# Changing Business Dynamism and Productivity: Shocks vs. Responsiveness

**Ryan A. Decker, John Haltiwanger, Ron S. Jarmin, and Javier Miranda***

October 2016

**Abstract**

The pace of business dynamism as measured by indicators such as job reallocation has declined in recent decades in the U.S., and theory suggests that this may have implications for productivity. The declining dynamism in sectors like Retail Trade disproportionately accounted for these trends in the 1980s and 1990s, and was productivity enhancing. In contrast, the pace of reallocation in High-Tech industries has a rising then falling pattern during the 1990s and 2000s that mimics the pattern of U.S. productivity growth. We investigate whether these trends in dynamism and productivity are related by drawing insights from canonical models of firm dynamics. Focusing on the High-Tech sector, we ask whether observed patterns of reallocation reflect changes in the volatility of idiosyncratic productivity shocks or changes in the marginal responsiveness of businesses to those shocks. Using Manufacturing TFP data we show that shock volatility has not declined but that the plant-level marginal responsiveness of business growth to productivity rises then falls in tandem with the hump-shaped behavior of both job reallocation and productivity growth in the High-Tech sector. The results are particularly notable for young businesses. During the 1990s, rising 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 precipitously implying as much as a two log point per year reduction in the annual contribution of reallocation to industry-level productivity growth. Using new economywide data on firm-level labor productivity, we further show that the post-2000 Manufacturing results generalize to the entire U.S. economy and the broad High-Tech sector specifically. Rising within-industry dispersion in firm-level labor productivity in the post-2000 period is consistent with an increase in frictions or distortions in the U.S. economy.

*Board of Governors of the Federal Reserve System, University of Maryland and NBER, U.S. Census Bureau, and U.S. Census Bureau, respectively. We gratefully acknowledge financial support from the Kauffman Foundation. Cody Tuttle provided excellent research assistance. We thank John Abowd, Rudi Bachmann, Martin Baily, Dave Byrne, Chris Foote, Lucia Foster, Bronwyn Hall, Kristin McCue, and conference or seminar participants at the 2015 Atlanta Fed Conference on Secular Changes in Labor Markets, the ASSA 2016 meetings, the September 2016 Brookings "productivity puzzle" conference, Drexel University, the Federal Reserve Board, George Mason University, Georgetown University and the New York Fed for helpful comments. We are grateful for the use of the manufacturing productivity database developed in Foster, Grim and Haltiwanger (2016) as well as the revenue productivity database developed in Haltiwanger et al. (2016), and we thank Peter Schott for providing guidance and data for constructing import penetration data. Any opinions and conclusions expressed herein are those of the authors and do not necessarily represent the views of the U.S. Census Bureau or of the Board of Governors or its staff. All results have been reviewed to ensure that no confidential information is disclosed.

## I. Introduction and motivation

A hallmark of market economies 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.[1]

Canonical models of firm dynamics and empirical evidence imply that there is a tight link between business dynamism and productivity growth. That is, theory and evidence suggest that a substantial fraction of aggregate productivity growth is accounted for by the reallocation of resources away from lower-productivity and toward higher-productivity firms. Firm entry and exit are an especially critical component of these productivity-enhancing reallocation dynamics. Thus, a *prima facie* concern arising from these trends in business dynamism is that they may have had adverse effects on aggregate productivity growth. The question is particularly important in light of the growing body of evidence showing that aggregate productivity in the U.S. has been declining since the early 2000s (Fernald (2014)).

The purpose of this study is twofold: first, we contribute to the literature on declining dynamism by showing that changing patterns of aggregate job reallocation have not been driven by changes in the distribution of productivity or profitability shocks faced by firms but, rather, have been driven by changes in the marginal responsiveness of individual businesses to their idiosyncratic productivity. Second, we contribute to the literature on declining aggregate productivity growth by showing that observed changes in business-level productivity responsiveness have had significant implications for aggregate productivity growth. In this respect, questions about declining business dynamism and slowing productivity growth are closely related. Our study can be thought of as complementary to the existing research on the productivity slowdown (including Byrne et al. (2016), Gordon (2016), or Syverson (2016)), most

[1] 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).

of which focuses on changes in the pace of technological innovation and questions about conceptual or measurement shortcomings of GDP.

At first glance, medium-run fluctuations in economy-wide productivity growth do not match up with patterns of declining business formation and business dynamism. Productivity growth accelerated in the late 1980s through the early 2000s before slowing down after 2003, while aggregate startup activity and job reallocation fell throughout the 1980-2014 period. However, a more careful review of theory and evidence resolves the inconsistency: during the 1980s and 1990s, the decline in entrepreneurship and reallocation was dominated by the Retail Trade sector, where evidence suggests that falling dynamism was actually consistent with rising productivity growth.[2] More generally, patterns of declining job reallocation in other sectors in the 1980s and 1990s were not characterized by a loss of high-growth firm activity but instead reflect a symmetric narrowing of the employment growth rate distribution (Decker et al. (2016)).[3]

Fernald (2014) highlights that the surge in productivity from the late 1980s to early 2000s and subsequent decline was led by the ICT-producing and intensive ICT-using sectors. Interestingly, the High-Tech sector exhibits a rise in business formation and pace of reallocation over the first period and a sharp decline in the post-2000 period, with the period since 2000 also being characterized by a decline in high-growth firm activity throughout the US economy more generally (Haltiwanger, Hathaway and Miranda (2014)).[4]

Changes in business dynamics and aggregate productivity growth have attracted much attention from researchers and policymakers, but the patterns observed in various datasets are still not well understood. We review the key facts about changes in dynamism then empirically show how recent patterns of business dynamics and productivity growth are related at the micro level. To do so, we take inspiration from canonical models of firm dynamics such as Jovanovic

[2] 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, Klimek and Miranda (2009)). For evidence, that establishments of large national chains are more productive and more stable see Foster et al. (2006) and Foster et al. (2015). We discuss this evidence further below.

[3] As shown by Decker et al. (2016), measures of gross job flows such as job reallocation are closely related to the dispersion of the distribution of firm growth rates. The growth rate distribution can be summarized with measures of dispersion and further explored with measures of skewness, which indicates the importance of high-growth firm activity. A symmetric narrowing of the firm growth rate distribution is a reduction of growth rate dispersion that does not involve a reduction in skewness, or high-growth firm activity.

[4] For this purpose, we follow Hecker (2005) and construct a High-Tech sector based on the 14 four-digit NAICS industry groups with the largest shares of STEM workers. The 14 industry groups are listed in the appendix.

(1982), Hopenhayn (1992), Hopenhayn and Rogerson (1993), and Ericson and Pakes (1995). These models suggest that the observed pace of reallocation or firm volatility is driven by the interaction between idiosyncratic (firm- or plant-specific) shocks and frictions on business-level adjustment (entry, exit, expansion, and contraction); moreover, such models posit a direct relationship between dynamics of individual firms and the evolution of aggregate productivity, which depends crucially on the allocation and reallocation of productive inputs. Viewed from this model-based perspective, a change in the pace of indicators of dynamism such as reallocation 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.[5] This latter cause may have negative implications for productivity.

We investigate these issues with a particular focus on the High-Tech component of the Manufacturing sector where we can construct measures of establishment-level total factor productivity (TFP) to empirically describe idiosyncratic shocks. Given measured productivity shocks faced by businesses, we can evaluate both changes in the distributional characteristics of idiosyncratic productivity ("changing shocks") and changes in business-level responses (in terms of growth and survival) to their own productivity ("changing responsiveness"). We compare and contrast our results for High-Tech Manufacturing with the remainder of the Manufacturing sector. Then, using new data on firm-level labor productivity for the entire U.S. private sector, we perform similar analyses of the relationship between firm-level productivity and growth for businesses outside of Manufacturing. While the evolution of the dispersion in labor productivity is inherently endogenous, our labor productivity exercises strongly suggest that the patterns we observe in Manufacturing generalize more broadly to other areas of the economy.

With reference to the model-based framework of changing shocks vs. changing responsiveness to shocks, we find that the dispersion of idiosyncratic productivity within High-Tech Manufacturing is rising over time while the persistence of productivity exhibits little or no trend.[6] Thus, there is little evidence that changes in patterns of idiosyncratic productivity shocks can account for the changing pattern of reallocation in the High-Tech sector. Instead, we find

[5] It may be that these two forces—changes in the distribution of shocks and changes in responsiveness to shocks—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.

[6] 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.

that business-level responsiveness to productivity shocks has changed significantly over time: During the 1980s and 1990s we find that plant-level survival and growth became more responsive to idiosyncratic TFP differences across plants in High-Tech Manufacturing, while in the post-2000 period responsiveness declined substantially. These results are particularly notable when we study exit alone, where we find that the intensity of productivity-based exit selection has weakened markedly. We conclude that the declining pace of aggregate reallocation is not being driven by changes in the distribution of business-level productivity conditions but is instead related to a dampening of the marginal responses of individual businesses to those conditions.

In addition to shedding light on the puzzle of declining business dynamism generally, our results have important implications for aggregate productivity. Simple decompositions show 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 growth in industry-level TFP by 2010. Moreover, evidence based on labor productivity suggests that the result of declining responsiveness since 2000 generalizes beyond High-Tech Manufacturing to other High-Tech businesses as well as other areas of the economy. The pre-2000 rise and post-2000 fall of productivity responsiveness in the High-Tech sector coincides with the rise and fall of aggregate productivity growth in the U.S., which was concentrated in ICT-related industries (Fernald (2014)). Our conceptual framework and empirical evidence suggest that these patterns of reallocation and productivity growth were related: A declining contribution of productivity-enhancing reallocation to aggregate productivity growth appears to be a significant factor in the productivity slowdown.

In our analysis below, we show that a decline in the responsiveness of businesses to their productivity is remarkably robust and widespread. Within Manufacturing, the post-2000 decline in responsiveness occurs both among young and mature businesses and both inside and outside the High-Tech sector. When productivity is measured as output per worker, allowing us to expand our analysis outside Manufacturing, we see that the change in the productivity/growth relationship is widespread across the major sectors of the U.S. economy. We also show that the responsiveness decline among High-Tech Manufacturing businesses can also be observed when we measure productivity responsiveness in terms of equipment investment instead of

employment growth. The decline in employment-growth responsiveness is not the result of a key composition shift in High-Tech Manufacturing—the shift of production from general-purpose to special-purpose technology production documented by Byrne (2015)—but is occurring within these categories of producers. A significant portion of the decline may be explained by patterns of globalization, but the majority of the decline remains unexplained after accounting for rising import competition.

The paper proceeds as follows. Section II describes key facts about the declining pace of business dynamism that are relevant for our analysis, and Section III describes the various datasets we employ. In section IV, we use data for Manufacturing to study whether the evidence implies a change in the distribution of shocks or a change in the response to those shocks with a particular focus on High-Tech Manufacturing, and we analyze the implications of our findings for aggregate productivity growth. Section V looks beyond Manufacturing and investigates the same questions using labor productivity and employment data for all U.S. sectors. Section VI explores possible mechanisms underlying the changing responsiveness patterns to productivity shocks in the Manufacturing sector. Concluding remarks are in section VII.

## II. Business Dynamics: Basic facts

Various studies have documented a decline in the annual pace of establishment-level job reallocation and other indicators of business dynamism in recent decades (see, e.g., Davis et al. (2007), Decker et al. (2014, 2016), Davis and Haltiwanger (2014), Hyatt and Spletzer (2013) and Malloy et al. (2016)).

Underlying the aggregate decline in reallocation is substantial variation across sectors. Figure 1 shows the trends in job reallocation (using HP trends) for selected NAICS 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 2 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 1 and 2 together

highlight that not all sectors have exhibited a monotonic decline in indicators of business dynamism and entrepreneurial 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 other High-Tech industries are classified as Manufacturing such as Computer Hardware and Peripherals (NAICS 3341) or Services. 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 A1 in the appendix.[7]

For a core part of our empirical investigation we focus on the Manufacturing sector, with a particular emphasis on High-Tech Manufacturing. Figure 3 shows the Hodrick-Prescott trends for the Information sector, the High-Tech sector as defined above, 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). Interestingly, Figure 3 shows a sharp decline in the pace of job reallocation in the post-2000 period in the High-Tech sector coinciding with the trend slowdown in productivity driven by a slowdown in IT-producing and using industries.

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

[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.

and Krizan (2006), and Foster et al. (2015)). 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 (about 30 log points) and more stable than single unit establishment firms (exit rates for single, unit establishments are more than 15 times higher than that for establishments of large, national chains). 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 more broad-based 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.[8] In the remainder of this paper, we focus primarily on the High-Tech sector (both in manufacturing and beyond manufacturing).

## III. Data and Measurement

The backbone datasets for our analysis are the Longitudinal Business Database (LBD), the Annual Survey of Manufactures (ASM) and revenue data from the Census Business Register that have recently been integrated into a firm-level version of the LBD. The LBD includes annual observations beginning in 1976, and we use the LBD through 2013 (this version of the data has consistent NAICS codes for the entire period as constructed by Fort and Klimek (2016)). 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. For a full description of the LBD, see Jarmin and Miranda (2002).

[8] See Decker et al. (2016) for a more thorough study of differing patterns of business dynamism across sectors and over time.

A unique advantage of the LBD is its comprehensive coverage of both firms and establishments. In the LBD, firm activity is captured up to the level of operational control instead of being based on an arbitrary taxpayer ID. The ability to link establishment and firm information allows firm characteristics such as firm size and firm age to be tracked for each establishment and firm. 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) 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 employment growth rates.

### *A. The ASM: Plant-Level TFP Measures*

For the main analyses in the paper, we focus on the Manufacturing sector where we can construct measures of establishment-level TFP. To do so, we supplement the LBD with 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.[9] 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. 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

[9] 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.

distributions (see FGH for details).[10] A second key advantage of integrating the ASM/CM data with the LBD is that it allows us to avoid using the ASM to construct measures of growth and survival. The rotating panel nature of the ASM makes this difficult on many different dimensions. Thus, our empirical approach is to study the relationship between plant-level TFP as measured by the ASM/CM in year t and the growth and survival of plants between t and t+1 as measured in the LBD.[11]

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

$$lnTFP_{et} = lnQ_{et}^{R} - \alpha_K lnK_{et} - \alpha_L lnL_{et} - \alpha_M lnM_{et} - \alpha_E lnE_{et} \quad (1)$$

where $Q^R$ 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).[13] A Divisia index approach is used for the latter so that industry-level cost shares are permitted to vary over time.

[10] The propensity score approach is based on a logit model that estimates the probability that a plant in the LBD (the universe) is in the ASM/CM as a function of detailed industry, firm size and firm age. It allows us to make the cross sectional distribution of plants in any given year be representative of the LBD on these dimensions. Note that these weights are appropriate for making the cross sectional distribution in any given year representative but are not the ideal weights for using samples of ASM/CM that are present in both t and t+1. We discuss this further below.
[11] 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 do not readily yield an innovation series for all years due to longitudinal representativeness challenges (see discussion below).
[12] Syverson (2011) provides an excellent summary.
[13] Cost shares yield factor elasticities under the assumptions of cost minimization and full adjustment of factors. We are not assuming the latter for each plant at each unit of time but rather this holds approximately when pooling across all plants in the same industry over time. We consider an alternative approach as described below using proxy methods to estimate revenue function elasticities.

