease in the responsiveness of plants in young firms; and (iii) the acceleration of the decline in responsiveness for plants of both young and mature firms 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 plants in young firms (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:

$$P_t = \sum_i \theta_{it} P_{it} \tag{3}$$

where $\theta_{it}$ is the employment weight for plant $i$ in period $t$ and $P_{it}$ is plant-level productivity

(deviated from the industry-year mean).[29] 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 $\theta_{it+1}^C$ is the predicted employment share for plant $i$ in period $t+1$ based upon the estimated

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[29] 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.

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 previous-year employment levels and the predicted growth rates in employment from the estimated model.[30] We measure the gains from model-driven 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; that is, we compute the following:

$$\left(P_{t+1}^{C,trend} - P_t\right) - \left(P_{t+1}^{C,no\ trend} - P_t\right)$$

where $P_{t+1}^{C,trend}$ is the counterfactual model-based productivity that includes trend effects, and $P_{t+1}^{C,no\ trend}$ is the counterfactual model-based productivity that excludes the trend in responsiveness. 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; that is, during the 1980s and 1990s, productivity responsiveness was rising so that reallocation made an increasing contribution to aggregate productivity growth. 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 points and

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[30] 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.

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.[31]

V. **Possible Mechanisms for Changing Responsiveness of Employment Growth in High Tech Manufacturing**

There are many possible factors that may be driving the reduced responsiveness of plant-level employment growth to productivity shocks in the High Tech sector in the post-2000 period. In this section, we investigate three possible mechanisms with a focus on the High Tech component of manufacturing.

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[31] 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.

*A.  Globalization*

Globalization may be playing a role since increased exposure to foreign trade facilitates adjustment by scaling international operations.  That is, it may be that rather than growing domestically, high-productivity young-firm establishments are more likely to expand and produce in other countries.  There is substantial evidence already that the decline in US manufacturing employment is closely linked to rising import penetration of production activity from low wage countries (see, e.g., Bernard, Jensen and Schott (2006), Schott (2006) and Pierce and Schott (2016)).  We build on that research to explore the impact of rising import penetration for changing responsiveness of U.S. establishments to productivity differentials.

Bernard, Jensen and Schott (2006) and Schott (2006) develop measures of import penetration ratios from low wage countries.  They generate measures at the detailed 4-digit SIC level from 1972-2005 and on a 6-digit NAICS basis from 1989-2005.  We extend the latter using the public domain information from Census on imports by country and industry.  We integrate these public domain data into our data infrastructure from 1981-2010.  Our ability to integrate this is facilitated by our having 4-digit SIC codes in the micro level data from 1981-1996 and 6-digit NAICS codes from 1981-2010. [32]

Figure 12 shows the average import penetration ratios for 6-digit NAICS industries in the High Tech and Non Tech industries from 1981-2010.  The import penetration ratios from low wage countries are very small in the 1980s, rise slightly in the 1990s and then rise dramatically in the post-2000 period.  Of particular interest for current purposes is that the rise is especially pronounced for the 6-digit NAICS industries in High Tech.

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[32] We integrate the SIC based import penetration ratios from 1981-88 and the NAICS based ratios from 1989-2010 into the micro data.  We use the internally consistent NAICS codes in the micro data from 1981-2010 to conduct our analysis.  The latter provides micro based concordances between NAICS and SIC for the 1981-88 period.

We exploit the 6-digit NAICS variation in import penetration ratios to explore the possible

role of globalization in accounting for the patterns of changing responsiveness we have detected.

Table 2 presents results of a modified version of estimating specification (2). The additional

regressors added are the 6-digit NAICS import penetration ratio for each year and the interaction

of this ratio with lagged TFP. We permit the coefficients on this interaction effect to differ

between plants belonging to young and mature firms. We report the same coefficients as in

Table 1 with the addition of these two interaction effects. We note that the main effect of the

import penetration (not reported) is negative and significant. Consistent with Bernard, Jensen

and Schott (2006), we find that plants in industries with especially large increases in import

penetration have lower net employment growth.

Our interest is in the role of globalization for changing responsiveness. The last two rows of

Table 2 show that the interaction effect for young plants of lagged TFP and the import

penetration ratio is estimated to be negative and significant. This implies that young-firm plants

in industries with especially large increases in import penetration ratios have larger decreases in

responsiveness. In Figure 13, we quantify the impact of changing import penetration ratios

using the estimated effects from Table 2. The overall effects show, consistent with Figure 10,

that the marginal effect of productivity on employment growth increased from the 1980s to

1990s for plants of young high tech firms and then declined in the post-2000 period. We

compute the fraction of these patterns accounted for by the changing import penetration ratios by

using the coefficients from Table 2 along with the aggregate pattern of import penetration ratios

depicted in Figure 12 for high tech. The impact of rising penetration is very modest in terms of

accounting for the change in the 1980s to 1990s. It goes the wrong way but it is small.

However, in the change in responsiveness from the 1990s to 2000s, the rapid rise in the import

penetration ratios accounts for a substantial share (about 16 percent) of the overall decline in responsiveness.

B. *Changing Responsiveness of Equipment Investment Rates*

The changing responsiveness of employment growth to productivity shocks, especially by plants of young firms, may be due to changing margins of adjustment. One possible change in the margin of adjustment is that establishments that have high productivity may be expanding through capital accumulation rather than employment growth. To investigate the possible role of capital-labor substitution, we examine the changing responsiveness patterns of equipment investment to productivity shocks. The ASM/CM data we are using has equipment investment flows in each year, so it is straightforward to construct equipment investment rates as the real investment in equipment divided by beginning-of-period equipment capital.

We estimate equation (2) using as the dependent variable the equipment investment rate instead of the employment growth rate.[33] Both investment and employment growth are endogenous margins of adjustment so we can think about our specifications as reduced form specifications relating both of these margins of adjustments to productivity shocks, controlling for initial size in the period. In estimating equation (2) for employment growth rates, we controlled for initial size by using lagged plant- and firm-level employment controls. In this analysis of equipment investment, we additionally control for the beginning of period (log)

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[33] The timing is slightly different for the equipment investment as opposed to the employment growth specifications. In the employment growth specification, the dependent variable is employment growth between March of t to March of t+1 as a function of initial size in t and the realization of productivity in period t. In the investment specification, the dependent variable is the investment rate in period t as a function of initial size (measured by both capital and labor) and the realization of productivity in period t. There is a time to build assumption in capital accumulation with investment in period t contributing to capital to be used in period t+1 (available for use at the beginning of period t+1). Given this time to build assumption, the difference in timing is not large – employment is from March t to March t+1. The investment rate instead captures the capital accumulation from January of t to January t+1. We note that Cooper and Haltiwanger (2006) used as a key moment to estimate and calibrate their adjustment cost model the correlation between the investment equipment rate in period t and the realization of the profitability in period t. Our specification can be interpreted as identifying how this covariance between investment and profitability is changing over time.

capital stock. Thus, our specification includes the key state variables: the realization of

productivity and initial capital and employment.[34]

Table 3 reports the estimated coefficients. Equipment investment for young-firm plants

is more responsive to the realization of productivity than for mature-firm plants. However, it is

apparent the responsiveness of equipment investment for young-firm plants is changing over

time. Figure 14 shows the changing marginal responsiveness of equipment investment to

productivity for plants of young and mature firms. Strikingly, the patterns in Figure 14 mimic

the patterns of employment growth responsiveness shown in Figure 10. Just as with employment

growth, equipment investment responsiveness increases from the 1980s to the 1990s but then

declines sharply in the post-2000 period. A young plant with TFP one standard deviation above

the industry-by-year mean in the 1990s had an equipment investment rate 8 percentage points

higher than a plant with the industry-by-year mean productivity; this difference is only 3

percentage points in the post-2000 period. The strong similarity between Figures 14 and 10

implies that the declining responsiveness of employment growth in Figure 10 in the post-2000

period is not accounted for by rising responsiveness of equipment investment over this same

period of time.[35]

C. *Changing Composition of High Tech*

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-

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[34] As a robustness check, we have re-estimated specification (2) with the employment growth rate as the dependent variable but adding lagged capital as a control. This alternative specification makes the employment growth rate specification consistent with the investment equipment rate specification. In unreported results, we find the coefficients reported in Table 1 are robust to including lagged capital as a control.

[35] In unreported results, we have found that for the non-tech component of manufacturing there is rising responsiveness of equipment investment to productivity from the 1980s to the 1990s and it remains high through the 2000s. Given the evidence in Table 1 and Figure 10 of the decline in responsiveness of employment growth over this entire period for non-tech manufacturing, there is evidence that capital-labor substitution plays a bigger role in accounting for the declining responsiveness of employment growth in this sector.

purpose" equipment manufacturing in the U.S highlighted by Byrne (2015).[36]  Manufacturers of

special-purpose products may be less responsive to productivity shocks due to demand

constraints or uncompetitive environments that reduce adjustment imperatives.

To investigate this hypothesis, we begin by examining the share of employment

accounted for by the general purpose industries identified by Byrne (2015) in the high tech

manufacturing data.  Figure 15 shows that during the 1990s the share of employment in the

general purpose technologies grew rapidly but has fallen substantially in the post-2000 period.