Given the large differences in output and input measures as well as the production technology across industries, we focus on a relative measure of TFP within 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. Importantly, this measure of establishment-level productivity allows us to avoid problems associated with the mismeasurement of industry-level prices, such as those documented by Byrne and Corrado (2015, 2016). 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.[14]

Our measure of TFP is based on revenue. In this respect, we are using a TFPR measure of productivity.[15] This means differences in establishment-level prices are embedded in our measure of productivity. Unfortunately, the Census Bureau does not collect establishment-level prices on a wide scale in the ASM and CM. However, as Foster, Haltiwanger and Syverson (2008) (henceforth FHS) have shown, it is possible to measure establishment-level prices for a limited set of products in Economic Census years (years ending in "2" and "7"). FHS create a physical quantity measure of TFP (which they denote as TFPQ) removing the establishment-level price for establishments producing a set of 11 homogeneous goods (for example, white pan bread). The within-industry correlation between TFPR and TFPQ is high (about 0.75). However, FHS also find an inverse relationship between physical productivity and prices consistent with

[14] 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.
[15] As defined by Foster, Haltiwanger and Syverson (2008), TFPR = P*TFPQ where the latter is physical productivity or technical efficiency. There are alternative revenue productivity concepts that we consider below.

establishments facing a differentiated product environment. In addition, FHS find establishment-level prices are positively related to establishment-level demand shocks and that such demand shocks are positively correlated with TFPR. As such, our measure of establishment-level productivity should be interpreted as reflecting both technical efficiency and demand factors (including product quality factors that may be embedded in prices). For our purposes, a key finding from FHS is that the relationship between growth and survival and TFPQ and demand shocks is quite similar to the relationship between growth and survival and TFPR. It is time variation in the relationship between growth and survival and our revenue-based measure of TFP that we are exploring.

While our specific TFP measure is common in related literature, we also consider an alternative productivity measure based on the revenue function estimation proxy method described by Wooldridge (2009). Given potentially heterogeneous and endogenous plant-level prices, this alternative revenue productivity measure is in principle only a function of exogenous TFPQ and demand shocks. In Appendix C, we describe exercises based on this revenue productivity residual (RPR) in place of TFP. As shown there, we find that our main results are robust to this alternative productivity specification. The results reported in the main text, however, rely on the TFPR measure described above.

### *B. Revenue Data from the Business Register: Measuring Revenue Labor Productivity.*

While our main empirical investigation focuses on establishment-level data for the Manufacturing sector where TFP is measurable, in Section IV we extend our analysis to the entire economy by constructing measures of firm-level labor productivity. For this purpose we make use of a new revenue-enhanced version of the Longitudinal Business Database (RE-LBD). The RE-LBD integrates employment measures from the LBD with revenue based output measures from administrative files. We describe basic features of its construction and underlying data here (see Haltiwanger, Jarmin, Kulick and Miranda (2016) for additional details).

The RE-LBD is a firm level file with revenue and employment measures. The RE-LBD incorporates firm-level revenue measures by collapsing the EIN revenue measures contained in the Business Register that belong to the same firm. Firm-level employment measures result from collapsing employment in the LBD across all establishments that belong to the same firm.

Revenue coverage begins in 1996 and runs through 2013. A critical aspect of the RE-LBD is that the procedure for calculating the current-year and previous-year employment variables is adjusted so that all employment growth represents organic changes in establishment-level employment rather than artificial growth created by mergers and acquisitions (M&A).

Several additional aspects of the RE-LBD are worth mentioning at this point. The Census Bureau is not always able to tie revenue and employment measures belonging to the same firm in the BR.[16] This results in employment observations with missing revenue data. The RE-LBD sample excludes observations with missing revenue.[17] To account for the missing data and the potential selection effects that might arise we use inverse propensity scores to weight the data. Propensity scores are developed using the full LBD compared with the RE-LBD with models that include firm size, firm age, the employment growth rate, broad industry and a multi-unit status indicator. We use inverse propensity scores that are generated independently based on models for continuers, births and deaths (details about the filters used and the construction of the propensity scores can be found in the data appendix to Haltiwanger et al. (2016)).

We construct a relative measure of firm-level labor productivity within detailed industries that mimics our TFP concept described above. Specifically, the measure we use is (the log of) revenue per worker deviated from detailed (6-digit NAICS) industry-by-year means. Again, by deviating from detailed industry-year means we control for several factors. First, we control for relative price differences across detailed industries so our measure of labor productivity is consistent with a relative gross output per worker measure within detailed industries. Second, prior research (see, e.g., Foster, Haltiwanger and Krizan (2001, 2006)) has shown that relative gross output per worker within industries has a high correlation with relative value added per worker within industries and a strong correlation with relative TFP measures within industries. This reflects the fact that there are similar patterns of, for example, materials shares across firms in the same industry as well as other factor shares such as capital shares.

For this firm level analysis, we assign a firm to a detailed industry based on its modal employment. This is a potential source of measurement error since large multi-unit establishment firms may be operating in multiple 6-digit NAICS industries. We note, however,

[16] This is because firms can report income and payroll activities under different EINs. When this happens the income EIN may fall outside of the set of EINs that the Census considers part of that firm when accounting for employment.

[17] Approximately 20 percent of the firm-year observations do not have output measures.

that over 95 percent of all firms and more than 99 percent of all young (less than five year old) firms are single unit establishment firms. This implies that the industry-by-year mean we deviate from is very similar in practice to the industry-by-year mean for single unit establishment firms. As discussed in appendix E, we have conducted sensitivity analysis that uses a more sophisticated approach to controlling for industry effects for multi-unit establishment firms that operate in multiple industries. We find our results are robust to this alternative approach.

Finally, given the difficulties associated with measuring the output and productivity of firms in the Finance, Insurance, and Real Estate sectors, we omit firms in those industries (NAICS 52-53) from all analysis below.

## IV. Change in shocks vs. change in responsiveness

### *A. Theoretical motivation*

Having described basic facts about business dynamism and our data, we now proceed with a framework guided by canonical models of firm dynamics. Models of firm[18] dynamics suggest that a within-sector decline in the pace of reallocation is either due to a change in the volatility of shocks faced by 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.

To be more specific, canonical models of firm dynamics with adjustment frictions yield decision rules for employment growth (or other input growth like investment/capital growth) that are a function of the two key state variables each period: the realization of productivity and the initial size of the firm. A reduced form representation of this decision rule is given by: $g_{ft+1} = f_{t+1}(A_{ft+1}, n_{ft})$ where $g_{ft+1}$ is the growth rate of firm $f$ between $t$ and $t+1$, $n_{ft}$ is initial size, and $A_{ft+1}$ is the realization of firm (idiosyncratic) productivity (which is typically observed prior to the growth decision). This implies that changes in the distribution of firm growth rates stem

[18] We use the term "firms" loosely in this subsection. 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 both establishment-level and firm-level dynamics.

from either changes in the distribution of $A_{ft+1}$ or the responsiveness of the firm to a given realization of $A_{ft}$.

There exists a 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 labor adjustment frictions from key micro moments on the distribution of firm-level employment growth rates.[19] 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.

These authors also 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. The intuition for this result is simple: Reaching optimal scale requires larger adjustments when shocks are more dispersed; but for any given shock distribution, parameters governing marginal responsiveness—which include adjustment cost parameters—determine the speed and frequency with which individual firms adjust. As in the Hopenhayn and Rogerson model, the Cooper, Haltiwanger and Willis models imply that increases in adjustment frictions induce a reduction in the dispersion of firm-level growth rates. Cooper, Haltiwanger and Willis (2007, see Table 10) also show that in the steady state a decrease in the dispersion of idiosyncratic shocks yields a decrease in the dispersion of firm-level growth rates.[20] 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.[21]

We note that the recent literature on uncertainty (see, *e.g.*, Bloom (2009) and Bachmann and Bayer (2013)) highlights that in some model setups there may instead 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

[19] Cooper and Haltiwanger (2006) use a similar approach for estimating the structure of firm-level capital adjustment frictions from key micro moments of the distribution of investment rates.
[20] In the analysis for their Table 10, they use a specification that has fixed and linear vacancy posting costs.
[21] She motivates this with interesting evidence that the cost of training of new workers has risen over time.

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.[22]

Our empirical approach in the next section is motivated by the insights of these theoretical models. Broadly speaking, these models yield the prediction that firm-level growth in a given period will be an increasing function of the realizations of productivity/profitability shocks conditional on initial endogenous state variables (i.e., initial employment) in each period. This implies that changes in the distribution of firm-level growth rates (e.g., dispersion) can be accounted for either by changes in the distribution of productivity/profitability of shocks or by 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

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

such analysis.[23] A benefit of our reduced form approach is that it 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 of U.S. Manufacturing*

In this section, we investigate these issues for the U.S. manufacturing sector with a focus on the High-Tech component of manufacturing. For our purposes, the High-Tech sector includes the 4-digit sectors in Table A.1 that are in manufacturing.[24] To help provide perspective on our findings for High-Tech Manufacturing we also consider the rest of the Manufacturing sector which for ease of exposition we call Non-Tech Manufacturing.

The first exercise we consider is to explore the evolution of the within-industry dispersion in (log) TFP, where dispersion is quantified as the standard deviation of the within-industry plant-level (log) TFP distribution. This is our measure for the dispersion of idiosyncratic productivity shocks faced by establishments. Figure 4 shows the evolution of within-industry productivity dispersion for plants in High-Tech Manufacturing (top panel) and Non-Tech Manufacturing (bottom panel). We report separate results for young and mature firms since the evidence presented above suggests that plants of young firms exhibit different paces of reallocation. 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. 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)). We find that the levels of within-industry TFP dispersion are about the same for plants of young and mature firms in both the High-Tech and Non-Tech areas of Manufacturing. In High-Tech Manufacturing, plants of young and mature

[23] 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.

[24] These include manufacturers in NAICS codes 3341 (computer and peripheral equipment), 3342 (communications equipment), 3344 (semiconductor and other electronic components), 3345 (navigational, measuring, electromedical, and control instruments), 3254 (pharmaceutical and medicine), and 3364 (aerospace product and parts).

firms exhibit a positive trend in dispersion that roughly mimics the overall. The same holds for Non-Tech Manufacturing.[25]

To help understand the implications of this rising within-industry dispersion of productivity, it is also useful to study 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 and the innovations to the process, but as discussed in Appendix B we find that persistence is reasonably stable with an AR1 estimated coefficient of about 0.6 to 0.7 and the pattern of dispersion in innovations match those of overall dispersion.

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 3 shows a pattern of rising reallocation during the 1990s and then 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. We estimate establishment-level regressions relating employment growth from $t$ to $t+1$ for all incumbents in period t and

[25] Figure A1 in the appendix reports overall dispersion (for all ages) for High-Tech Manufacturing, Non-Tech Manufacturing, and the entire Manufacturing sector. 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. In Appendix C, we also report a version of Figure A1 that is based on the Wooldridge (2009) revenue productivity residual (RPR) estimation instead of our TFPR measure; Figure C1 reports these results, confirming that the general upward trend of TFPR is robust to the RPR productivity concept.

measured TFP in period $t$ with appropriate controls. We define employment growth for establishments between periods $t$ and $t+1$ using the Davis, Haltiwanger and Schuh (1996) (hereafter DHS) concept that can accommodate entry and exit.

Equation (2) is our basic specification:

$$\begin{aligned} g_{e,t+1} = \lambda_{t+1} + \beta_y * TFP_{et} * Young_{et} + \delta_{1y} * TFP_{et} * Young_{et} * Trend_t \\ +\delta_{2y} * TFP_{et} * Young_{et} * Trend_t^2 \\ +\beta_m * TFP_{et} * Mature_t + \delta_{1m} * TFP_{et} * Mature_{et} * Trend_t \\ +\delta_{2m} * LP_{et} * Mature_{et} * Trend_t^2 + X'_{et}\Theta + \varepsilon_{e,t+1} \end{aligned} \tag{2}$$

where $g_{e,t+1}$ is the DHS employment growth rate for establishment $e$ between time $t$ and time $t+1$ , $TFP_{et}$ is total factor productivity for establishment $e$ at time $t$ deviated from (six-digit NAICS) industry-by-year means, and $Trend_t$ is a simple linear time trend (which we also include as a quadratic term in many specifications). $Young_{et}$ is a dummy equal to 1 if the plant's firm is young (age less than five) in year $t$, $Mature_{et}$ is a dummy equal to 1 if the plant's firm is mature in year $t$, and $X_{et}$ is a set of controls discussed further below. Note that trend terms are not entered as main effects since there is a full set of year effects. The latter capture general trends as well as national cyclical effects. We estimate equation (2) using our propensity score weights. All of the terms involving TFP are fully saturated with young and mature dummies, as the evidence in the 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.[26] There is already much evidence that high-productivity establishments are more likely to survive and grow (see, *e.g.*, Syverson, 2011). Put differently, standard models of exit in the literature relate the decision to exit between $t$ and $t+1$ to the realization of TFP in period $t$ along with other controls (*e.g.*,

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

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. In this sense, equation (2) produces a reduced-form yet direct estimate of policy functions generated by canonical models.

Our interest is in investigating whether the response to idiosyncratic productivity shocks has changed over time. The inclusion of the $Trend_t$ variable allows us to estimate a time-varying relationship between productivity and growth. 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. In the exercises described following our discussion of the regression analysis, we exploit this time-varying productivity responsiveness estimation to understand the changing contribution of job reallocation to aggregate productivity growth.

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).[27] 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 Manufacturing while the second column shows the estimates for the plants in Non-Tech Manufacturing (we discuss the third and fourth columns further below). 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 easiest to interpret the variation across age groups and time by sector graphically which we show in Figure 5 (described below). 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

[27] 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.

the five percent level. For plants in Non-Tech Manufacturing, four of the six coefficients in column 2 of Table 1 are statistically significant at the 10 percent level or better. Columns 3 and 4 of Table 1 report results for the changing responsiveness of exit (which underlies part of the patterns of the first two columns) which we discuss below.

The estimates for parameters $\beta_y$ and $\beta_m$ are given by the "TFP*Young" and "TFP*Mature" rows of Table 1. These positive coefficients show that, consistent with previous literature, growth and productivity are positively related. On average, establishments that are more productive than others in their industry are more likely to grow, while those that are less productive are more likely to contract or exit. This relationship is stronger among establishments of young than mature firms, consistent with stronger selection dynamics at work among recently entered businesses. The positive relationship between productivity and growth at the establishment level is consistent with a positive contribution of reallocation to aggregate productivity growth.

The estimates for parameters $\delta_{1y}$ and $\delta_{1m}$ are given by the "TFP*Young*Trend" and "TFP*Mature*Trend" rows of Table 1, respectively. These are our key coefficients of interest as they show how the marginal responsiveness of establishments to their own idiosyncratic productivity has changed with time. Notably, in the High-Tech Manufacturing sector these coefficients are positive and significant for plants of both young and mature firms, suggesting that productivity responsiveness strengthened in the early years of the sample (which begins in 1980), while the coefficients are close to zero in the Non-Tech Manufacturing sector. Both inside and outside of High-Tech, however, the coefficients on the quadratic term are negative, suggesting interesting dynamics in productivity responsiveness that we now describe graphically.

Figure 5 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 5 show the patterns for High-Tech Manufacturing and Non-Tech Manufacturing plants, respectively. As mentioned above, the figure makes apparent that plants of young firms are more responsive to productivity than are plants of mature firms, particularly in High-Tech. 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, for example, a learning

model in which 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 Manufacturing, shown on Figure 5a. 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.

Continuing our study of Figure 5a, note that the magnitudes of the coefficients readily lend themselves to quantitatively meaningful interpretations since productivity is deviated from its industry-year mean (and hence has mean zero). Recall that Figure 4a shows the standard deviation of within-industry productivity for High-Tech Manufacturing establishments; multiplying the relevant standard deviation by the relevant coefficient on Figure 4a suggests that a young-firm plant with productivity that was one standard deviation above its industry-year mean had an employment growth rate that was about 12 percentage points higher than the industry average in the 1980s, and it was about 17 percentage points higher in the 1990s but only about 10 percentage points higher in the 2000s. Among mature firms, the growth advantage was about 5 percentage points in the 1980s, 6 percentage points in the 1990s, and 3 percentage points in the 2000s. For plants of both young and mature firms, if productivity dispersion had remained constant throughout the period then the decline in relative growth from the 1990s to the 2000s would have been even larger.[28]

[28] More precisely, to calculate the growth advantage of the plant that is a standard deviation above the mean versus the average plant in an industry, we simply multiply the standard deviation by the responsiveness coefficient. Rising productivity dispersion means that the gap in productivity separating the average plant and the plant that is one standard deviation above average grows over time; for example, Figure 5a shows that a young-firm plant with productivity one standard deviation above the industry-year mean was about 35 log points more productive than average at the beginning of the time series and almost 50 log points more productive than average by 2010. The net growth advantage figures calculated in the text reflect offsetting effects from rising dispersion (and hence rising productivity advantage) and declining marginal responsiveness, with the declining responsiveness factor being so large that it typically outweighs the rising dispersion factor.