Given these compositional changes, it is possible that the changing responsiveness reflects

differential responsiveness across industries.  To explore this possibility, we estimated

specification (2) separately for each 6-digit industry but without any trend interactions.  With the

estimated responsiveness coefficients by 6-digit industry, we computed the employment-

weighted responsiveness in each year using the actual year 6-digit employment weights.[37]

Figure 16 shows the implied changing responsiveness over time due to composition effects.  It is

apparent there is no implied increase in responsiveness due to composition effects from the

1980s to the 1990s.  There is a modest increase in responsiveness from the 1990s to the 2000s

from composition effects.  This is because on average the marginal responsiveness in special

purpose technologies is slightly higher than in general purpose high tech technologies.  These

findings suggest that the rising and then declining pace of job reallocation in high tech cannot be

accounted for by changing composition of high tech.

VI. **Concluding Remarks**

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[36] We thank Christopher Foote for this insight.
[37] We use employment weights given our interest in the implications of changing responsiveness for job reallocation.

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 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. Further, we find that amongst young-firm plants in High Tech there is a change in the responsiveness of growth and survival to plant-level TFP.

We investigate three possible mechanisms underlying the declining responsiveness of young high tech plants to productivity. First, we explore the possibility that globalization may be playing a role since increased exposure to foreign trade facilitates adjustment by scaling international operations. We find evidence in support of this hypothesis in that it is especially in detailed industries with large increases in import penetration from low wage countries that young high tech plants have exhibited large declines in responsiveness in the post 2000 period. Such changes in import penetration account for about 16 percent of the decline in responsiveness of young plants in High Tech manufacturing in the post-2000 period. Second, we investigate the hypothesis that the changing responsiveness reflects plants changing their margin of adjustment from employment to capital. For example, it might be that in the post-2000 period young, high-productivity plants in the high tech sector were more likely to expand with machines than workers. We find no evidence in support of this hypothesis. Instead, in the post-2000 period there is a decline in the responsiveness of equipment investment to productivity for young high tech plants. Finally, we investigate the hypothesis that the declining responsiveness of growth to productivity during the post 2000s is the transition from "general-purpose" to "special-purpose" equipment manufacturing in the U.S as highlighted by Byrne (2015). Businesses manufacturing these special-purpose products may be less responsive to productivity due to demand constraints or uncompetitive environments that reduce adjustment imperatives. We find no evidence in support of this hypothesis.

In sum, our results therefore suggest that most of the decline in responsiveness in the high tech sector in the post-2000 period is not yet accounted for. Given the outsized role this sector has played in productivity acceleration and decline (see, e.g., Fernald (2014)) understanding this changing pattern of responsiveness in high tech should be a high priority.

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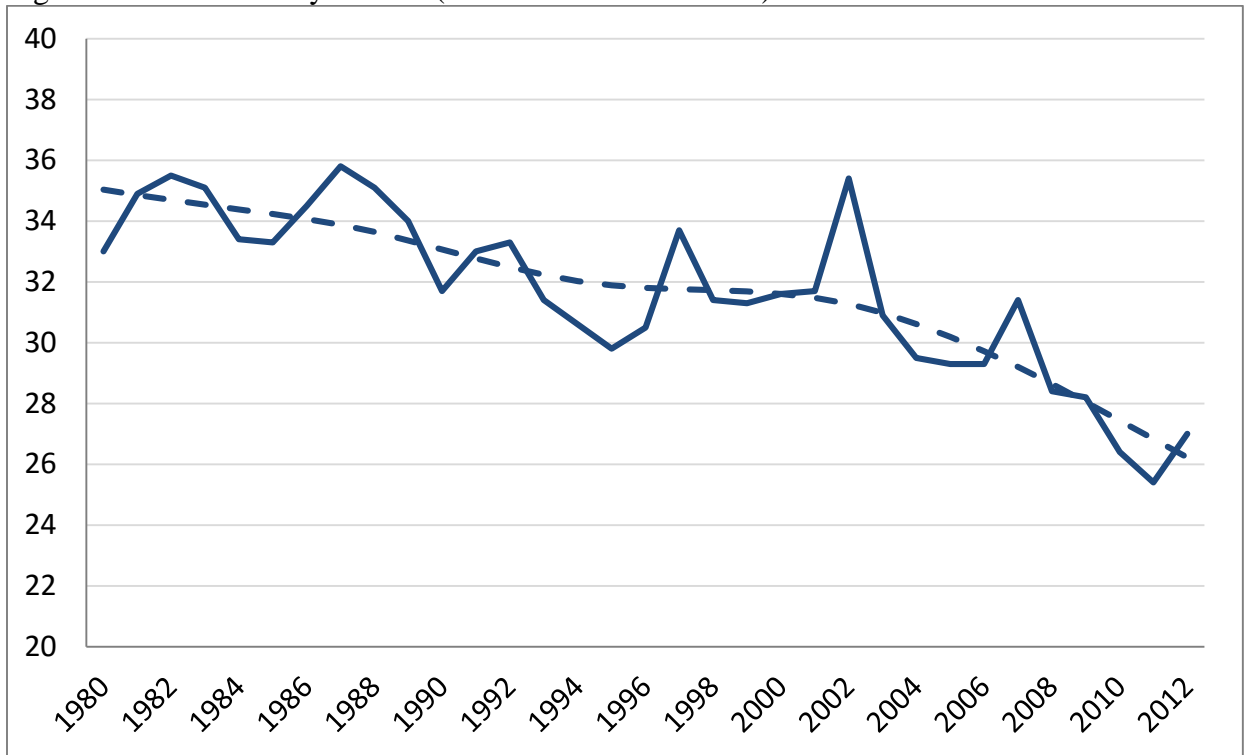


Note: Y axis does not start at zero. Dashed line indicates HP trend with parameter set to 100. Author calculations from Business Dynamics Statistics.

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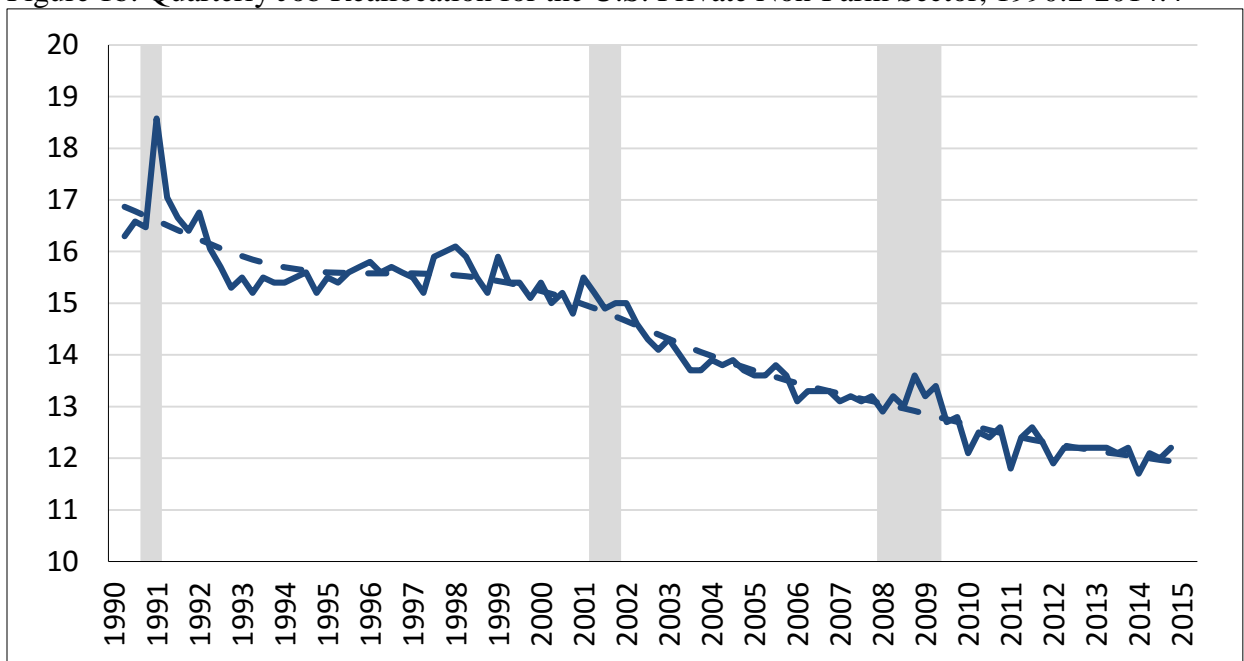


Note: Y axis does not start at zero. Gray bars indicate NBER recession dates. Dashed line indicates HP trend with parameter set to 1600. Source: BLS Business Employment Dynamics extended back to 1990:2 by Davis, Faberman and Haltiwanger (2012).

Figure 2: Sectoral Trends in Job Reallocation
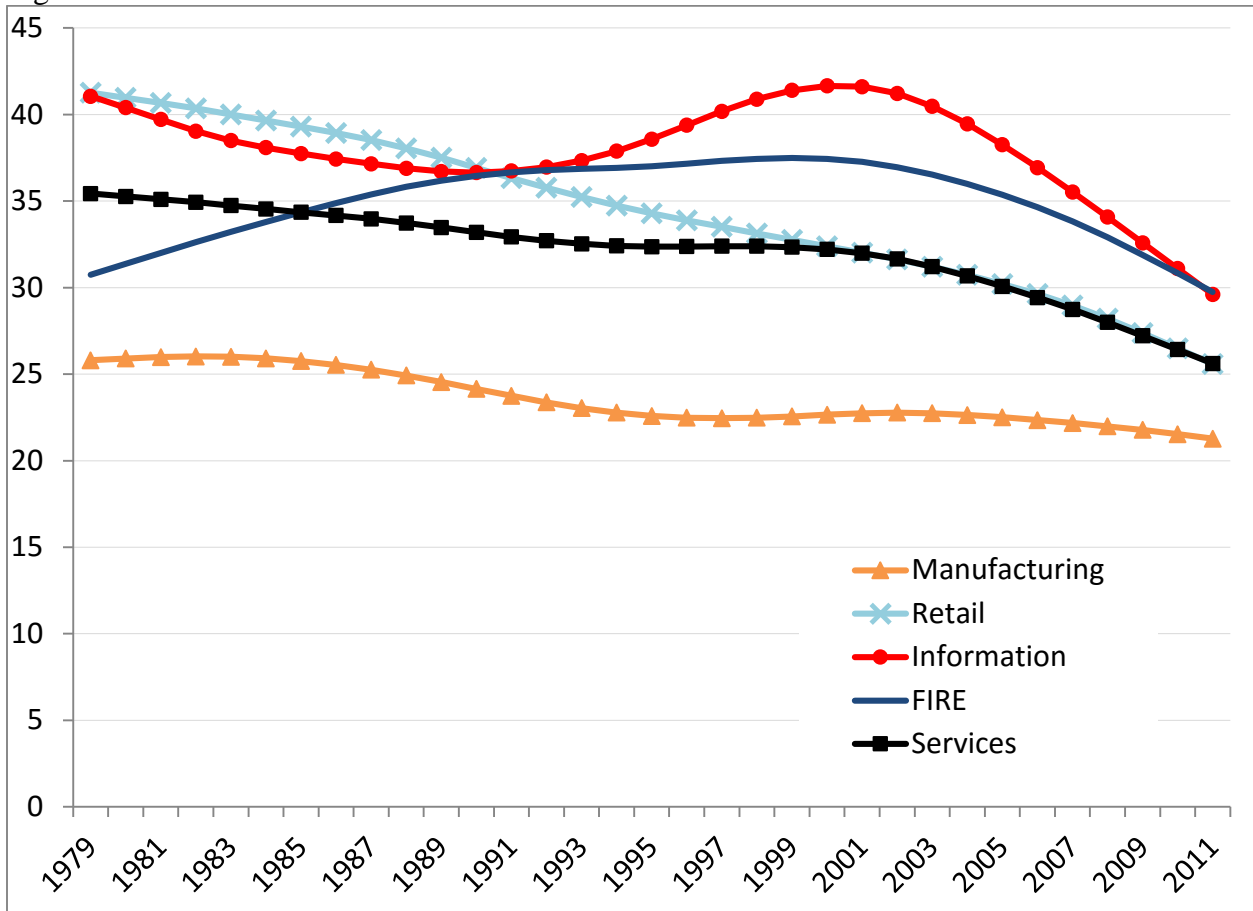


Note: Data are HP trends using parameter set to 100. Industries are defined on a consistent NAICS basis. Data include all firms (new entrants, continuers, and exiters). Author calculations from the Longitudinal Business Database.

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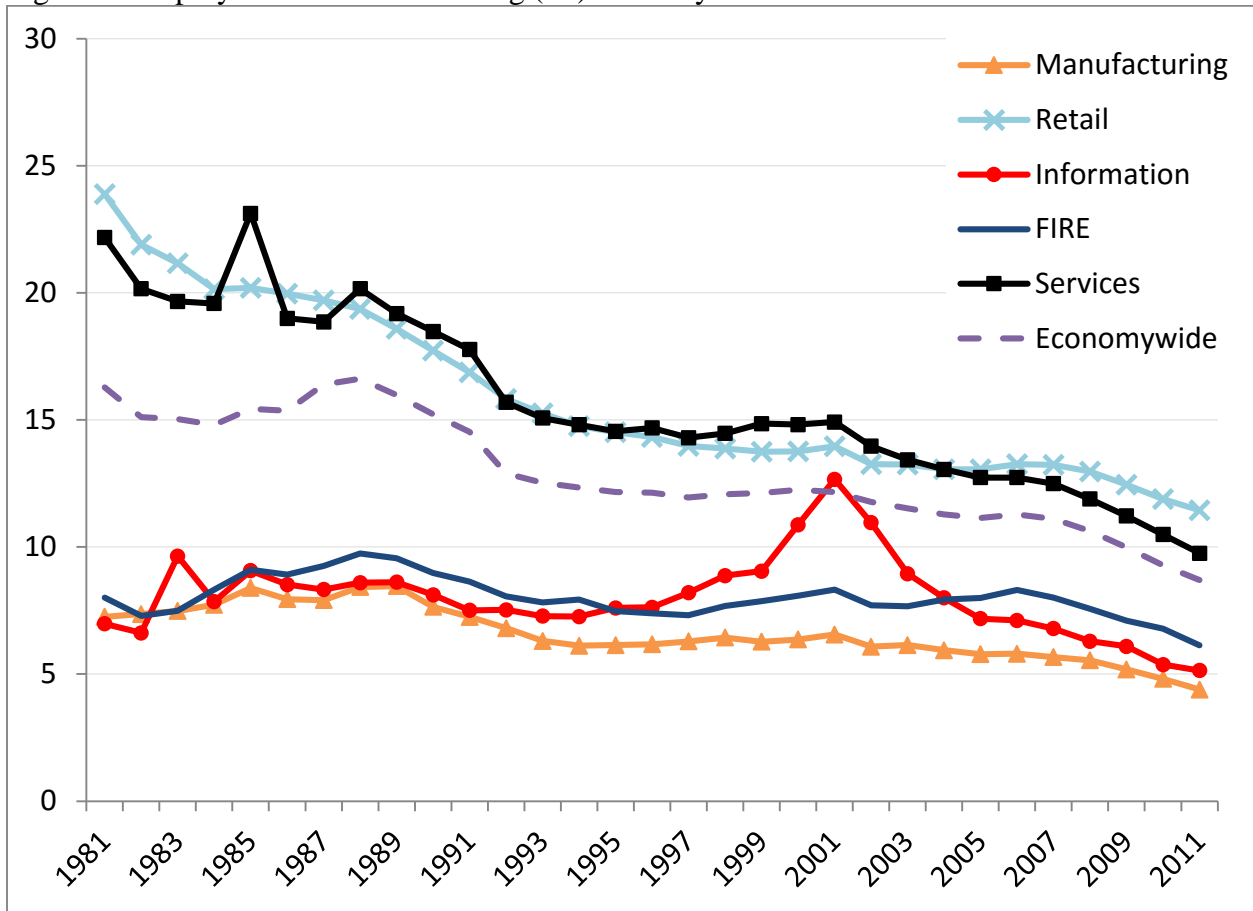


Note: Young firms have age less than 5. Industries are defined on a consistent NAICS basis. Data include all firms (new entrants, exiters, and continuers). Author calculations from the Longitudinal Business Database.

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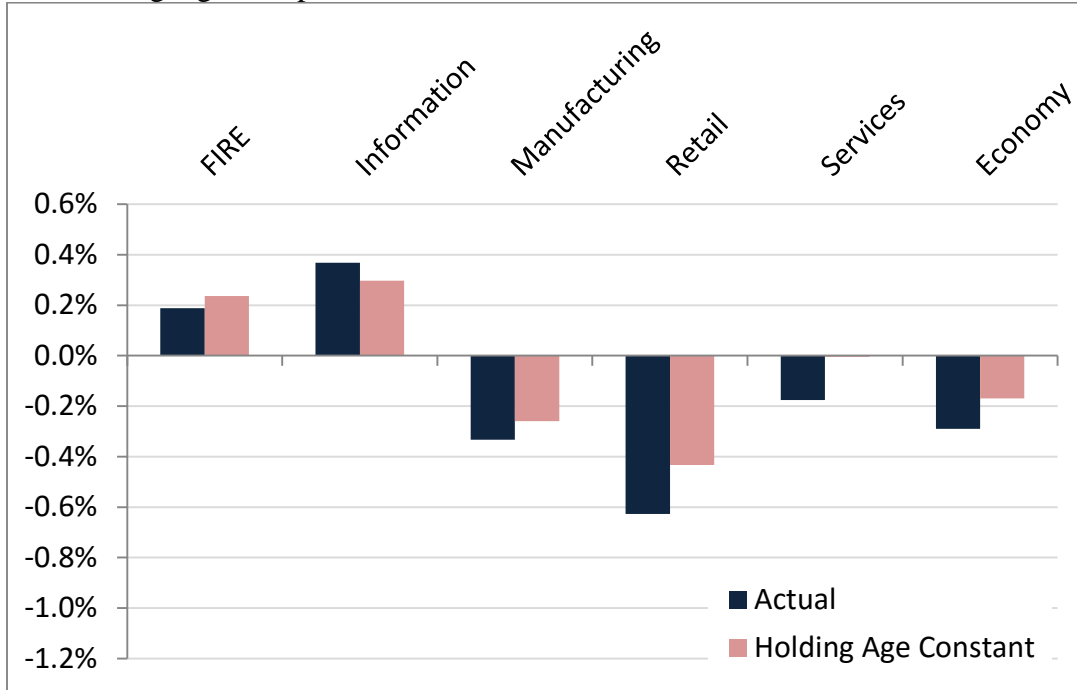