Figure 5b shows the analogous patterns for Non-Tech Manufacturing. Here again we find that plants in young firms are more responsive to TFP than plants in mature firms. For Non-Tech Manufacturing there has been a decline in the share of young business activity throughout the period implying a decline in overall responsiveness due to composition effects. Within age groups, we find a decline in responsiveness throughout the period with an acceleration of the decline in the post-2000 period. As above, we can construct rough estimates of the changing growth gap between high- and average-productivity plants (within industries) using standard deviation estimates from Figure 4b. Among young firms, the growth rate gap between plants with productivity a standard deviation above the mean and plants at the mean was roughly 10 percentage points in the 1980s, 9 percentage points in the 1990s, and only 6 percentage points in the 2000s. Among mature firms, the growth advantage was about 5 percentage points throughout the time period, though the advantage would have fallen had productivity dispersion remained flat.

In Figure C3 of Appendix C, we report analogous results based on the Wooldridge (2009) revenue productivity residual (RPR) estimation method. Results are quite similar.[29] Thus, using a measure of revenue productivity that more plausibly only reflects idiosyncratic productivity and demand shocks, we find evidence of changing responsiveness rather than changing shocks driving the decline in dynamism 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 Manufacturing. 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. Among Non-Tech Manufacturing plants, responsiveness declines throughout the 1980s-2000s with an acceleration after 2000.

There may be interactions between the effects we have detected. The rising dispersion of

[29] Figure C3 reports decade averages of coefficients from the regression in (3) but using RPR in place of TFP. We again observe a pattern of responsiveness for young-firm plants in High-Tech Manufacturing that rises from the 1980s to the 1990s, then falls in the 2000s. The decline from the 1990s to the 2000s among young High-Tech businesses is not as notable in the RPR-based regressions as it is in the TFPR-based regressions, but it is still significant as we show below in aggregate productivity counterfactuals. High-Tech Manufacturing plants of mature firms see broadly steady responsiveness from the 1980s to the 1990s followed by a sharp decline in the 2000s. The bottom panel of Figure C3 likewise shows that the RPR responsiveness patterns among Non-Tech Manufacturing plants are quite similar to those based on TFP and reported on Figure 5.

TFP (and its innovations) in the post-2000 period could be contributing to declining responsiveness through expansion of inaction bands, as noted in our theoretical framework discussion above. 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. Columns 3 and 4 of Table 1 report results from regressions in which a binary exit indicator serves as the dependent variable (making this a linear probability model). We find that part of our declining responsiveness in the post-2000 period is due to a declining responsiveness of exit to productivity shocks. Figure A2 provides the graphical representation of the changing responsiveness of exit. For High-Tech Manufacturing, we find exit for young plants became more responsive during the 1990s and then responsiveness declined. For Non-Tech Manufacturing, exit for young plants became less responsive throughout the period. For mature plants (both tech and non tech), exit responsiveness does not change much from the 1980s to the 1990s but then declines in the post-2000 period.

The findings on exit are interesting in their own right as they imply that in the post-2000 period low-productivity plants are more likely to survive, which will be a drag on aggregate productivity. The reduced covariance between survival and productivity can also 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 for changing dispersion. During the 1990s, we find increased responsiveness of exit but mild increases in dispersion in productivity. This also holds for the alternative RPR measure of productivity (see appendix Figure C.1)

Taken together, these results have important implications for the evolution of firm dynamics in recent decades. We find significant evidence that the way in which individual businesses respond to their productivity or profitability environment has changed over time. The relationship between productivity and growth remains robust, but it has weakened over time (particularly since 2000). From the standpoint of the firm dynamics models described above, our results can be viewed as evidence that policy functions have changed over time, particularly for

young businesses but also for older ones.[30] These changes are consistent with an increase in adjustment costs or other frictions that reduce marginal productivity responsiveness in these models. The changes are most striking among High-Tech businesses, where we observe a pattern of rising and falling productivity responsiveness that coincides with the ICT-driven acceleration and deceleration of aggregate productivity growth documented by Fernald (2014) and others.

### *C. Implications for aggregate (industry-level) productivity*

How important are the changes in responsiveness for aggregate fluctuations in productivity growth? 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 that 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 (industry-level) aggregate index using the actual plant-level data:

$$TFP_t = \sum_e \theta_{et} TFP_{et} \tag{3}$$

where $\theta_{et}$ is the employment weight for establishment $e$ in year $t$ and $TFP_{et}$ is establishment-level productivity (deviated from the industry-year mean).[31] This construction of aggregate productivity readily lends itself to shift-share counterfactuals. We next use the estimated regression models described above to generate a counterfactual index given by:

[30] These results contrast with Karahan, Pugsley and Sahin (2016), who argue that the dynamics of incumbent firms (in a Hopenhayn framework) have not changed over this same time period. These authors point to aggregated average growth rates for various incumbent age classes as evidence for stable incumbent firm dynamics. We differ from their approach by directly estimating incumbent firm policy functions at the establishment level. In their framework, our results suggest that factors in addition to changes in the growth of the labor force are likely relevant for understanding the decline in startup rates, though we view the labor force demographic evidence as an important component of the final explanation.

[31] FGH show that the index of industry-level productivity in (3) yields fluctuations in industry-level productivity that mimic the patterns of productivity from aggregated statistics. For example, FGH construct measures of industry-level productivity growth using traditional growth accounting techniques with aggregated plant-level data yielding industry output and input measures. The correlation between such traditional measures and the industry-level measures that emerge from (3) from pooled industry by year data is 0.70 when employment weights are used in (3) and is 0.80 when output weights are used in (3).

$$TFP_{t+1}^{C} = \sum_{e} \theta_{e,t+1}^{C} TFP_{et} \tag{4}$$

where $\theta_{et+1}^{C}$ is the predicted employment share for establishment $e$ in period $t+1$ based upon the estimated model, that is, based on the assumption that plants respond to productivity shocks by growing or shrinking according to model parameters. In other words, the regression model provides a prediction for employment growth of every establishment based upon "state" variables including firm age and productivity in year $t$; this prediction implies an employment level for year $t+1$ that allows us to generate a counterfactual employment share $\theta_{e,t+1}$ for each establishment.[32] Make careful note of all time subscripts in (4); we hold constant plant-level productivity (and hence, in an aggregate sense, we keep the unweighted productivity distribution unchanged). Using equations (3) and (4), we can measure the productivity gains from model-driven reallocation as $TFP_{t+1}^{C} - TFP_{t}$, isolating the productivity growth that comes only from shifting employment shares.

We can compute the gains from reallocation under different model-based 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 change in the contribution of reallocation to productivity growth implied by changing trend responses; that is, we compute the following:

$$\Delta_{t}^{t+1} = \left(TFP_{t+1}^{C,trend} - TFP_{t}\right) - \left(TFP_{t+1}^{C,no\ trend} - TFP_{t}\right) \tag{5}$$

where $TFP_{t+1}^{C,trend}$ is the counterfactual model-based productivity that includes the estimated trend effects described above, and $TFP_{t+1}^{C,no\ trend}$ is the counterfactual model-based productivity that excludes the trend in responsiveness. We compute this diff-in-diff counterfactual calculation for each year; it can be thought of as an estimate of the degree to which the weakening responsiveness of establishments to productivity can account for slowed productivity

[32] We set the cyclical effects to zero by setting the state-level change in unemployment to zero.

growth. Note that in this exercise we employ the overall growth coefficients from the first two columns of Table 1; these include both changes in the intensive margin and the changes in exit selection that we examined in more detail on the third and fourth columns of Table 1 (as well as Figure A2).

The results of this counterfactual exercise are depicted on Figure 6; the figure can be interpreted as follows. Each annual observation reports $\Delta_t^{t+1}$ from (5), or the amount by which the trend effects in the regression model have increased or reduced reallocation-driven productivity growth from year $t$ to $t+1$, taking the year $t$ distribution of productivity as given. For example, the observation for $t+1=1981$ has $\Delta_{1980}^{1981}=0$ because the trend variable begins then, and for High-Tech Manufacturing the year 2001 again gives $\Delta_{2000}^{2001}=0$. But the 2004 observation for High-Tech shows that the model-generated productivity growth from 2003 to 2004 would have been about 1/2 a log point higher ($\Delta_{2003}^{2004}=-0.005$) if the adjustment dynamics immediately reverted to the stronger responsiveness of the year 1981 (or 2001), given the unweighted productivity distribution of 2003.

For High-Tech Manufacturing plants, the increasing responsiveness over the 1980s and 1990s yields an implied counterfactual increase in the annual 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 certainly extrapolating out of sample—since the pattern in Figure 6 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.[33]

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 Manufacturing plants, the changing responsiveness has relatively little impact until the post-2000 period, consistent with the estimates in Table 1 that are near zero on

[33] Another source of caution is that since we are using at TFPR measure the rising dispersion of TFPR may reflect endogenous factors in a manner similar to the labor productivity measures we use in the next section. Under this view, the counterfactual may partially reflect transitory or one-time gains. We note however that we obtain similar implications using the RPR measure in appendix C.

the linear trend terms but negative on the quadratic terms. By 2005 the acceleration of the decline in responsiveness in this part of manufacturing yields as much as a half a log point drag on productivity per year.

In Appendix C, we report results from this counterfactual exercise that rely on the Wooldridge (2009) revenue productivity residual (RPR) method. The results for High-Tech Manufacturing are broadly consistent with the TFPR-based results, as shown on Figure C4, with rising responsiveness implying an increasing contribution of reallocation to aggregate productivity growth in the 1990s followed by a decreasing contribution in the 2000s. Interestingly, among Non-Tech Manufacturing plants we find that the RPR method results in an earlier decline in the reallocation contribution than does the TFPR approach.

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" comparison, 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) growth that we have not estimated in this context.[34] Fernald (2014) and Byrne et al. (2016) highlight many factors that are likely contributing to within-plant (and within-firm) declines in productivity growth in the post-2000 period. In addition to the factors they emphasize, there may be a role for declining entrepreneurship in declining within-firm productivity growth. If young firms play a critical role in the innovative process, then a decline in the share of young firm activity can also contribute to a declining pace of within-firm productivity growth. Exploring this hypothesis should be a priority in future research.

## V. Beyond Manufacturing

Thus far, our analysis has focused on the Manufacturing sector. As mentioned above, this is a sector in which we have high-quality data on TFP, which allows us to map the

[34] As mentioned previously, investigating within-plant TFP changes is challenging because the ASM/CM data is not ideally suited for quantifying within-plant productivity changes. In unreported results we analyze changes in within-firm productivity.

theoretical framework discussed above to the data on employment growth. While we find the evidence from Manufacturing—and High-Tech—High-Tech Manufacturing in particular—to be compelling, an important question is whether the patterns of productivity dispersion and responsiveness we have documented are present in other areas of the economy. Much of the innovation that characterizes the U.S. economy, particularly after 2000, has been in the Information sector (e.g., software publishing, internet portals, and so on). Moreover, the patterns of changes in business formation and in the dispersion and skewness of firm growth rates are even more dramatic in non-manufacturing components of the High-Tech sector (see Decker et al. (2016)). Relatively little is known about the connection between reallocation dynamics and productivity growth outside of Manufacturing.[35]

While the question of productivity responsiveness and aggregate productivity growth is difficult to answer in the absence of precise concepts and data for TFP in the non-manufacturing sectors, we can provide evidence using output per worker as our productivity concept. For this purpose, we employ the RE-LBD dataset (described in Section III above), which permits the measurement of revenue per worker at the firm level. A key strength of the RE-LBD is its comprehensive coverage of the U.S. private, non-farm sector from the mid-1990s to 2013. We emphasize that our analysis in this section differs from the previous section not only in its labor-based definition of productivity but also in the use of firms as the unit of analysis (rather than establishments).

When studying TFP and Manufacturing, we adopted a "shock responsiveness" interpretation of the relationship between business-level growth and productivity; here we adopt a looser interpretation with an acknowledgement that gross output per worker (the measure of labor productivity we use in this section) is endogenous, reflecting not only TFP but also the endogenous intensity of other inputs such as capital. Perhaps more importantly, changing dispersion of measured labor productivity will also reflect changes in adjustment frictions.

To understand this latter point, consider the following characterization of the implied dynamics by the canonical models of adjustment frictions discussed above (in Appendix D we provide a more formal treatment of these arguments). In any given period, firms have new

[35] Significant exceptions include the numerous studies of Retail Trade cited above that highlight the shift in the business model toward large, national chains that has been productivity enhancing. See, for example, Foster, Haltiwanger and Krizan (2006), Jarmin, Klimek and Miranda (2009) and Foster et al. (2015).

realizations of TFP. Firms with positive realizations have an increase in the marginal revenue product of labor while the opposite is true for firms with negative realizations. With adjustment frictions, adjustment in factors of production takes time but in general those with positive realizations grow while those with negative realizations contract. The adjustment of employment will work toward reducing dispersion in the marginal revenue products of labor. Given that the average revenue product of labor (measured labor productivity) and marginal revenue product of labor are closely related (under Cobb-Douglas assumptions they are proportional), measured labor productivity will exhibit similar patterns.

This logic implies that if adjustment frictions increase then this will endogenously slow down the tendency for marginal revenue products to be equalized and will yield an increase in the dispersion of measured labor productivity.[36] Thus, observed increases in the within-industry dispersion in labor productivity may reflect increases in the dispersion of shocks, increases in adjustment frictions or both.[37]

Even using labor productivity measures it is still the case that an increase in adjustment frictions will reduce the covariance between firm employment growth and labor productivity. Following the same logic as above, an increase in adjustment frictions will imply that differences in marginal revenue products will be reduced more slowly because employment adjustment will be slower. That is, the covariance between employment growth and idiosyncratic differences in measured labor productivity will be reduced with an increase in adjustment frictions.

Given these issues, we interpret these results as providing insights into the changing distribution of labor productivity across firms in the same industry and the changing covariance

[36] It is this type of insight that has led researchers such as Hsieh and Klenow (2009) to interpret increases in the dispersion of the average product of labor as representing an increase in the distortions or wedges that are impeding the equalization of marginal revenue products. The strict interpretation by Hsieh and Klenow (2009) depends on strong functional form assumptions (see Haltiwanger (2016) and Haltiwanger, Kulick and Syverson (2016)) but this perspective is potentially relevant in our setting. We take a more agnostic position here acknowledging that changes in dispersion of labor productivity may reflect shocks, changes in frictions or both. If we used the Hsieh and Klenow (2009) assumptions of Cobb-Douglas production with constant returns to scale and iso-elastic demand with common markups, then we would interpret the rising dispersion in labor productivity within sectors as reflecting increasing wedges or distortions. We cannot rule out this interpretation, and it is consistent with our findings of smaller responsiveness of growth to productivity differences within sectors. The simple model we consider in Appendix D elaborates on these issues.