Figure 4b:  Annual Change in Job Reallocation Rate from 1997/99 to 2004/06 by Sector:  Actual and Holding Age Composition Constant
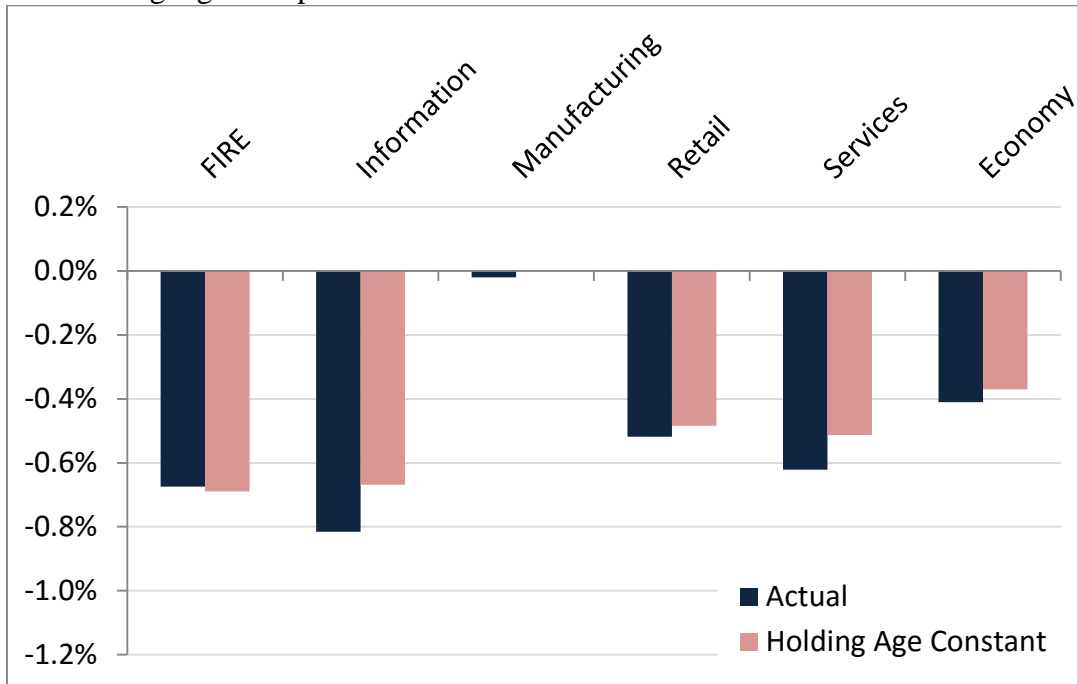


Note: Sectors are defined on a consistent NAICS basis. Author calculations from the Longitudinal Business Database.

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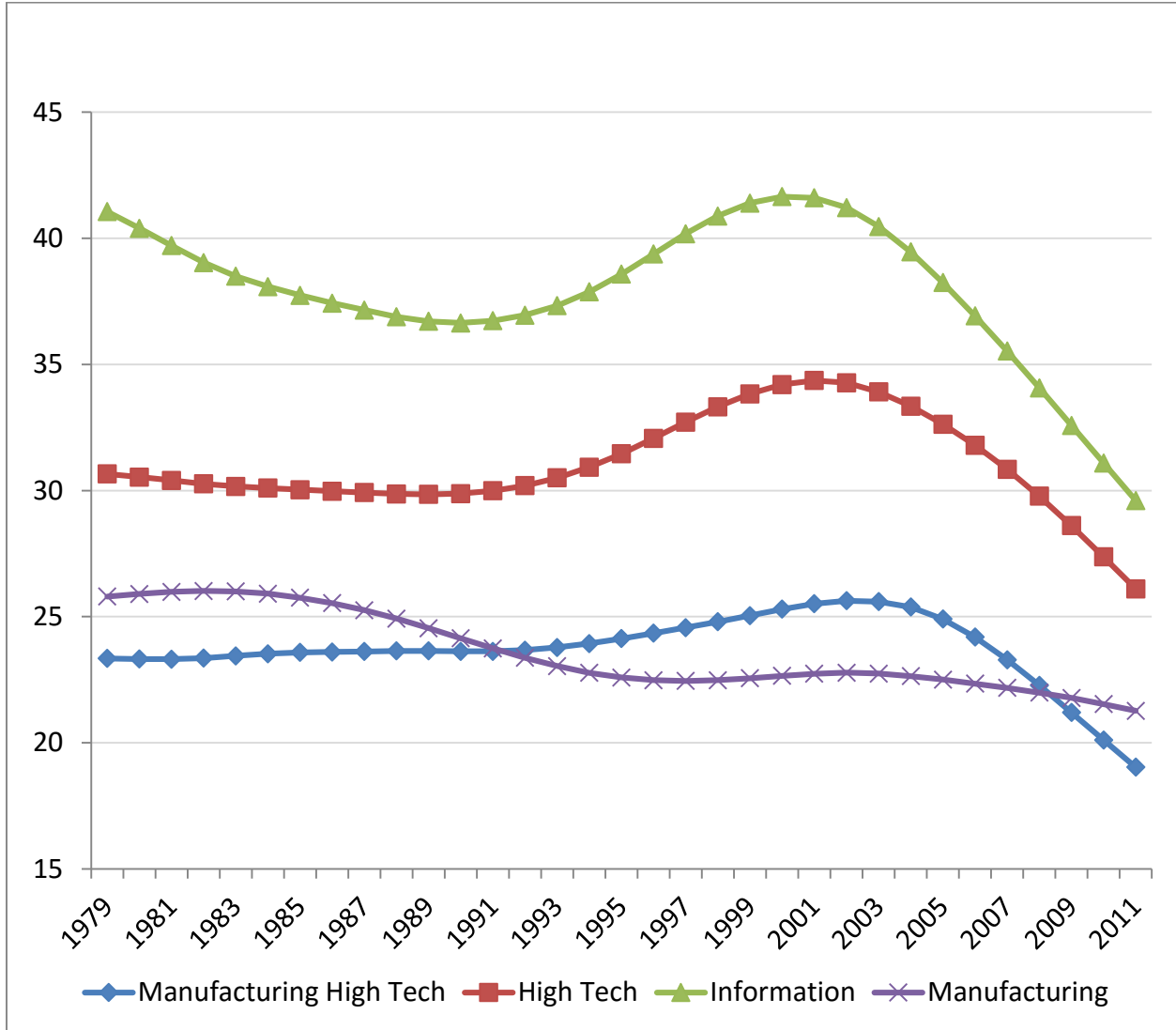


Note: Y axis does not start at zero. High Tech is defined as in Hecker (2005). Information and Manufacturing sectors are defined on a consistent NAICS basis. Author calculations from the Longitudinal Business Database.

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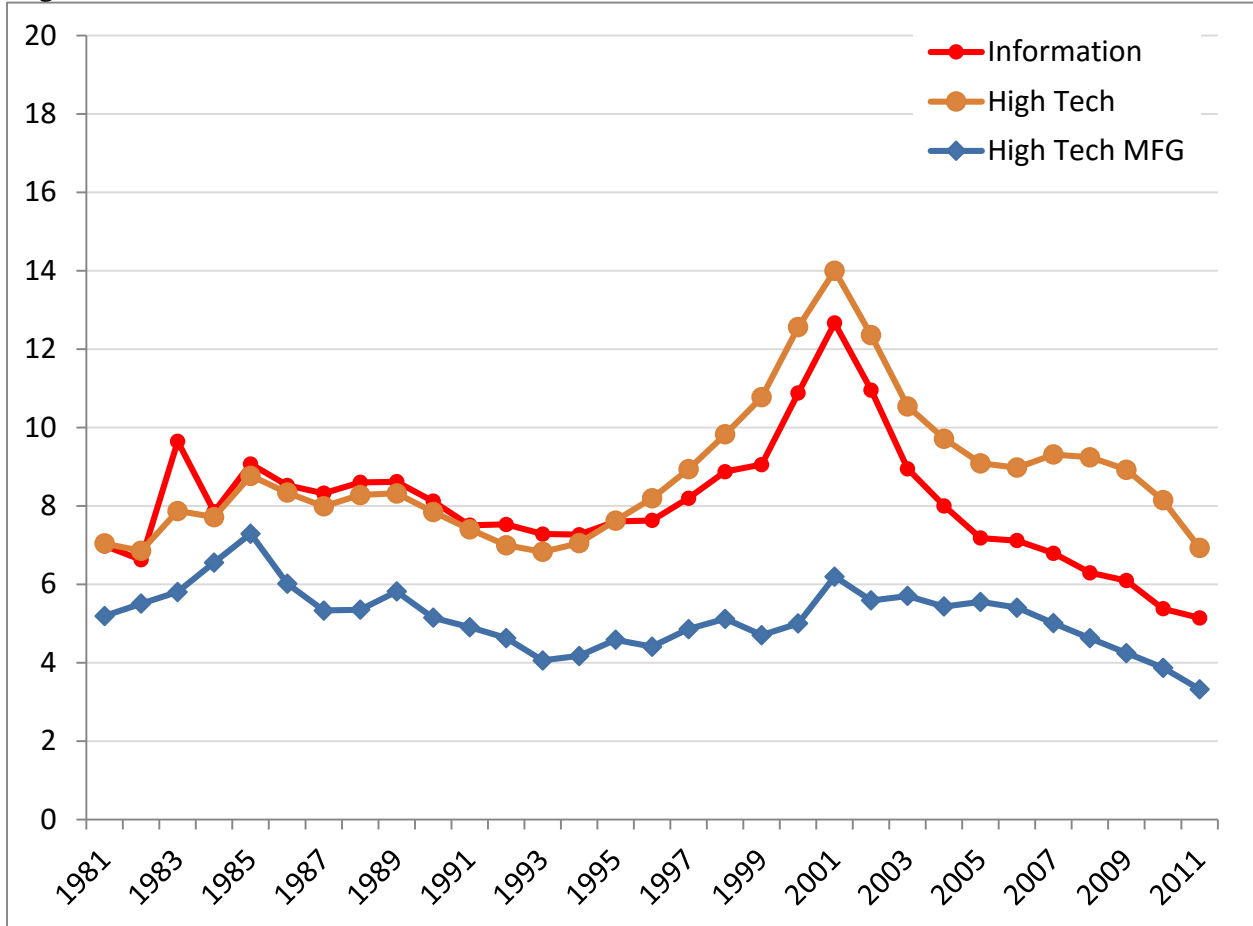


Note: Young firms have age less than 5. High Tech is defined as in Hecker (2005). Information and
Manufacturing sectors are defined on a consistent NAICS basis. Author calculations from the
Longitudinal Business Database.