[37] There may be other factors at work as well. For example, changes in the dispersion of capital intensity across firms in the same industry will yield changes in the dispersion of measured labor productivity. This could arise if there is some change in the production structure of firms and may be relevant, for example, in the presence of biased technological change where not all firms adopt new technologies. Alternatively, changes in capital intensities may reflect changes in the adjustment frictions for capital. Thus, changes in responsiveness of employment growth detected by our analysis may in fact reflect changes in the responsiveness of capital accumulation.

between realizations of labor productivity and firm survival and growth. The changing distribution of measured labor productivity should not be thought of as simply a proxy for the distribution of shocks but rather the interaction of the distribution of shocks and adjustment.[38] With these limitations in mind, we proceed with our investigation.[39]

### *A. Productivity and growth at the firm level*

Figure 7a (the top panel of Figure 7) reports the interdecile range of within-industry labor productivity differences across firms in the High-Tech sector. Note that our definition of High-Tech is broader in this section than it was in our discussion of Manufacturing results; in our labor productivity exercises, High-Tech includes not only High-Tech Manufacturing but also industry groups from Services and Information. Consistent with TFP dispersion in High-Tech Manufacturing, the dispersion of labor productivity in High-Tech broadly has risen over our sample period, a trend that is evident among both young and mature firms. Notably, however, the dispersion of labor productivity is much higher among young firms than mature firms, while TFP dispersion is roughly equal for young and mature (see Figure 4). This could reflect greater dispersion in other factor inputs, such as capital, among younger businesses. Figure 7b shows that labor productivity dispersion is also rising among firms outside the High-Tech sector, with a difference between young and mature firms again apparent. In Figure A3 of Appendix A, we report that the pattern of rising dispersion is pervasive across the major sectors of the economy including Information, Manufacturing, Retail Trade, and Services.

Our finding of rising within-industry productivity dispersion is broadly consistent with other work documenting increased differences between firms. For example, Andrews, Criscuolo and Gal (2015) find a widening productivity gap between "frontier firms" and others, concluding that the pace of technological diffusion has slowed. While the authors do not provide direct evidence for the hypothesis that slowed technological diffusion is the cause of increasing productivity dispersion, the diffusion hypothesis could play a role. Weakening responsiveness of

[38] This is also true for TFP dispersion, though to a much weaker degree. Changing responsiveness of entry or exit to TFP shocks can affect measured TFP dispersion through selection. The selection effect is present for labor productivity dispersion as well, in addition to the much more significant and direct mechanism described previously.
[39] Many studies have used the covariance relationship between gross output per worker and employment growth to study the contribution of reallocation dynamics to industry level productivity growth. For examples as well as surveys of the literature see Baily, Bartelsman and Haltiwanger (2001), Foster, Haltiwanger and Krizan (2001, 2006) and Syverson (2004, 2011).

growth and survival to productivity that we document in the next section is an alternative, but not mutually exclusive, explanation. Both explanations allow for a decoupling of technological progress and aggregate productivity growth.[40] However, as we have discussed above, declining responsiveness is potentially consistent with increased adjustment frictions or other forces that slow down the tendency for marginal revenue products to be equalized.

In other potentially related work, Song et al. (2016) document rising inter-firm wage dispersion, suggesting that patterns of rising income inequality are closely linked to the evolution of the firm distribution.[41] Given commonly theorized ties between labor productivity and wages, a connection between the productivity and wage distributions is likely and represents an important avenue for future research (see Davis and Haltiwanger (1991) and Dunne et al. (2004) for earlier empirical treatments of the subject).

The evidence on labor productivity dispersion throughout the entire U.S. economy is generally consistent with the evidence on TFP dispersion in Manufacturing; in particular, there is no evidence of a decline in dispersion, suggesting that changes in productivity shock patterns are not the cause of declining aggregate job reallocation.[42] We now study the relationship between labor productivity and growth using an approach similar to our analysis in Section IV. We measure DHS employment growth, but in this case we use firm-level growth rather than establishment-level growth. We then estimate the following equation:

$$g^{E}_{f,t+1} = \lambda_{t+1} + \beta_y * LP_{ft} * Young_{ft} + \delta_{1y} * LP_{ft} * Young_{ft} * Trend_t \qquad (6)$$

[40] Andrews, Criscuolo and Gal (2015) (ACG) provide evidence of rising productivity dispersion within broad sectors using ORBIS data on both labor productivity (similar to our approach here) and multifactor productivity (similar to our analysis in Section IV). While ORBIS coverage of the U.S. is weaker than its coverage of other countries, we view our evidence as strongly supportive of the notion that gaps between the most productive firms and other firms have increased since the late 1990s. In that sense our work is complementary to the work of ACG, though we caution that their measures of productivity dispersion are sufficiently conceptually different from ours as to make direct quantitative comparisons difficult. ACG measure the difference between "frontier firms" and average firms, where the frontier firms are usually defined as the top 50 or 100 firms within a broad (2-digit) sector, and in the case of the U.S. their unit of analysis is actually the establishment (Pinto Ribeiro, Menghinello and De Backer (2010)). Our measure of dispersion is defined within detailed (6-digit NAICS) industries and is based upon percentiles rather than the selection of an absolute number of businesses.

[41] Song et al. (2016) find rising between-firm wage dispersion both in the aggregate and within industries. They point to evidence suggesting that these patterns are driven by increased "segregation" or selection of high-earning workers into high-paying firms (rather than being driven primarily by changes in firm-level earnings premiums). More work is needed to determine whether these patterns in firm-level wage dispersion are related to our findings on increased firm-level productivity dispersion.

[42] We also note that labor productivity dispersion is significant. For example, in the economywide data, in 1996 the 90th percentile firm was about 6.2 times as productive as the 10th percentile firm; by 2012 that ratio was 6.8.

$$+\delta_{2y} * LP_{ft} * Young_{ft} * Trend_t^2$$
$$+\beta_m * LP_{ft} * Mature_t + \delta_{1m} * LP_{ft} * Mature_{ft} * Trend_t$$
$$+\delta_{2m} * LP_{ft} * Mature_{ft} * Trend_t^2 + X'_{ft}\Theta + \varepsilon_{f,t+1}$$

Equation (6) is almost identical to (2) except that growth, productivity, and size are all measured at the firm level (versus the establishment level as in (2)). The variable $LP_{ft}$ is our measure of firm-level labor productivity, which is (log) deviated from detailed industry-year mean. We estimate this equation over a shorter time period (1997-2013) reflecting the limitations of our revenue dataset, but we include the same controls in $X_{ft}$ (see Section IV). As we discuss above, this specification stretches the "shocks vs. responsiveness" interpretation we adopted in our TFP-based regressions, but it is still useful for studying the relationship between growth and productivity and can be similarly used in counterfactual exercises. We estimate (6) using propensity score weights.

Table 2 reports results of the regression from (6) for all firms and for the High-Tech and Non-Tech sectors separately. The first three columns report regressions using the DHS growth rate denominator inclusive of exit; the last three columns report results using only a binary exit outcome as the dependent variable. Figure 8 graphically shows the time series pattern of the coefficients for overall growth.

As shown on Figure 8a (the top panel of Figure 8), we find a significant positive relationship between productivity in year $t$ and employment growth from $t$ to $t+1$ among both young and mature firms in both High-Tech and Non-Tech industries, consistent with our TFP results and existing literature (e.g., Syverson (2011)). The productivity/growth relationship is stronger for young than for mature firms. All categories of firms see a reduction in the strength of the productivity/growth relationship. The reduction in strength is greater for young High-Tech firms than young Non-Tech firms.

The probability of exit is decreasing strongly in productivity, with young firms being particularly sensitive to productivity selection. Figure 8b shows that the negative relationship between productivity and exit is moderating among all young firms, with a particularly strong effect among young High-Tech firms. Broadly speaking, the evidence suggests that the survival and growth differential between high- and low-productivity firms in the High-Tech sector is declining over time.

In summary, we find that the relationship between productivity and growth at the firm level, while robust, is weakening over time in most sectors of the economy and among both young and mature firms. The same is true for exit with a general weakening of the productivity selection mechanism across sectors and age classes. The decline in this relationship is particularly pronounced in the High-Tech sector. The results on both labor productivity dispersion and the relationship between labor productivity and growth broadly confirm our TFP-based results from Manufacturing and suggest that the patterns documented in the latter sector are likely to hold in other areas of the economy. As we argued above, the framework of firm dynamics models, applied to our evidence, suggests that slowing reallocation indicates the presence of increased frictions rather than changes in the distribution of idiosyncratic productivity shocks. Our evidence shows rising dispersion of idiosyncratic shocks in manufacturing and rising dispersion of labor productivity more broadly. The former, holding other factors constant, should have yielded an increase in the pace of reallocation. The latter is inherently endogenous but is consistent with rising frictions and distortions.

### *B. Reallocation and aggregate labor productivity*

Following the approach from Section IV, we can quantify the labor productivity regression results by relating them to aggregate productivity growth using shift-share analysis. With the only differences being the use of labor productivity (versus TFP) and firm-level data (versus establishment), we again construct a base-year index using the analogue to equation (3) and a model-based diff-in-diff counterfactual using equation (5).[43] We report results for High-Tech and Non-Tech firms on Figure 9.

While this exercise is mechanically identical to that performed with TFP in Section IV, we caution that the economic interpretation is more complicated. As mentioned above, labor productivity dispersion is more endogenous to productivity responsiveness than is TFP dispersion in the sense that there are more mechanisms for endogeneity in the former case than in the latter. While selection effects can make the dispersion of both TFP and labor productivity

[43] The analogue to the productivity index in (3) yields industry-level indices that are very similar to a traditional index of gross output per worker at the industry level. The correlation between the industry level indices from the analogue to (3) and traditional indices is 0.76. At the economy-wide level, the correlation between the growth rate in traditional gross output per worker labor productivity measures and the employment-weighted micro based estimate is 0.81.

endogenous to responsiveness, in the case of labor productivity dispersion there is the additional mechanism of slowed responsiveness meaning a slowed pace of marginal revenue product equalization and related issues associated with capital deepening and other factors. Labor productivity dispersion rose during the 1996-2013 period, and this increase is likely at least partially endogenous to the decline in responsiveness we document. This complicates the shocks/responses intuition that guided our discussion of related exercises in Section IV.

In particular, these considerations imply that the productivity counterfactuals in Figure 9 partially reflect cumulative factors in addition to simple annual responsiveness mechanisms. The lost productivity growth we estimate for each year partly reflect both current and cumulative past shocks to which firms still have yet to fully adjust. The diff-in-diff calculation each year is thus an estimate of the gains there would be from reallocation if adjustment dynamics suddenly reverted to their more responsive 1997 rates using the current dispersion of productivity, which is in part driven by previous adjustment dynamics.

With the above details in mind, we note that the effects we find are quite large. By 2012, the weakening productivity/growth relationship accounts for about 6 log points of reallocation-driven aggregate productivity growth. In contrast to the TFP-based results from Manufacturing, our labor productivity-based calculations for the entire economy show a similar pattern for firms inside and outside High-Tech. In unreported results we find that this is driven by particularly strong declines in the sensitivity of exit to productivity among firms outside High-Tech. Moreover, Figure A4 in Appendix A shows diff-in-diff results for only the Manufacturing sector, with results separated by High-Tech and Non-Tech Manufacturing as in our TFP-based exercises. Within Manufacturing, we do indeed find stronger results for High-Tech than for other firms, which is qualitatively consistent with our TFP-based investigation.

## VI. Investigating mechanisms in Manufacturing

In this section we return to our analysis of the Manufacturing sector using TFP data from the ASM/CM/LBD linked data employed in Section IV. While a thorough examination of the causes of the empirical patterns we describe above is beyond the scope of the present study, we can provide evidence on several common hypotheses with a particular focus on High-Tech Manufacturing businesses: capital substitution, globalization, and composition changes within High-Tech.

### *A. The response of equipment investment*

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 the analogue to equation (2), this time using as the dependent variable the equipment investment rate instead of the employment growth rate.[44] 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. When 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) capital stock. Thus, our specification includes the key state variables: the realization of productivity and initial capital and employment.[45]

Table 3 reports the estimated coefficients plants in High-Tech Manufacturing. Consistent with theory, literature, and the employment-based results we describe above, equipment investment is positively related to plant productivity. Moreover, plants of young firms are more

[44] 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 throughout 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.

[45] As a robustness check, we have re-estimated specification (3) 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.

responsive than plants of mature firms, as in our employment growth results. However, it is apparent the responsiveness of equipment investment is changing over time, particularly for young-firm plants.

Figure 10 shows the changing marginal responsiveness of equipment investment to productivity for plants of young and mature firms in recent decades. Strikingly, the patterns in Figure 10 mimic the patterns of employment growth responsiveness shown in Figure 5. Just as with employment growth, equipment investment responsiveness increases from the 1980s to the 1990s but then declines sharply in the post-2000 period. We can again quantify the magnitude of these changes in responsiveness by referencing productivity dispersion numbers from Figure 4a. In the 1990s, a young-firm plant with TFP one standard deviation above the industry-year mean had an equipment investment rate 8 percentage points higher than a plant with the industry-by-year mean productivity; this difference is less than 4 percentage points in the post-2000 period. The growth advantage among mature firms falls as well.

The strong similarity between Figures 10 and 5 implies that, among High-Tech Manufacturing businesses, the post-2000 declining responsiveness of employment growth in Figure 5 is not accounted for by rising responsiveness of equipment investment over this same period of time. In unreported results, however, we find that among Non-Tech Manufacturing businesses there is rising investment responsiveness from the 1980s to the 1990s, with responsiveness remaining elevated in the 2000s. Given the employment-responsiveness evidence from Table 1 and Figure 5, it does appear that capital-labor substitution may play a role in changing employment growth dynamics outside of the High-Tech sector.

### *B. 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, firms are more likely to expand and produce in other countries, a dynamic that could eliminate or even reverse the standard positive correlation between growth and productivity. 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 (2008) 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. Their measures vary by 4-digit SIC industry from 1972-2005 and by 6-digit NAICS industry from 1989-2005. We extend the latter using the public domain information from Census on imports by country and industry.[46] 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; hence, we need not rely on aggregate SIC/NAICS concordances.[47]

Using these extended import data, we find that 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 (as shown on Figure A5 in Appendix A). Of particular interest for current purposes is that the rise is especially pronounced for the 6-digit NAICS industries in High-Tech.

We exploit the 6-digit NAICS variation in import penetration ratios to explore the possible role of this dimension of globalization in accounting for the patterns of changing responsiveness we have detected. Table 4 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 4 show that the interaction effect for young plants of lagged TFP and the import

[46] To construct low-wage import penetration data by year and industry, Bernard, Jensen and Schott first construct domestic absorption for each industry. Next, they construct total imports of goods produced by each industry that are sourced in a low-wage country, which are defined as countries whose GDP per capita is less than 5 percent of the U.S. Import penetration is the ratio of low-wage imports to total domestic absorption, by industry and year. We thank Peter Schott for providing the import data and guidance necessary for extending the dataset.

[47] 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.

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 11, we quantify the impact of changing import penetration ratios using the estimated effects from Table 4. The overall effects show, consistent with Figure 5, 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 4 along with the aggregate pattern of import penetration ratios for High-Tech Manufacturing. 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.

While this investigation does not uncover specific micro mechanisms that yield the connection between import penetration to changing dynamism and productivity responsiveness, it does tell us this is a promising area for future research.

### *C. Changing Specialization of High-Tech*

We also 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 documented by Byrne (2015). Businesses manufacturing these special-purpose products might be less responsive to productivity due to demand constraints or uncompetitive environments that reduce adjustment imperatives. We investigate this hypothesis in Appendix F. We verify evidence of the changing structure of High-Tech manufacturing but find no evidence that this accounts for the declining responsiveness observed in High-Tech Manufacturing.

## VII. Conclusion

The post-2000 period in the U.S. has been characterized by declines both in various measures of business dynamism and in aggregate productivity growth. The decline in both has been most dramatic in the High-Tech areas of the economy.