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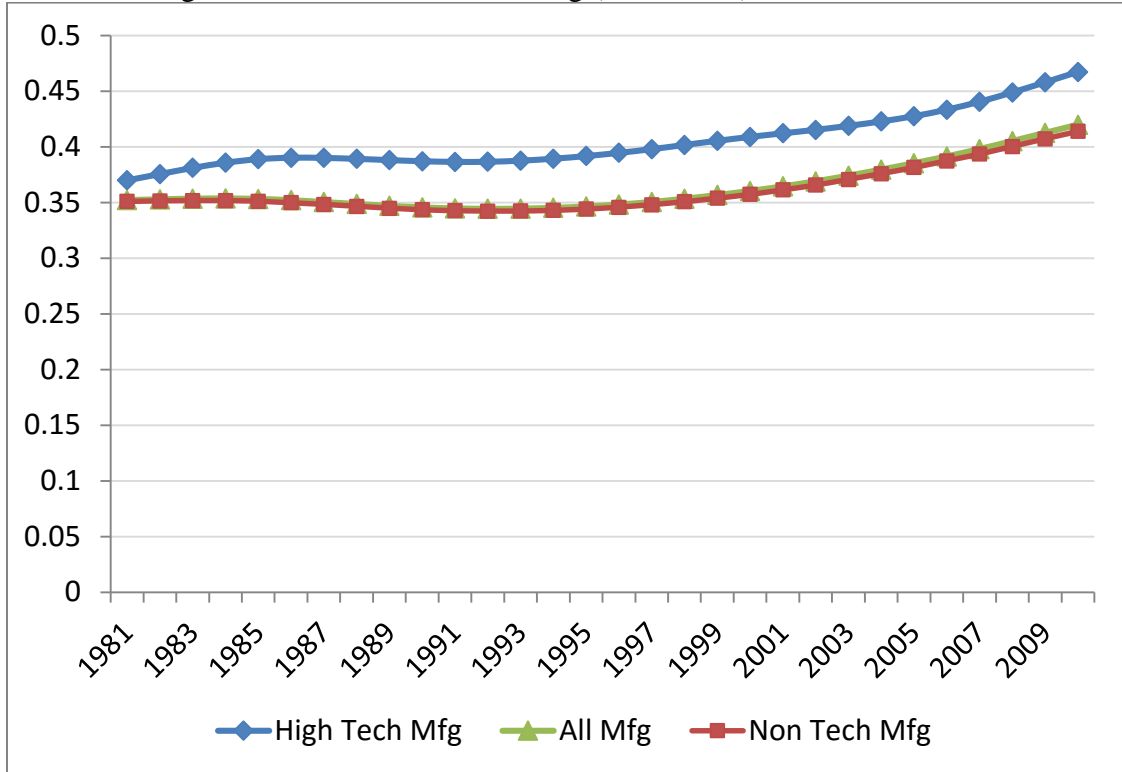


Note: The standard deviation is the based on within-detailed industry log TFP. High Tech is defined as in Hecker (2005). Manufacturing is defined on a consistent NAICS basis. Author calculations from the Longitudinal Business Database, the Annual Survey of Manufacturers, and the Census of Manufacturers.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

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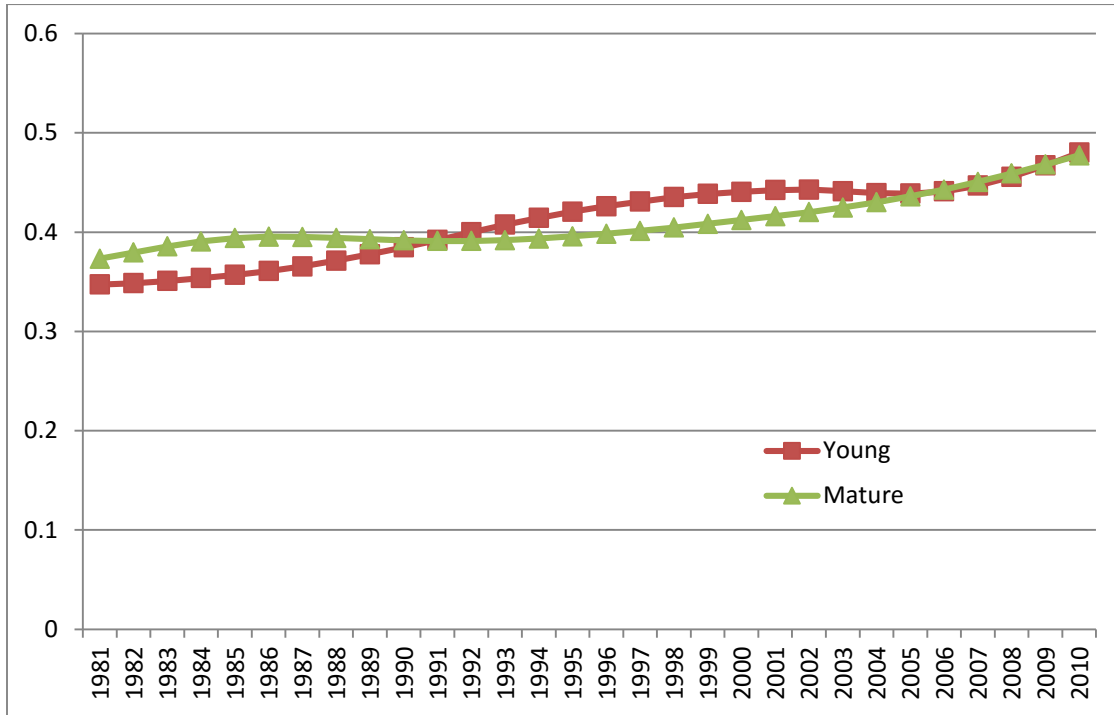


Figure 8b: Within-Industry TFP Dispersion (Std Dev) in Non Tech Manufacturing:  Young vs. Mature
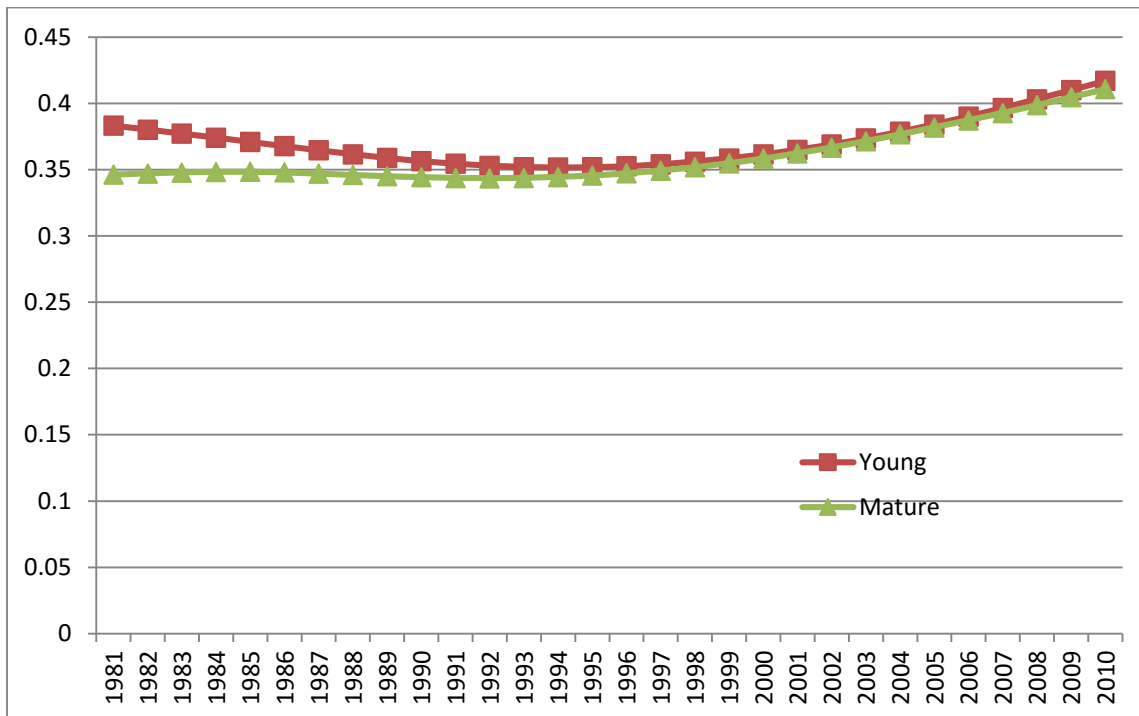


Note: Young firms have age less than 5. The standard deviation is the based on within-detailed industry log TFP.   High Tech is defined as in Hecker (2005). Author calculations from the Longitudinal Business Database, the Annual Survey of Manufacturers, and the Census of Manufacturers. HP Trends Depicted.