A key insight from previous literature on declining business dynamism, that patterns of young firm activity and gross job flows differ markedly across sectors, is of particular relevance to the productivity question. During the 1980s and 1990s, the decline in dynamism was dominated by the Retail Trade sector related to the 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 retail business models 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 such as High-Tech. In the 1990s, the High-Tech sector exhibited increases in the pace of reallocation and indicators of entrepreneurship. Since 2000, this is the sector with the largest declines in these indicators.

Drawing insights from canonical models of firm dynamics, we first study whether declines in measures of business dynamism—such as gross job reallocation—are related to changes in the idiosyncratic productivity or profitability "shocks" faced by individual businesses or to changes in how businesses respond to those shocks. Focusing on the Manufacturing sector and using a large dataset on establishment-level TFP, we find that the distribution of productivity has not become less volatile or otherwise evolved in a way that would be expected to reduce job reallocation. However, by directly estimating the employment growth policy functions governing business-level responses to productivity, we learn that marginal productivity responses at the business level have tracked patterns of aggregate reallocation. In the High-Tech sector, responsiveness rose in the 1990s then fell in the 2000s, consistent with reallocation data for that sector. For the manufacturing sector broadly, responsiveness declined steadily throughout 1980-2010. We conclude that aggregate patterns of reallocation are closely related to changes in the marginal responses of individual businesses to their own productivity; canonical models of firm dynamics suggest that this declining marginal responsiveness is likely related to increased costs or frictions on adjustment.[48] These TFP-based results for the Manufacturing

[48] Using industry variation, Goldschlag and Tabarrok (2014) find no evidence that federal regulation counts relate with changes in the pace of gross flows. Davis and Haltiwanger (2014) find evidence relating employment protection policies to lower rates of reallocation. Molloy et al. (2016) find no evidence of a role for land use regulations or improved worker-firm matches.

sector are broadly echoed by an alternative approach based on a revenue productivity residual (RPR) definition of productivity in place of TFP.

We find further support for the notion that responsiveness has declined by studying firm-level labor productivity for the entire U.S. economy and the High-Tech sector (including High-Tech businesses outside of Manufacturing). Consistent with our TFP-based results from Manufacturing, we find evidence of a sharp weakening of the relationship between firm-level growth and productivity in the post-2000 period with particularly strong declines in the High-Tech sector. We also find rising dispersion of within industry firm-level labor productivity dispersion consistent with declining responsiveness that emerges from some type of increase in frictions or distortions.

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 Manufacturing 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 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. Our economywide evidence based on labor productivity finds similarly substantial declines in the contribution of reallocation to aggregate productivity.

Though the primary focus of this paper is to document declining productivity responsiveness and analyze its implications using multiple data sources and methodologies, we also briefly investigate three possible mechanisms underlying these changing patterns of firm dynamics. First, 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 (though we find some support for this hypothesis in the Non-Tech areas of Manufacturing). Second, 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. Finally, we investigate compositional changes in Manufacturing reflecting movement from general-purpose to special-purpose technology production, finding no evidence of a role of these shifts in declining responsiveness.

In addition to shedding light on the drivers of declining business dynamism, these findings about "between-firm" productivity growth represent a novel and important contribution to the literature on the productivity slowdown in the U.S. Aggregate productivity growth depends not only on innovation and the adoption of new technologies and management practices but also on the allocation and reallocation of productive inputs to their most efficient uses. We document a slowdown in the mechanisms driving allocative efficiency, and we do so using both compelling evidence from Manufacturing and highly suggestive evidence from the entire private sector of the U.S. economy. The weakening of the relationship between productivity and growth at the business level, which we show is quantitatively significant, represents a substantial source of accounting "drag" on aggregate productivity growth and suggests that the post-2000 patterns of declining business dynamism in the U.S. are not benign for improvements in living standards. Understanding the drivers of declining reallocation is therefore an important priority for economic research.

## References


Acemoglu, Daron, Ufuk Akcigit, Nicholas Bloom, and William R. Kerr. 2013. "Innovation, Reallocation, and Growth." NBER Working Paper No. 18993.

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

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

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

Baily, Martin Neil, Eric Bartelsman, and John Haltiwanger. 2001. "Labor Productivity: Structural Change and Cyclical Dynamics." *Review of Economics and Statistics*, 83(3), 420-433.

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

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

Bernard, Andrew B., J. Bradford Jensen, and Peter K. Schott. 2006. Survival of the Best Fit: Exposure to Low-Wage Countries and the (Uneven) Growth of US Manufacturing Plants. J*ournal of International Economics* 68(1): 219-237.

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

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

Byrne, David M. and Carol A. Corrado. 2015. “Recent Trends in Communications Equipment Prices.” *FEDS Notes*, no. 2015-06-02.

Byrne, David M. and Carol A. Corrado. 2016. “ICT Prices and ICT Services: What Do They Tell Us about Productivity and Technology?” Working paper.

Byrne, David M., John G. Fernald and Marshall B. Reinsdorf. 2016. “Does the United Have a Productivity Slowdown or a Measurement Problem?” *Brookings Papers on Economic Activity*, Spring 2016.

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

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

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

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

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

Davis, Steven J. and John Haltiwanger. 1991. “Wage Dispersion Between and Within U.S. Manufacturing Plants, 1963-1986.” *Brookings Papers on Economic Activity: Microeconomics*, 1991, pp. 115-200.

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

Davis, Steven J., John Haltiwanger, Ron Jarmin, and Javier Miranda. 2007. "Volatility and Dispersion in Business Growth Rates: Publicly Traded versus Privately Held

Firms." Chap. 2 in *NBER Macroeconomics Annual 2006* edited by Daron Acemoglu, Kenneth Rogoff, and Michael Woodford, vol. 21, pp. 107-80. Cambridge, MA: MIT Press.

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

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

Decker, Ryan A., John Haltiwanger, Ron S. Jarmin, and Javier Miranda. 2016. "Where Has All the Skewness Gone? The Decline in High-Growth (Young) Firms in the U.S.*" European Economic Review* 86 (July) 4-23.

Dunne, Timothy, Lucia Foster, John Haltiwanger, and Kenneth R. Troske. 2004. "Wage and Productivity Dispersion in United States Manufacturing: The Role of Computer Investment." *Journal of Labor Economics* 22 no. 2:397-430.

Elsby, Michael W. L. and Ryan Michaels. 2013. "Marginal Jobs, Heterogeneous Firms, and Unemployment Flows." *American Economic Journal: Macroeconomics* 5 no. 1:1-48.

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

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

Fort, Teresa and Shawn Klimek. 2016. "The Effects of Industry Classification Changes on US employment composition." Mimeo.

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

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

Foster, Lucia, John Haltiwanger, and C.J. Krizan. 2001. "Aggregate Productivity Growth: Lessons from Microeconomic Evidence." In *New Developments in*

*Productivity Analysis*, eds. Edward Dean, Michael Harper and Charles Hulten, 303-363. Chicago: University of Chicago Press.

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

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

Goldschlag, Nathan and Alex Tabarrok. 2014. "Is Regulation to Blame for the Decline in American Entrepreneurship?" GMU Working Paper in Economics No. 15-11.

Gordon, Robert J. 2016. *The Rise and Fall of American Growth: The U.S. Standard of Living since the Civil War*. Princeton: Princeton University Press.

Haltiwanger, John. 2016. "Firm Dynamics and Productivity: TFPQ, TFPR and Demand Side Factors." *Economia*, Forthcoming.

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

Haltiwanger, John, Ron S. Jarmin, Robert Kulick and Javier Miranda. 2016. In *Measuring Entrepreneurial Businesses: Current Knowledge and Challenges* edited by John Haltiwanger, Erik Hurst, Javier Miranda, and Antoinette Schoar. Chicago: University of Chicago Press.

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

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

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

Haltiwanger, John, Robert Kulick, and Chad Syverson, 2016. "Misallocation Measures: Glowing Like the Metal on the Edge of a Knife." Mimeo.

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

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

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

Hsieh, Chang-Tai and Peter J. Klenow. 2009. "Misallocation and Manufacturing TFP in China and India." *Quarterly Journal of Economics*, 124(4): 1403-48.

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

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

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

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

Karahan, Fatih, Benjamin Pugsley, and Aysegul Sahin. 2016. "Understanding the 30-Year Decline in the Startup Rate: A General Equilibrium Approach." Mimeo.

Levinsohn, James and Amil Petrin (2003). "Estimating Production Functions Using Inputs to Control for Unobservables." *Review of Economic Studies* 70 no. 2:317-41.

Lucas, Robert E. 1978. "On the Size Distribution of Business Firms." *The Bell Journal of Economics* 9 no. 2:508-23.

Molloy, Raven, Christopher L. Smith, Riccardo Trezzi, and Abigail Wozniak. 2016. "Understanding Declining Fluidity in the U.S. Labor Market." *Brookings Papers on Economic Activity*.

Olley, G. Steven and Ariel Pakes. 1996. “The Dynamics of Productivity in the Telecommunications Industry.” *Econometrica*, 64 no. 6:1263-98.

Pierce, Justin and Peter Schott. 2016. “The Surprisingly Swift Decline of U.S. Manufacturing Employment.” *American Economic Review* 107 no. 7:1632-62.

Pinto Ribeiro, Samuel, Stefano Menghinello and Koen De Backer. 2010. “The OECD ORBIS Database: Responding to the Need for Firm-Level Micro-Data in the OECD.” *OECD Statistics Working Papers* No. 2010/01, OECD Publishing, Paris.

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

Schott, Peter. 2008. “The Relative Sophistication of Chinese Imports.” *Economic Policy*, 5-49.

Song, Jae, David J. Price, Fatih Guvenen, Nicholas Bloom and Till von Wachter. 2016. “Firming Up Inequality.” Working paper.

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

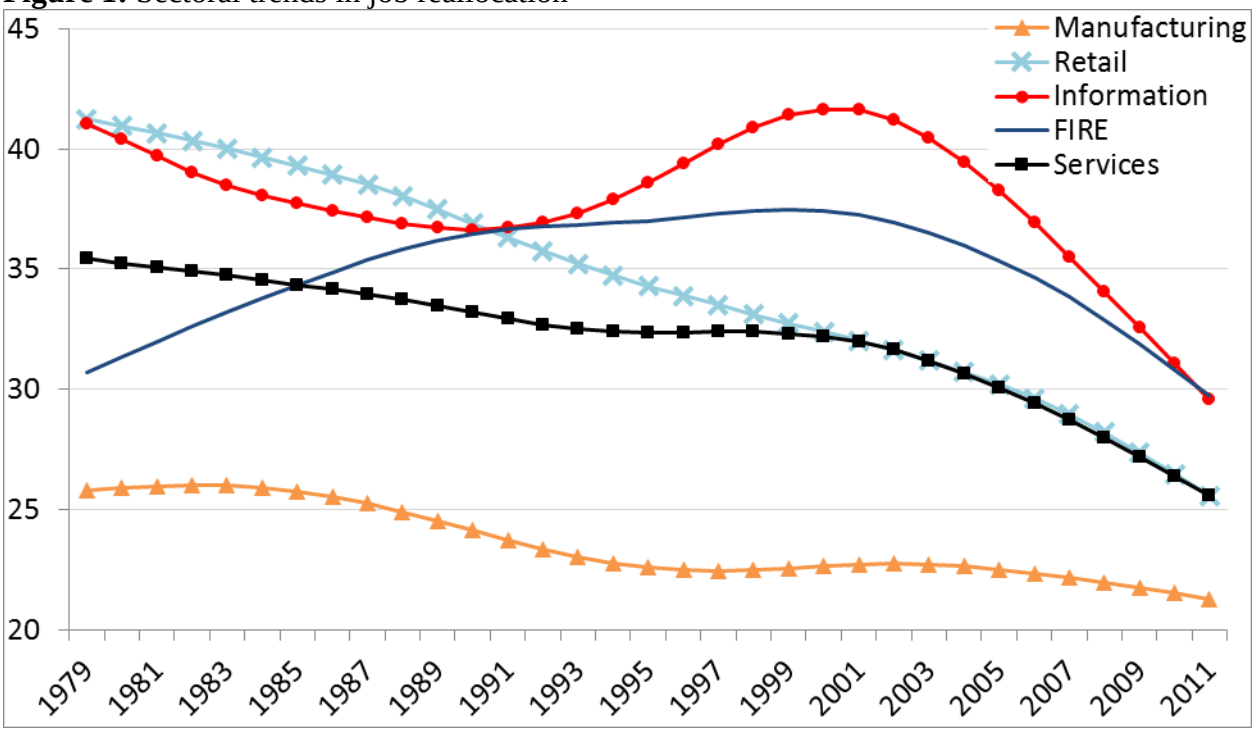
Syverson, Chad. 2011. “What Determines Productivity?” *Journal of Economic Literature* 49(2): 326-65.

Syverson, Chad. 2016. “Challenges to Mismeasurement Explanations for the U.S. Productivity Slowdown.” NBER Working Paper no. 21974.

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

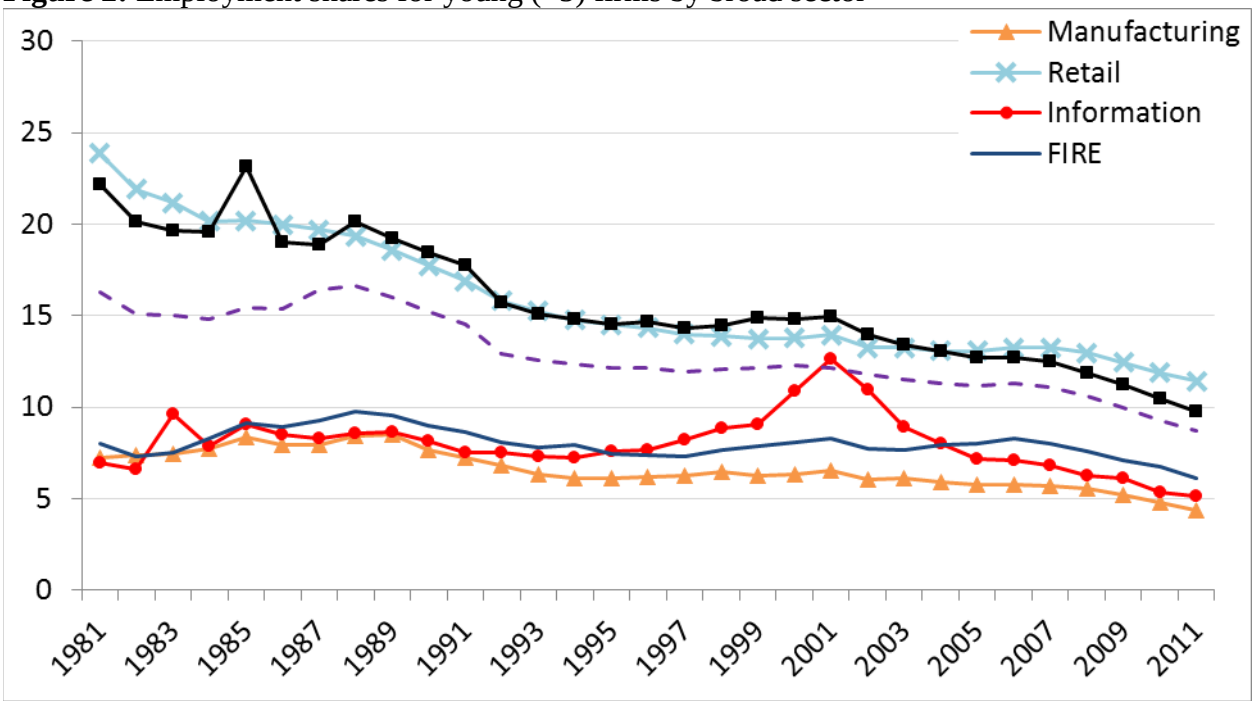
Wooldridge, Jeffrey M. 2009. “On Estimating Firm-Level Productivity Functions Using Proxy Variables to Control for Unobservables.” *Economics Letters* 104 no. 3:112-4.

**Figure 1:** Sectoral trends in job reallocation



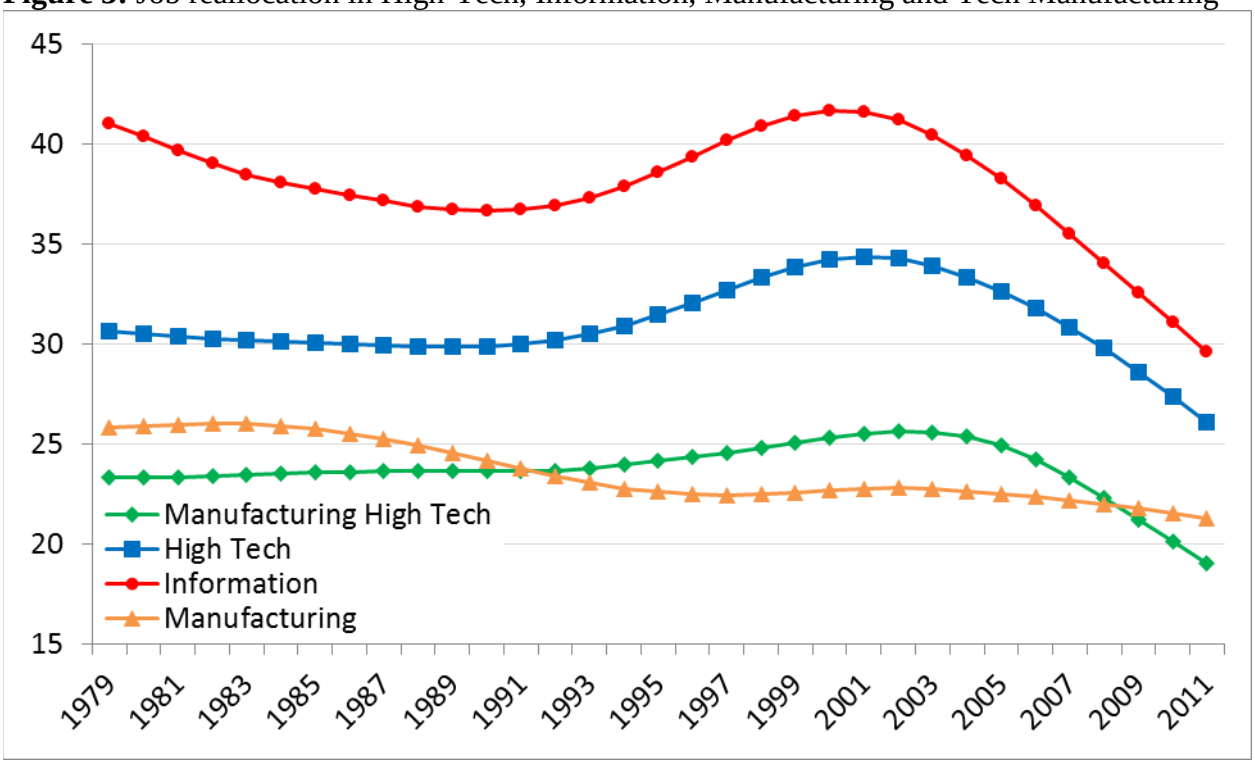

Note: Y axis does not start at zero. Data are HP trends using parameter set to 100. Industries are defined on a consistent NAICS basis. Data include all firms (new entrants, continuers, and exiters). Author calculations from the Longitudinal Business Database.

**Figure 2:** 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.

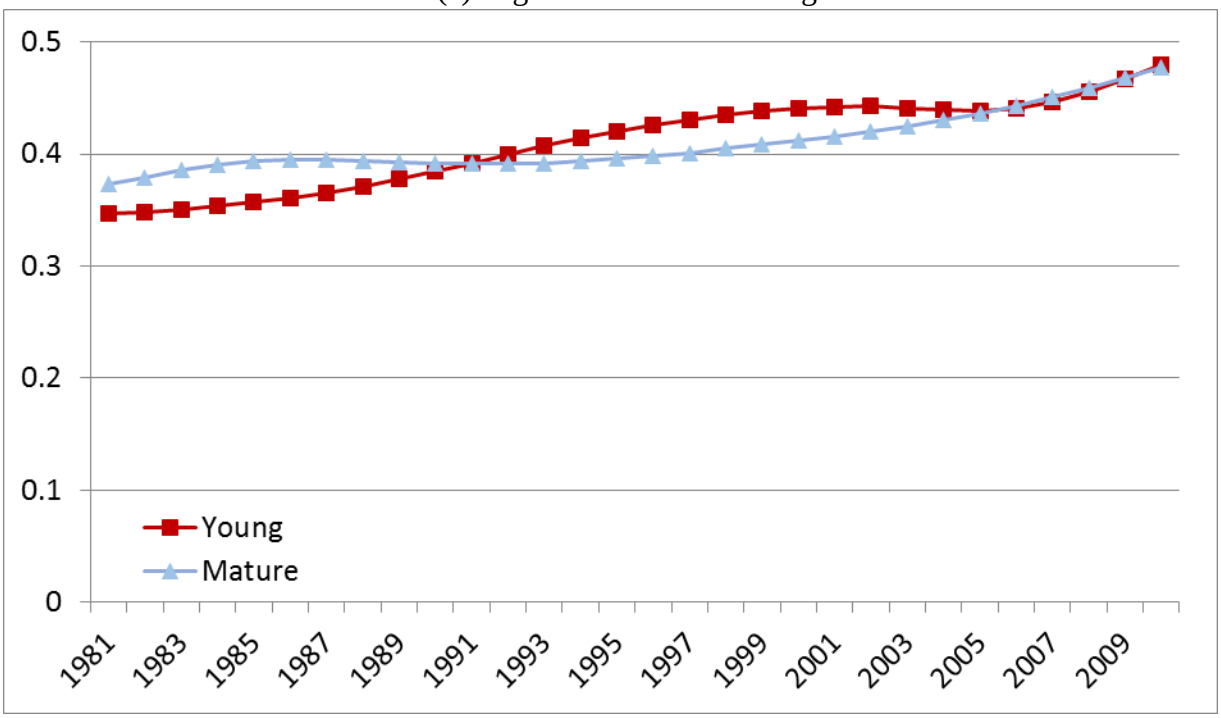
**Figure 3:** Job reallocation in High-Tech, Information, Manufacturing and Tech Manufacturing



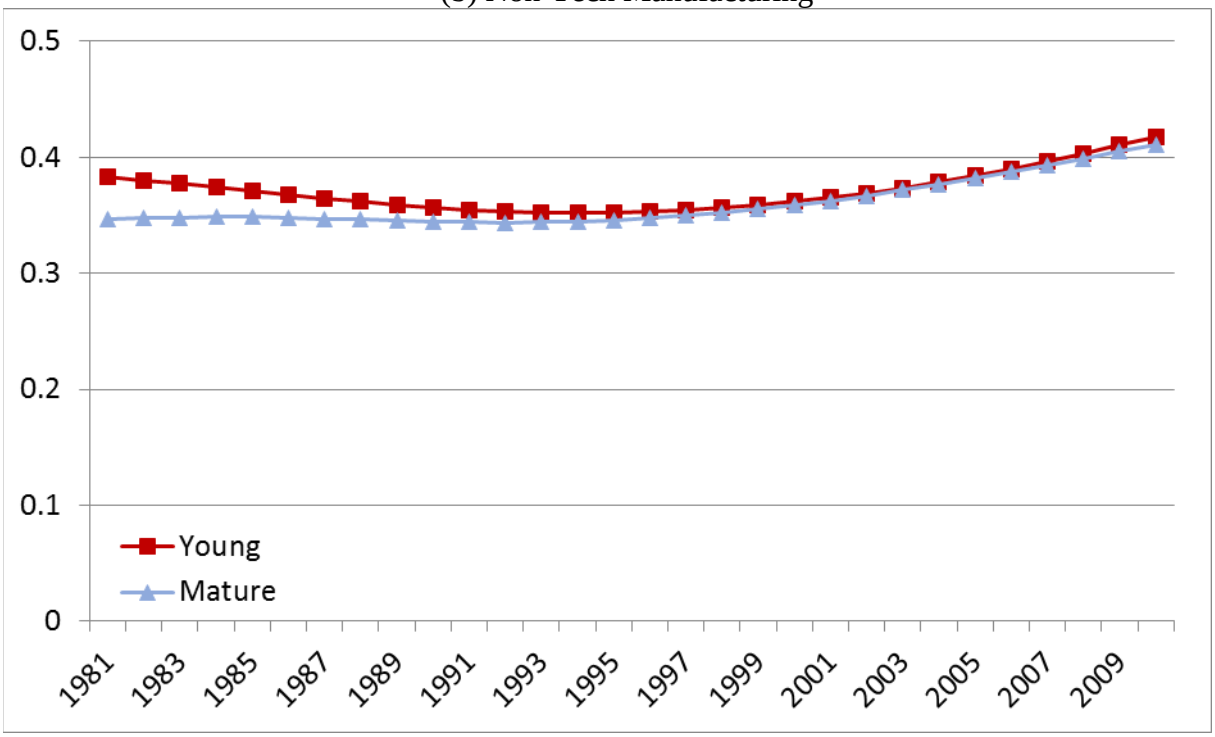

Note: Y axis does not start at zero. High-Tech is defined as in Hecker (2005). Information and Manufacturing sectors are defined on a consistent NAICS basis. Author calculations from the Longitudinal Business Database.

**Figure 4:** Within-industry TFP dispersion (standard deviation), young vs. mature

(a) High-Tech Manufacturing



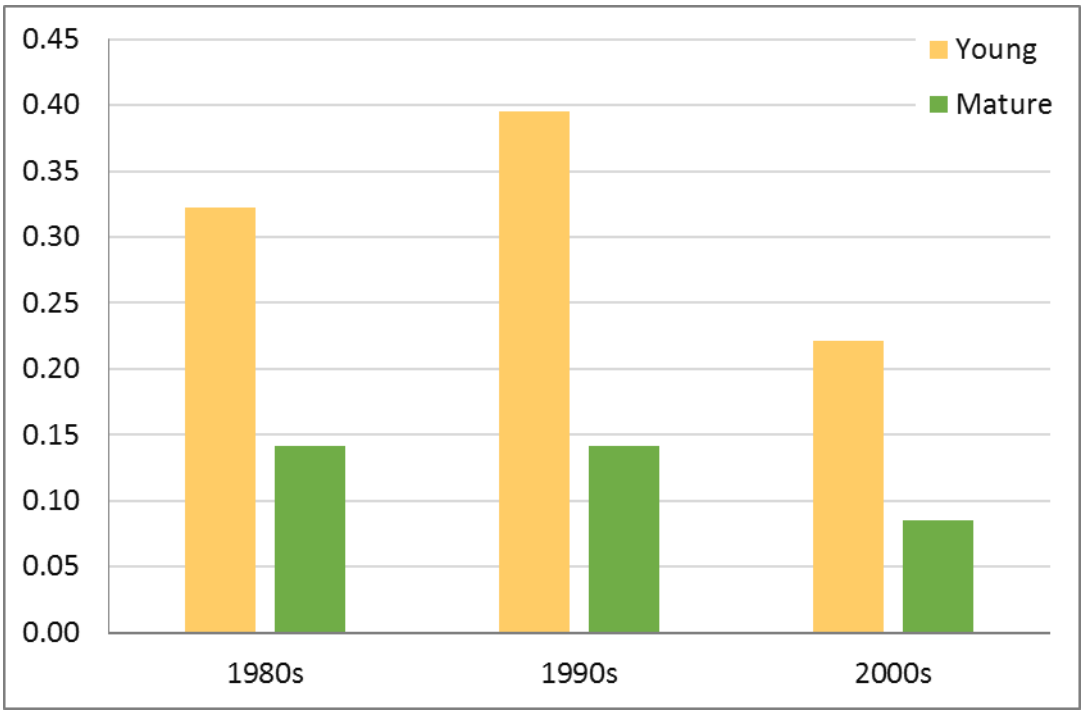

(b) Non-Tech Manufacturing



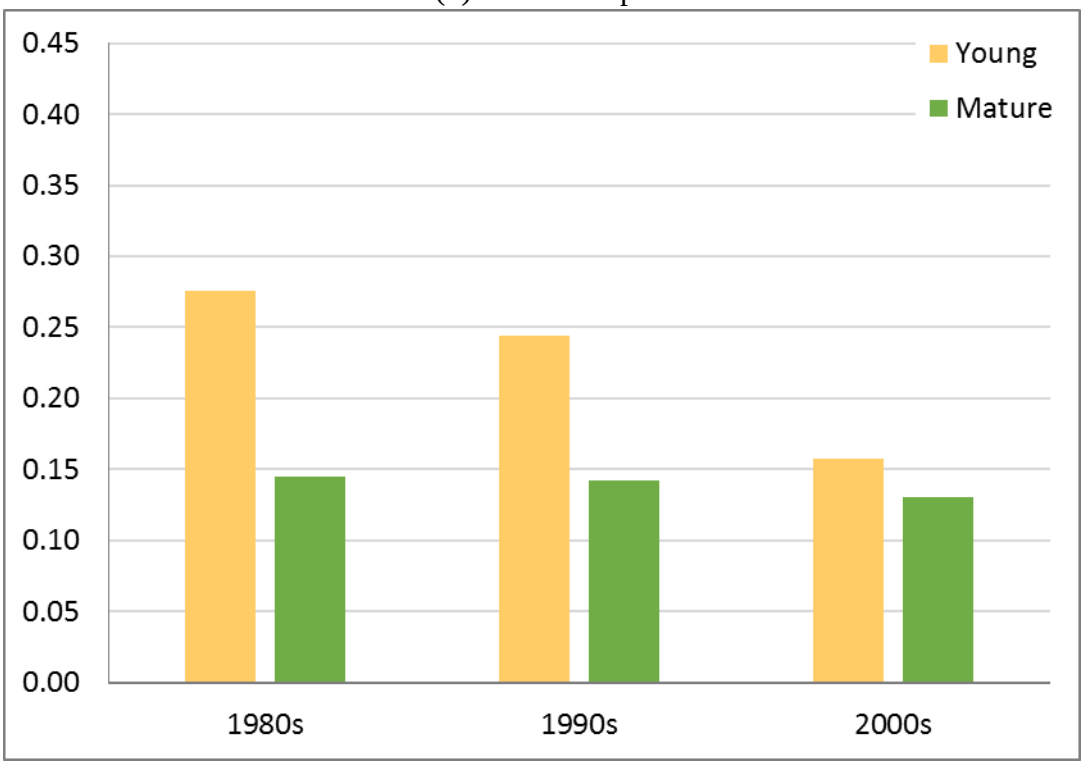

Note: Young firms have age less than 5. Manufacturing plants. The standard deviation is the based on within-detailed industry log TFP. High-Tech is defined as in Hecker (2005). Author calculations from the Longitudinal Business Database, the Annual Survey of Manufacturers, and the Census of Manufacturers.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

**Figure 5:** Marginal effect of TFP on plant-level net employment growth: young vs. mature

(a) High-Tech plants

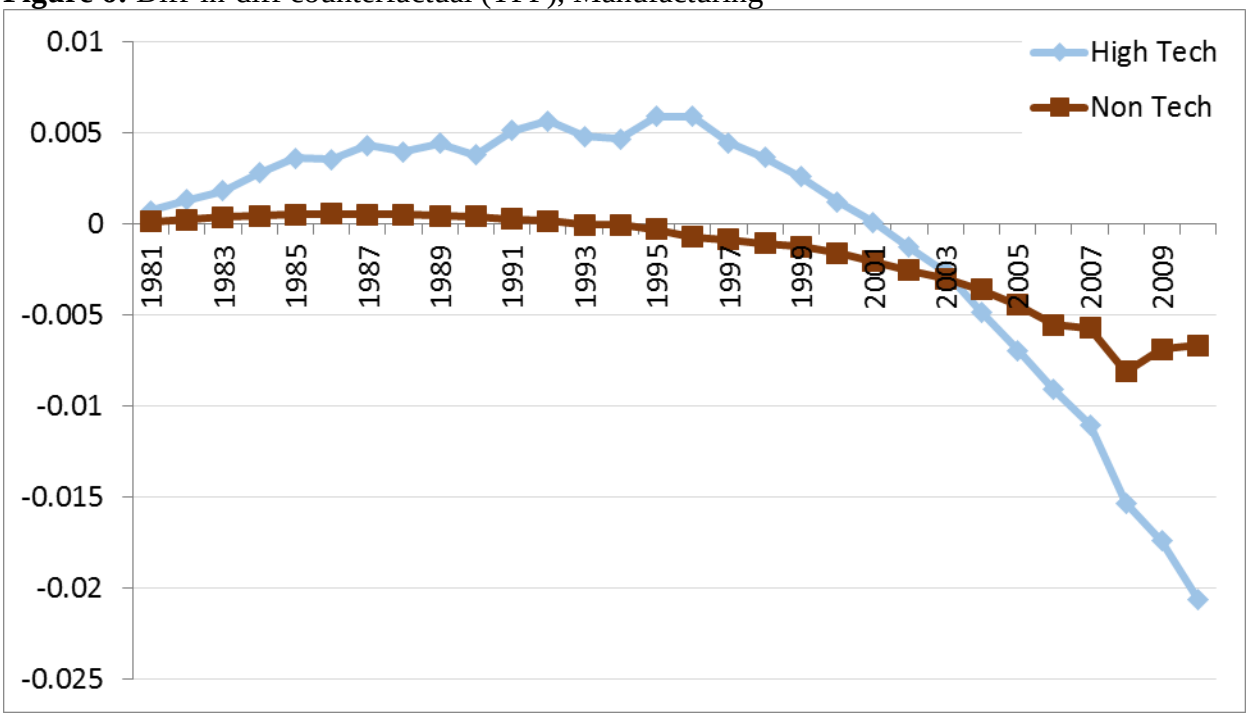



(b) Non-Tech plants




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.