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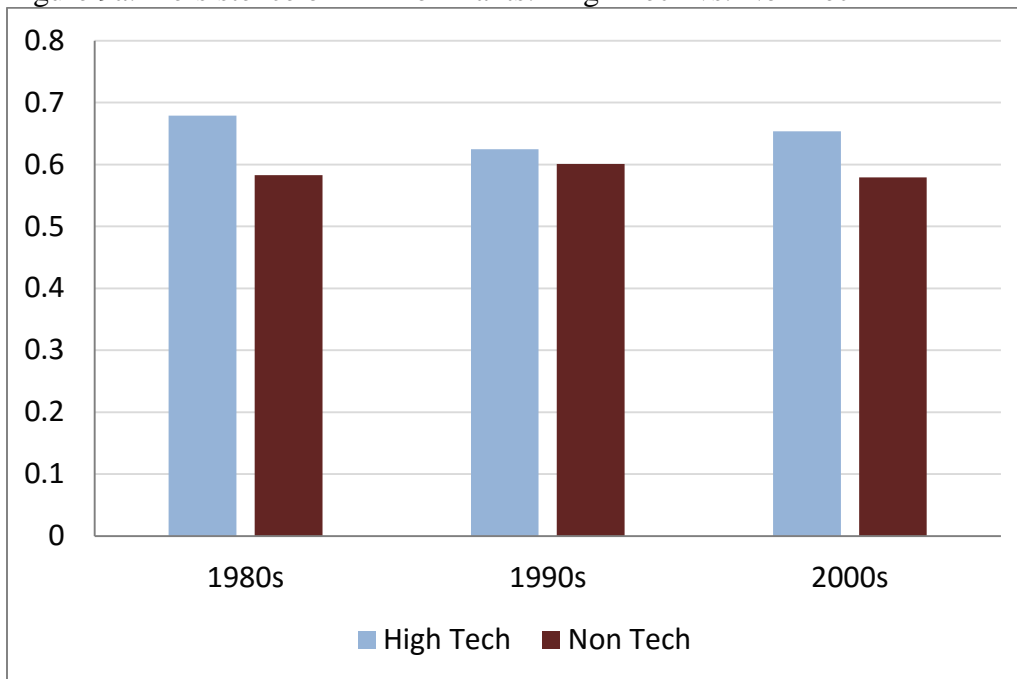


Note: High Tech is defined as in Hecker (2005). Author calculations from the Longitudinal Business Database, the Annual Survey of Manufacturers, and the Census of Manufacturers.

Figure 9b: Standard Deviations of Innovations to TFP for Plants: High Tech vs Non Tech
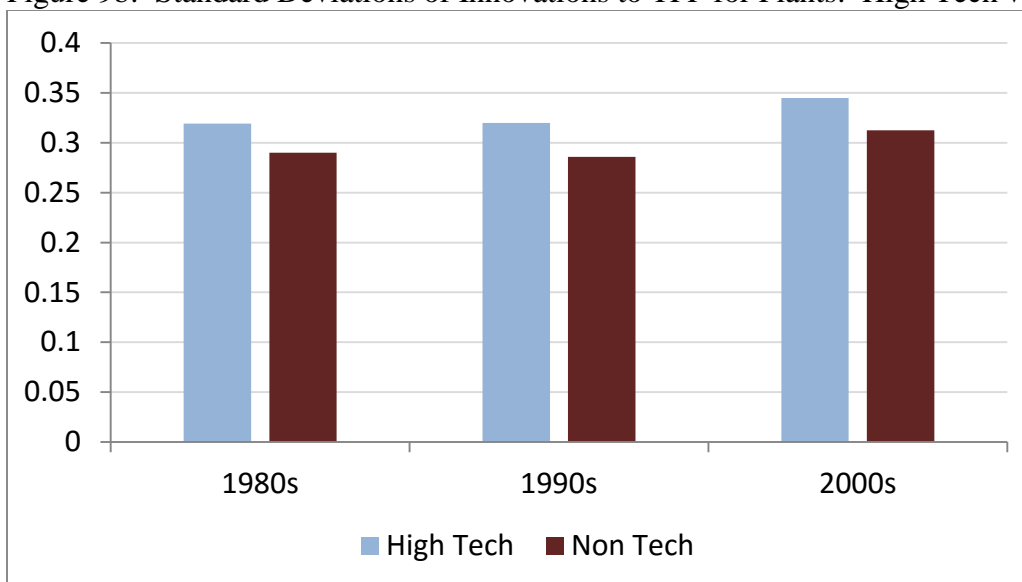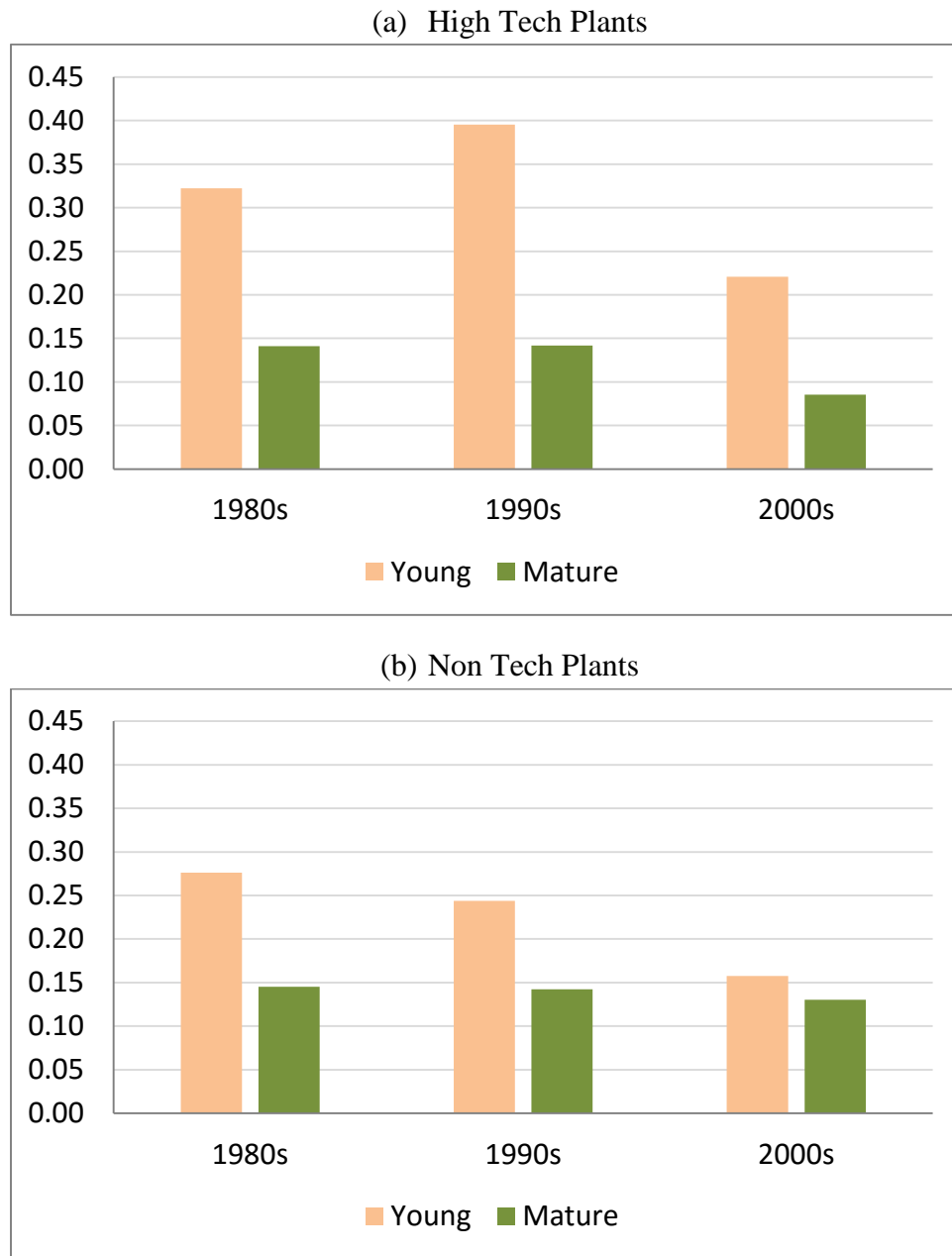
Figure 10: Marginal Effect of TFP on Plant-Level Net Employment Growth: Young vs. Mature