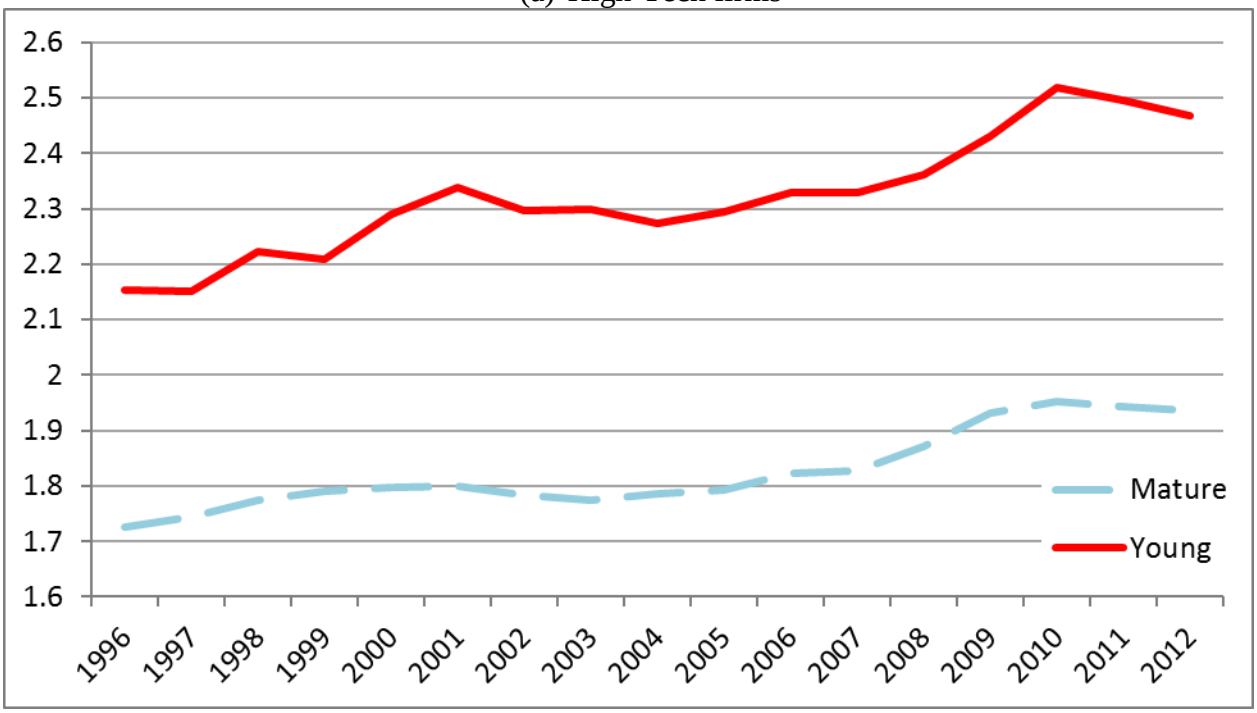
**Figure 6:** Diff-in-diff counterfactual (TFP), Manufacturing



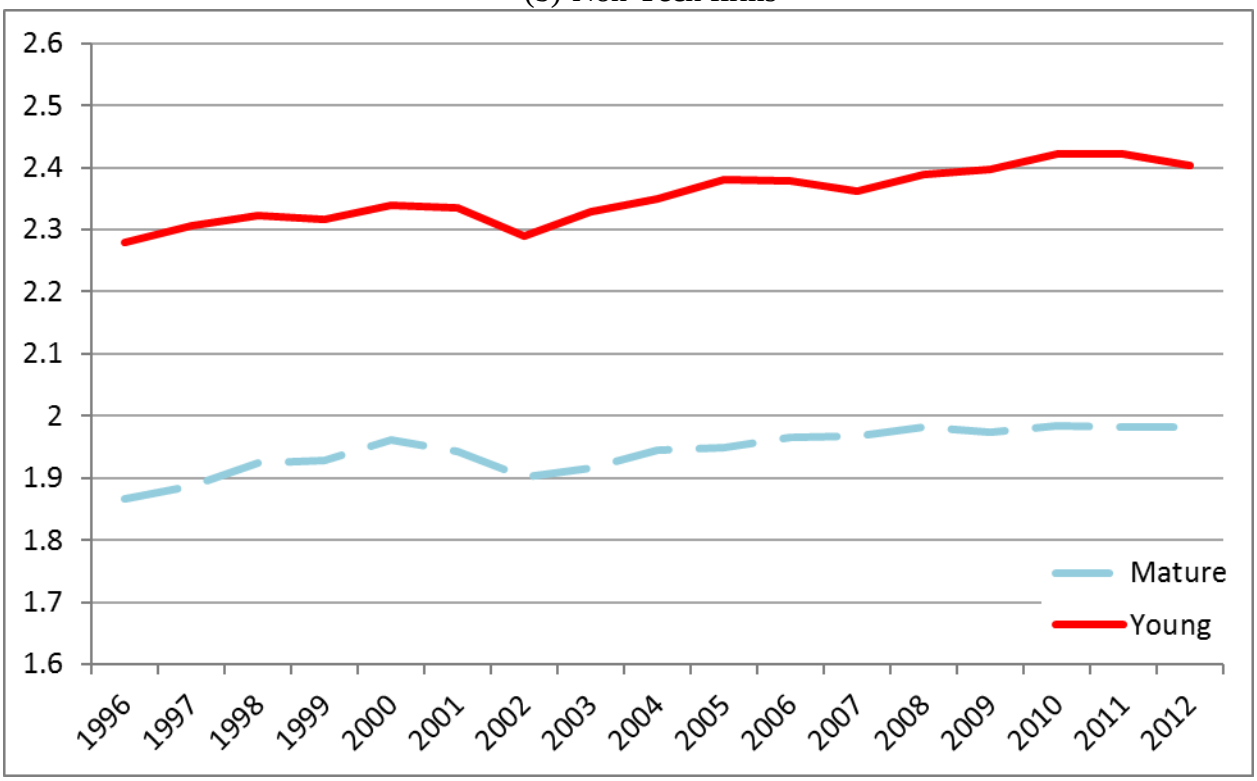

Note: Figure depicts counterfactual change in reallocation contribution to aggregate TFP growth. High-Tech is defined as in Hecker (2005). Author calculations from the Longitudinal Business Database, the Annual Survey of Manufacturers, and the Census of Manufacturers.

**Figure 7:** Within-industry dispersion in labor productivity, young vs. mature

(a) High-Tech firms



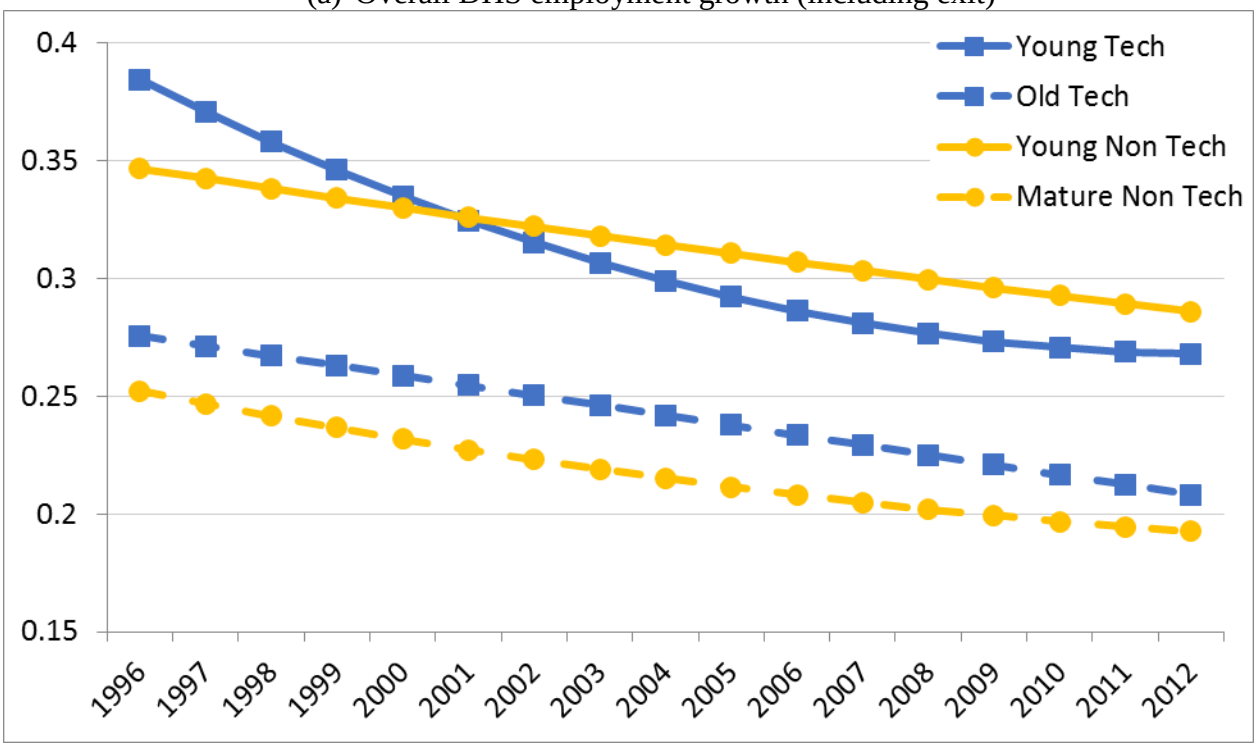

(b) Non-Tech firms



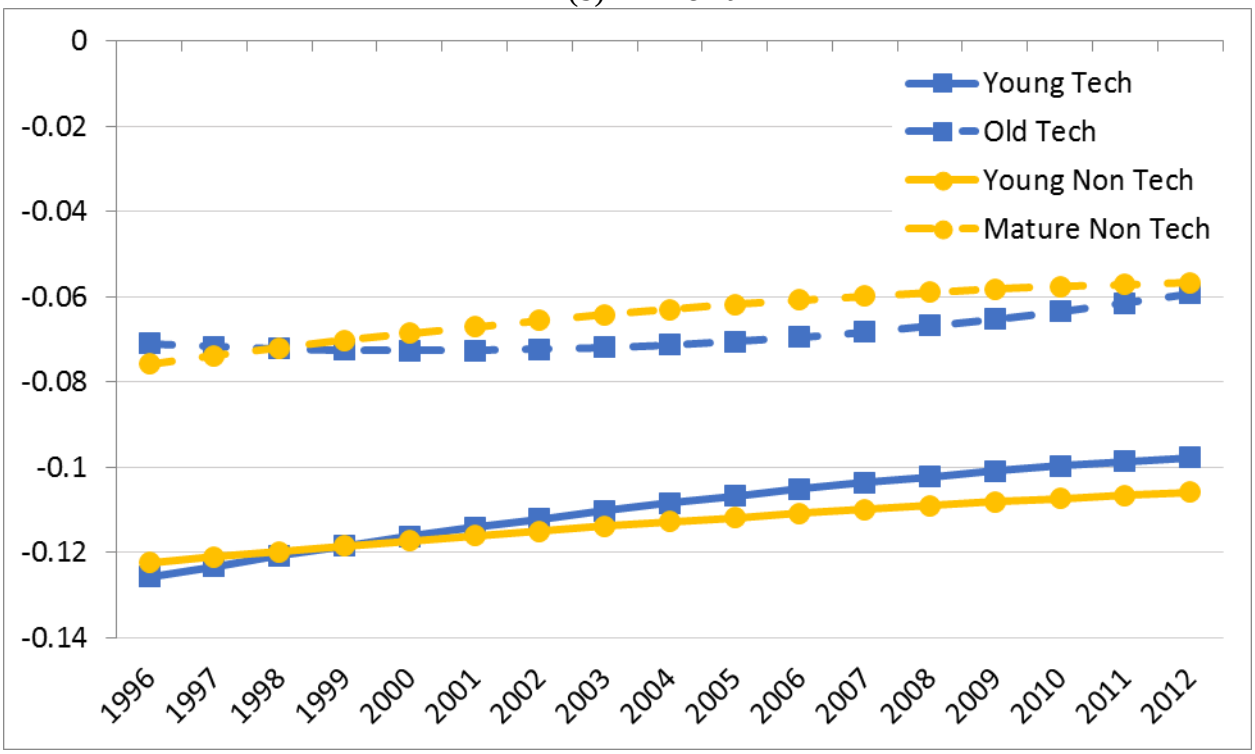

Note: Y axes do not begin at zero. Data reflect interdecile range of log labor productivity deviated from industry by year means. Young firms have age less than five. High-Tech is defined as in Hecker (2005). Author calculations from the RE-LBD.