(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
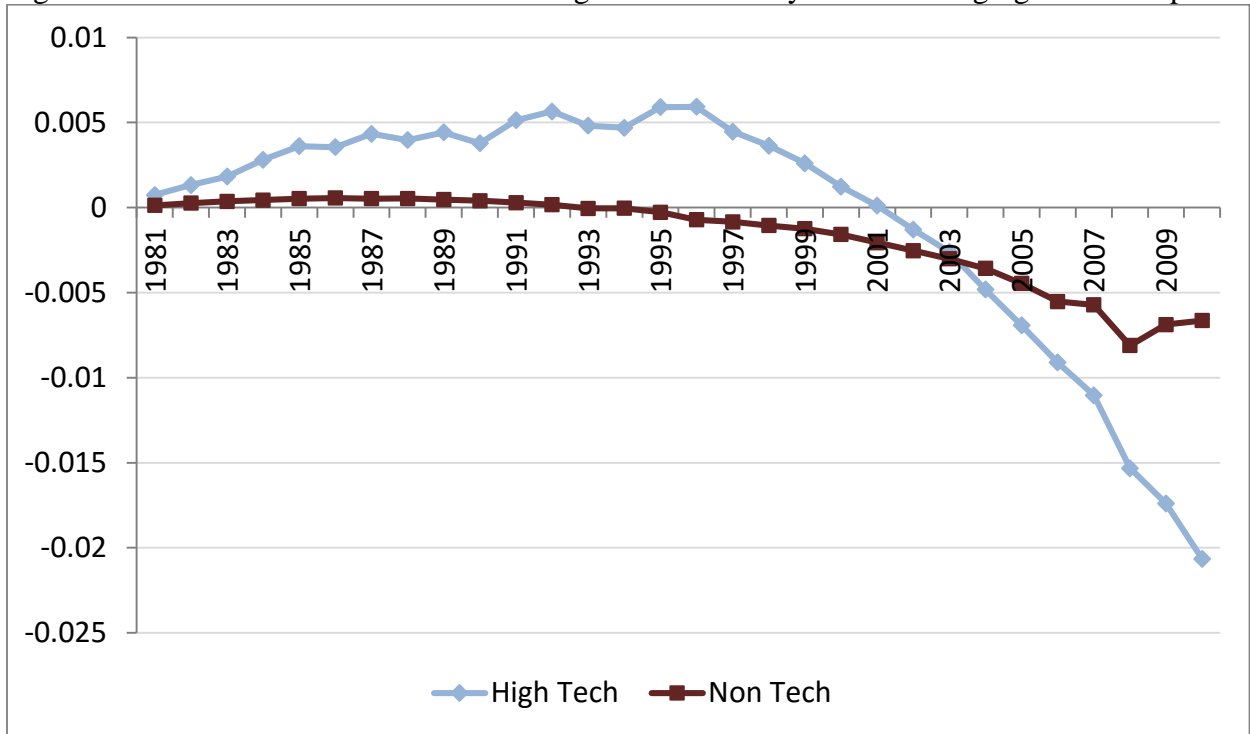


Note: High Tech is defined as in Hecker (2005). Author calculations from the Longitudinal Business Database, the Annual Survey of Manufacturers, and the Census of Manufacturers.

Figure 12.  Import Penetration Ratios from Low Wage Countries
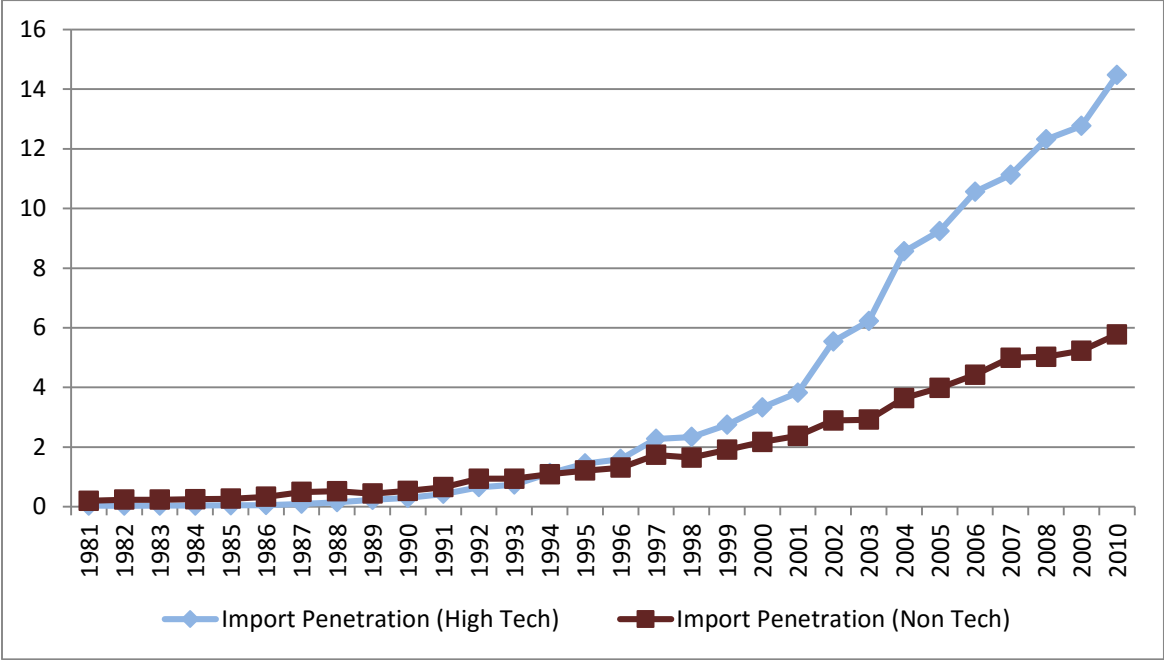


Source:  Extended versions of Import Penetration Ratios from Bernard, Jensen and Schott (2006) and (2006).  Reported statistics are averages across 6-digit NAICS industries for High Tech and Non Tech industries.

Figure 13. Impact of Changing Globalization on Changing Responsiveness in High Tech Manufacturing



Note: Overall for young and mature are the change in marginal responsiveness of employment growth to productivity across decades. Globalization reflects implied change in marginal responsiveness accounted for by changes in import penetration ratios from low wage countries.

Figure 14: Marginal Effect of TFP on Plant-Level Equipment Investment in High Tech: Young vs. Mature
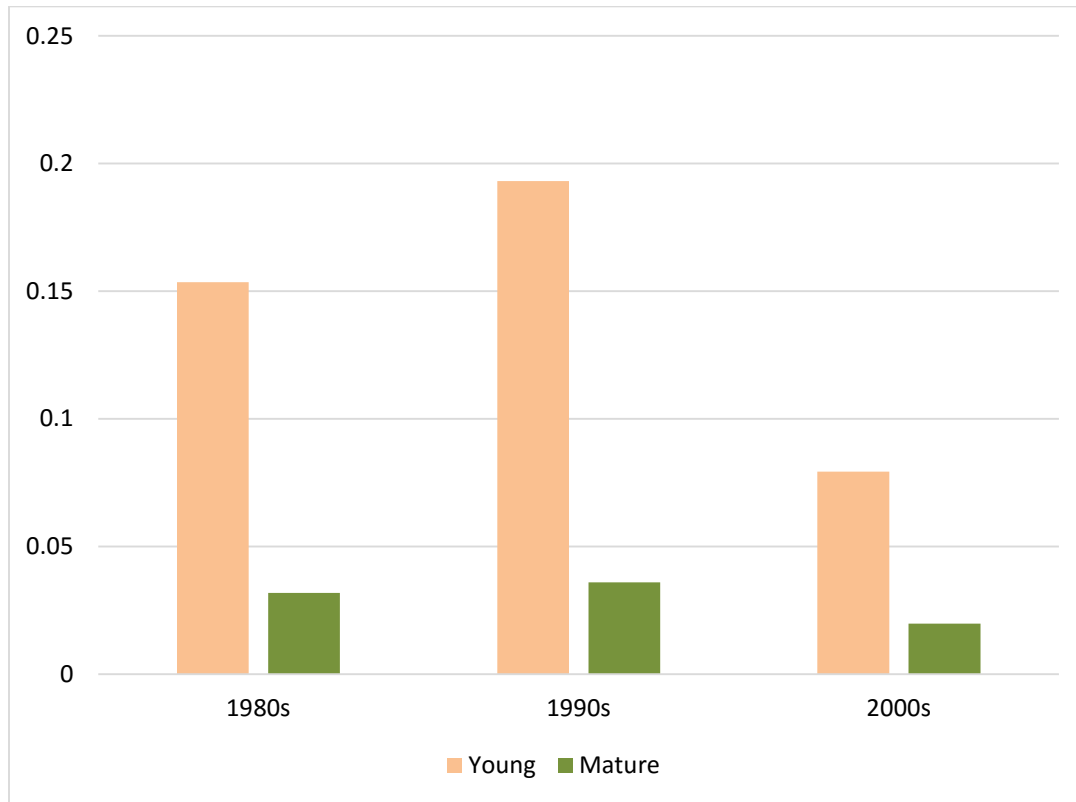


Note: Young firms have age less than 5. High Tech is defined as in Hecker (2005). Author calculations from the Longitudinal Business Database, the Annual Survey of Manufacturers, and the Census of Manufacturers.

Figure 15. Share of Employment in General Purpose High Technology Industries in Total High Tech Manufacturing
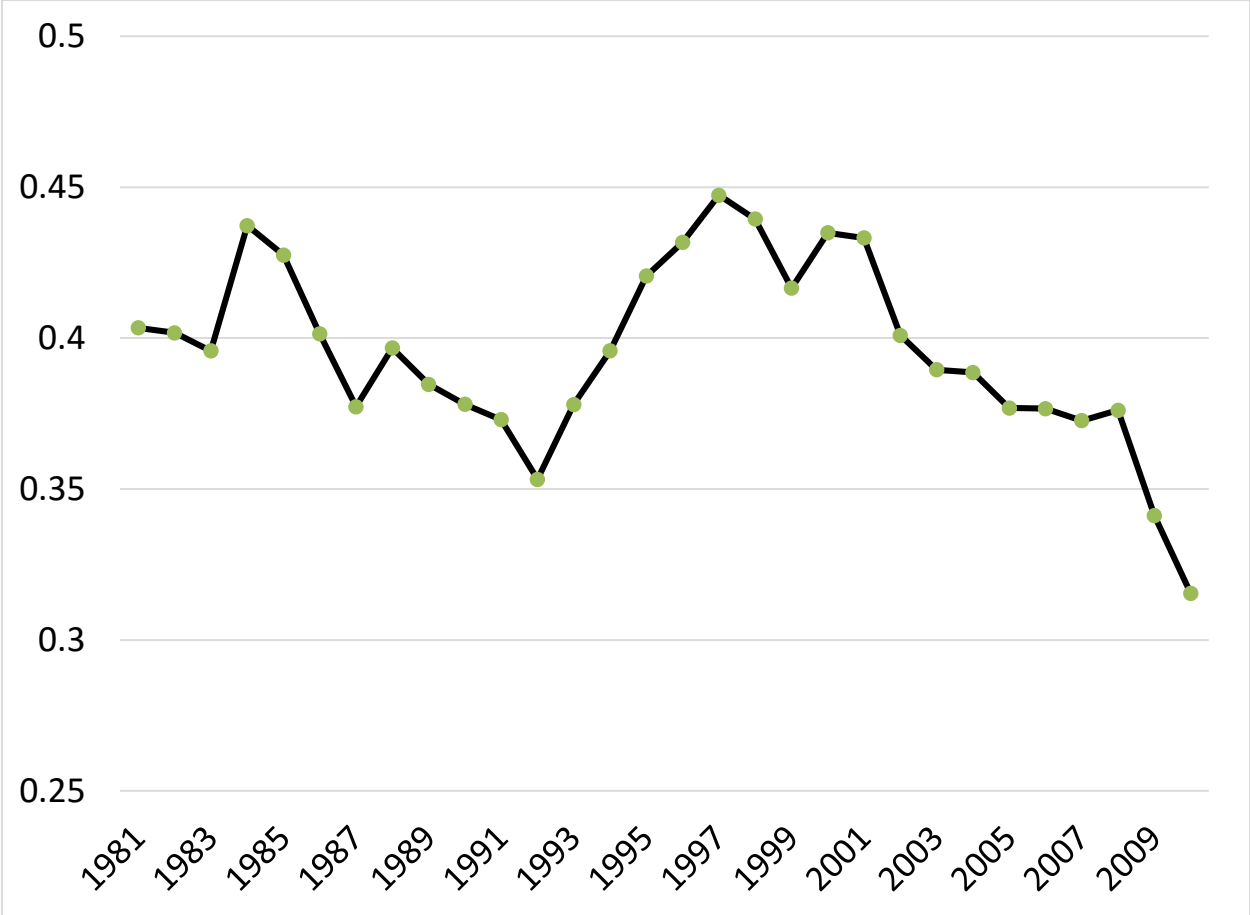


Note:  Tabulations from the LBD by authors.  General purpose high tech 4-digit industries are NAICS 3341 (Computers), NAICS 3342 (Communication Equipment) and NAICS 3344 (Semi-conductors).

Figure 16 Implied Change in Responsiveness Due to Industry Composition Changes Within High Tech
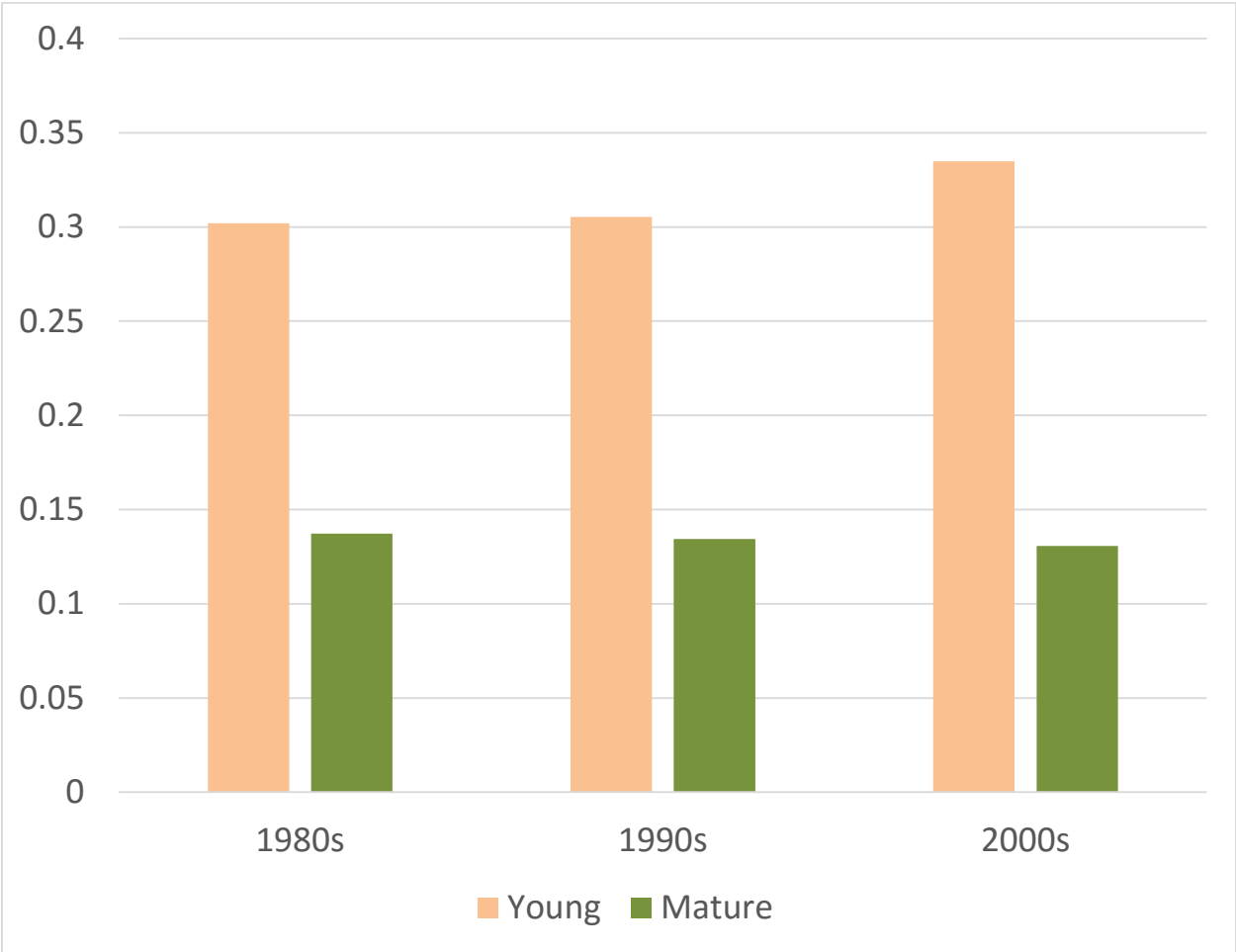


Note: Specification (2) as in Table 1 estimated for every 6-digit NAICS industry but without any trend effects. Reported coefficients are employment-weighted averages of the 6-digit NAICS industry estimated coefficients. Employment-weights vary by year.

Table 1: Estimated Impact of Lagged Productivity on Plant-Level Employment 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 2: Estimated Impact of Lagged Productivity on Plant-Level Employment Growth with Import Penetration Ratio Effects, High Tech Industries

| | |
|---|---|
| TFP*Young | 0.2085*** |
| | (0.0390) |
| TFP*Young*Trend | 0.0298*** |
| | (0.0061) |
| TFP*Young*TrendSQ | -0.0011*** |
| | (0.0002) |
| TFP*Mature | 0.1246*** |
| | (0.0174) |
| TFP*Mature*Trend | 0.0052** |
| | (0.0026) |
| TFP*Mature*TrendSQ | -0.0003*** |
| | (0.0001) |
| TFP*Young*Import Penetration | -0.0037*** |
| | (0.0011) |
| TFP*Mature*Import Penetration | 0.0002 |
| | (0.0004) |

Notes:  Standard Errors in Parentheses.  Tech Sample is more than 120000 plant-year observations from 1981-2010.  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, and a main effect for the 6-digit import penetration ratio.  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 3: Estimated Impact of Productivity on Plant-Level Equipment Investment Rate

| | |
|---|---|
| TFP*Young | 0.0826*** |
| | (0.0236) |
| TFP*Young*Trend | 0.0189*** |
| | (0.0037) |
| TFP*Young*TrendSQ | -0.0008*** |
| | (0.0001) |
| TFP*Mature | 0.0232** |
| | (0.0105) |
| TFP*Mature*Trend | 0.0024 |
| | (0.0016) |
| TFP*Mature*TrendSQ | -0.0001* |
| | (0.00005) |

Notes: Standard Errors in Parentheses. Tech Sample is more than 120000 plant-year observations from 1981-2010. Young firms have age less than 5. Unreported are estimates of controls including year effects, state effects, firm age dummies, firm employment size dummies, log plant level employment in period t, dummies for initial capital, 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)