**Figure 8:** Labor productivity and growth at the firm level (economywide)

(a) Overall DHS employment growth (including exit)

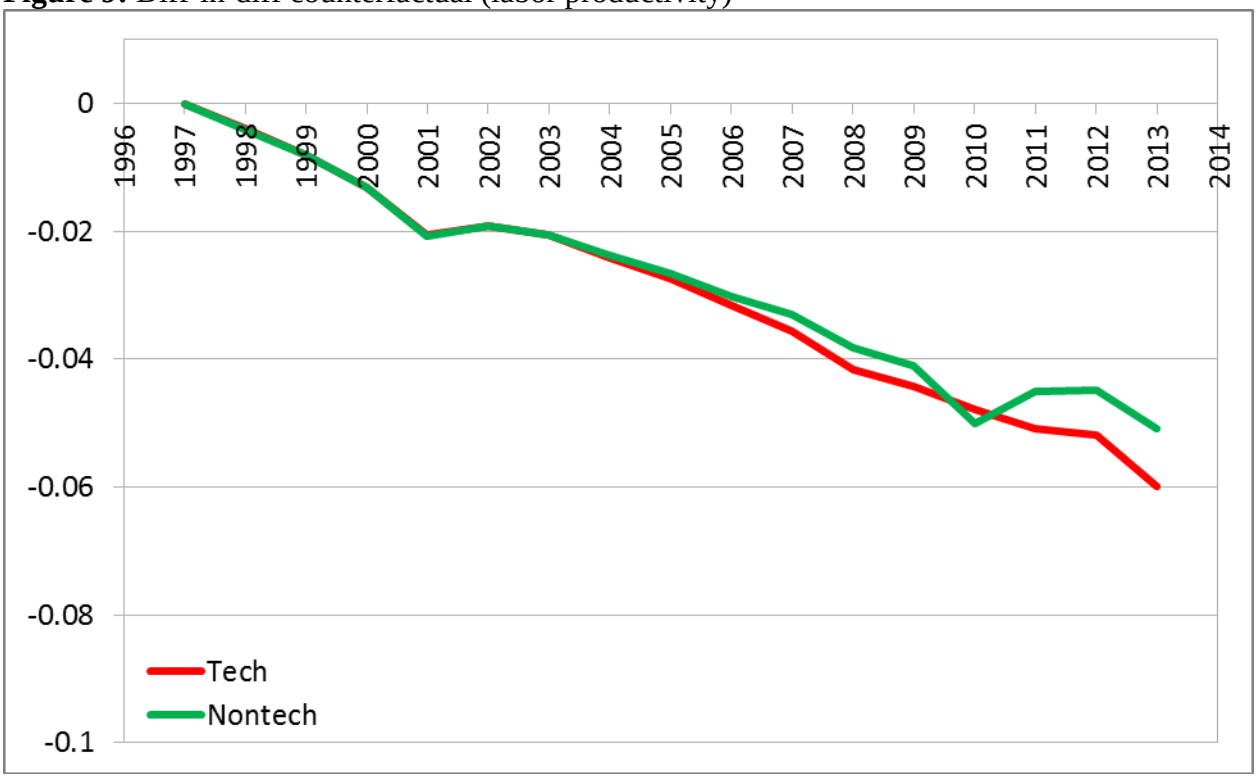



(b) Firm exit



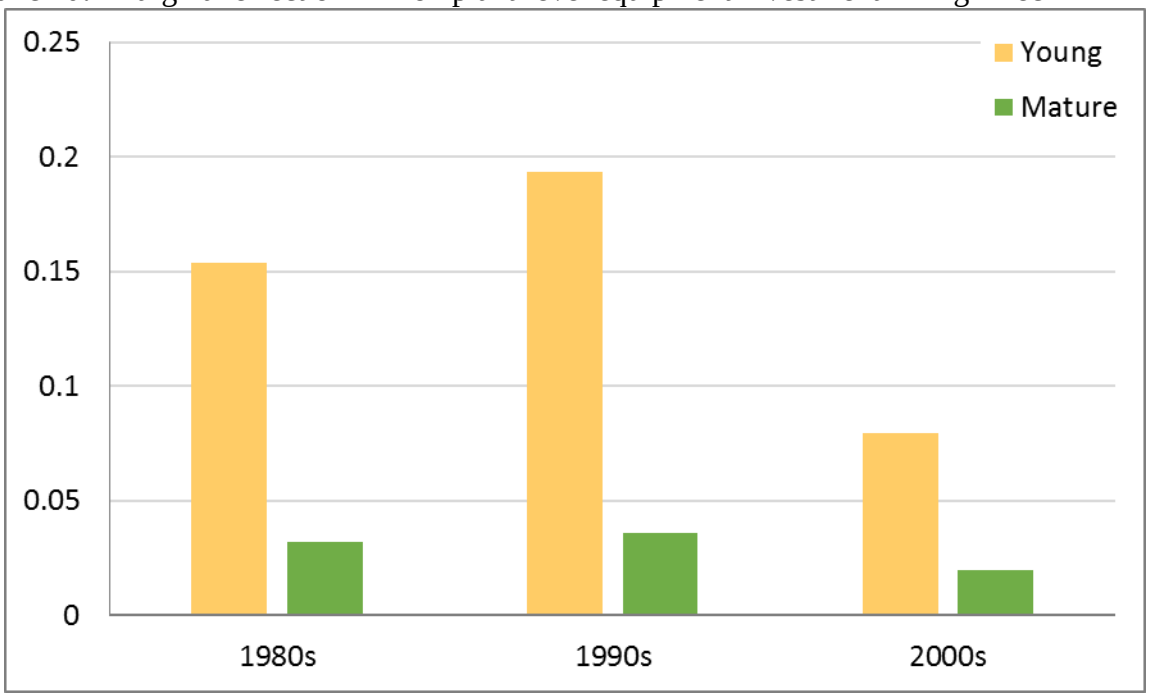

Note: Annual coefficients constructed from Table 2. Young firms have age less than five. High-Tech defined as in Hecker (2005). Author calculations from the RE-LBD. Finance, Insurance and Real Estate (NAICS 52-53) omitted.

**Figure 9:** Diff-in-diff counterfactual (labor productivity)



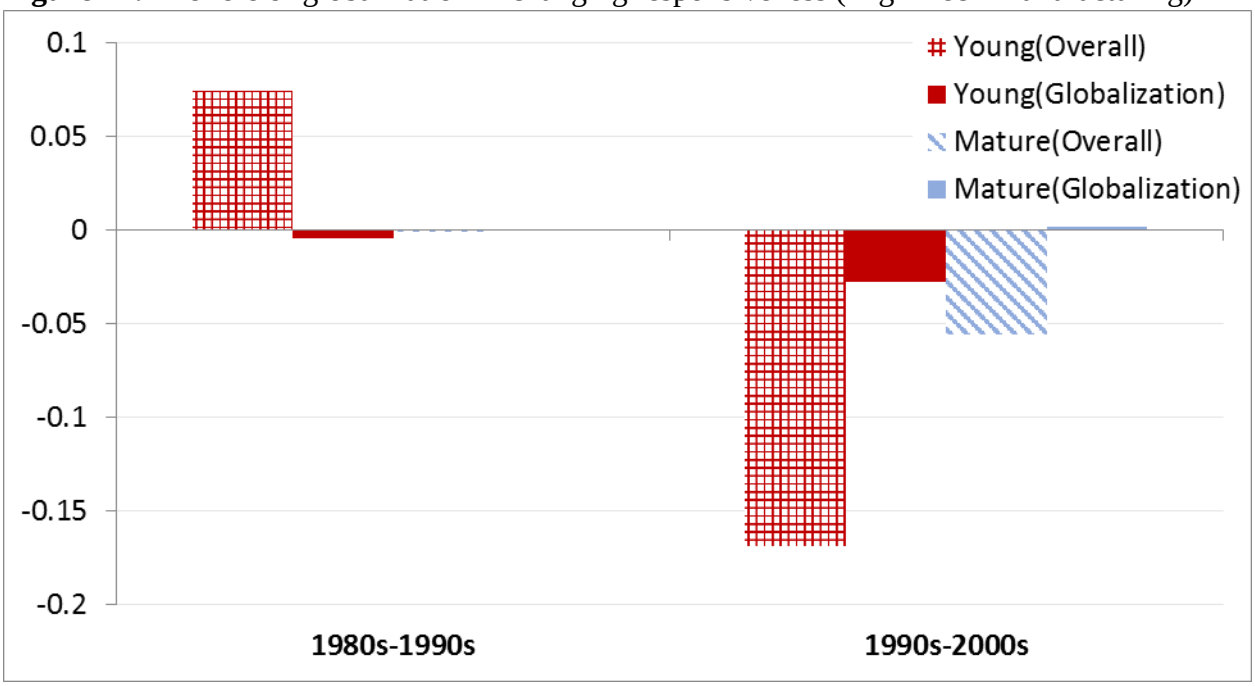

Note: Figure depicts counterfactual change in reallocation contribution to aggregate labor productivity growth. High-Tech is defined as in Hecker (2005). Author calculations from the RE-LBD.

**Figure 10:** Marginal effect of TFP on plant-level equipment investment in High-Tech




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:** The role of globalization in changing responsiveness (High-Tech Manufacturing)




Note: "Overall" bars 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.

**Table 1:** Estimated Impact of Lagged Productivity on Plant-Level Employment Growth and Exit

| | Growth including exit | | Exit | |
|---|---|---|---|---|
| | High-Tech | Non Tech | High-Tech | Non Tech |
| TFP*Young | 0.2025*** | 0.2767*** | -0.0292* | -0.0905*** |
| | (0.0390) | (0.0090) | (0.0162) | (0.0037) |
| TFP*Young*Trend | 0.0317*** | 0.0014 | -0.0160*** | -0.0005 |
| | (0.0061) | (0.0014) | (0.0025) | (0.0006) |
| TFP*Young*Trend$^2$ | -0.0012*** | -0.00024*** | 0.0005*** | 0.0001*** |
| | (0.0002) | (0.00005) | (0.0001) | (0.00002) |
| TFP*Mature | 0.1228*** | 0.1439*** | -0.0403*** | -0.0464*** |
| | (0.0174) | (0.0043) | (0.0072) | (0.0018) |
| TFP*Mature*Trend | 0.0054** | 0.0005 | -0.0016 | -0.0012 |
| | (0.0026) | (0.0007) | (0.0011) | (0.0003) |
| TFP*Mature*Trend$^2$ | -0.0003*** | -0.00004* | 0.0001*** | 0.00005*** |
| | (0.0001) | (0.00002) | (0.00003) | (0.00001) |

Notes: Standard Errors in Parentheses. Dependent variable in Overall Growth columns is DHS growth rate. Dependent variable in Exit columns is indicator=1 if exit, 0 otherwise (linear probability 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 Relationship Between Firm-level Employment Growth and Exit and Labor Productivity

| | Growth including exit | | | Exit | | |
|---|---|---|---|---|---|---|
| | All firms | High-Tech | Nontech | All Firms | High-Tech | Nontech |
| LP*Young | 0.3484*** | 0.3845*** | 0.3467*** | -0.1225*** | -0.1258*** | -0.1224*** |
| | 0.0004 | 0.0020 | 0.0005 | 0.0002 | 0.0009 | 0.0002 |
| LP*Young*Trend | -0.0047*** | -0.0141*** | -0.0043*** | 0.0014*** | 0.0026*** | 0.0014*** |
| | 0.0001 | 0.0006 | 0.0001 | 0.0001 | 0.0002 | 0.0001 |
| LP*Young*Trend$^2$ | 0.0000*** | 0.0004*** | 0.0000*** | 0.0000*** | -0.0001*** | 0.0000*** |
| | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| LP*Mature | 0.2530*** | 0.2755*** | 0.2522*** | -0.0756*** | -0.0710*** | -0.0758*** |
| | 0.0004 | 0.0021 | 0.0004 | 0.0002 | 0.0009 | 0.0002 |
| LP*Mature*Trend | -0.0055*** | -0.0042*** | -0.0056*** | 0.0019*** | -0.0008*** | 0.0020*** |
| | 0.0001 | 0.0006 | 0.0001 | 0.0000 | 0.0002 | 0.0000 |
| LP*Mature*Trend$^2$ | 0.0001*** | 0.0000 | 0.0001*** | 0.0000*** | 0.0001*** | -0.0001*** |
| | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| N | 55383000 | 55383000 | 55383000 | 55383000 | 55383000 | 55383000 |
| $R^2$ | 0.1090 | 0.1263 | 0.1083 | 0.0937 | 0.1053 | 0.0931 |

Dependent variable in all regressions is firm-level employment growth rate (DHS). All regressions include controls for state business cycle (change in state unemployment rate) and firm employment size in period t-1. Labor productivity is measured as log difference from 6-digit NAICS industry mean. High-Tech is defined as in Hecker (2005). Observations rounded to nearest thousand.
*** p<0.01; ** p<0.05; * p<0.10

**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*Trend$^2$ | -0.0008*** |
| | (0.0001) |
| TFP*Mature | 0.0232** |
| | (0.0105) |
| TFP*Mature*Trend | 0.0024 |
| | (0.0016) |
| TFP*Mature*Trend$^2$ | -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.
$^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

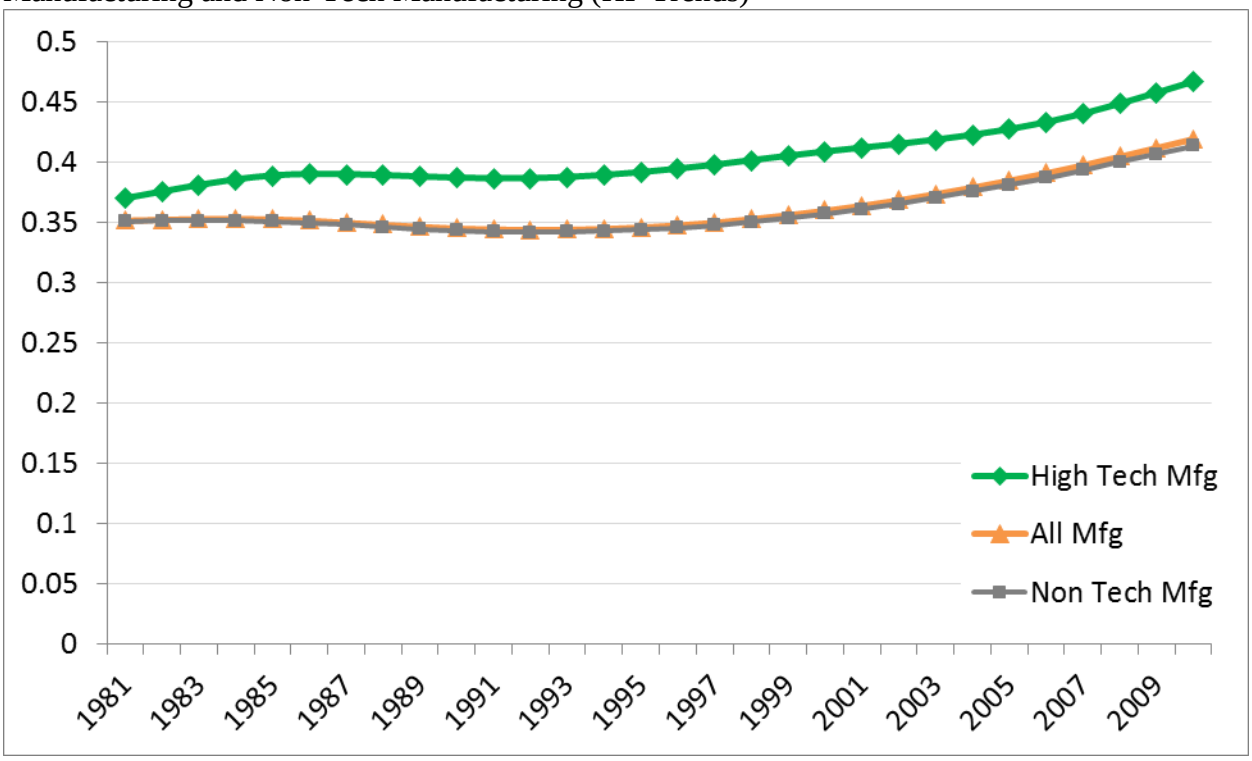
**Table 4:** Estimated Impact of Lagged Productivity on Plant-Level Employment Growth with Import Penetration Ratio Effects (High-Tech)

| | |
|---|---|
| TFP*Young | 0.2085*** |
| | (0.0390) |
| TFP*Young*Trend | 0.0298*** |
| | (0.0061) |
| TFP*Young*Trend$^2$ | -0.0011*** |
| | (0.0002) |
| TFP*Mature | 0.1246*** |
| | (0.0174) |
| TFP*Mature*Trend | 0.0052** |
| | (0.0026) |
| TFP*Mature*Trend$^2$ | -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. $^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

## Appendix A. Figures and tables to supplement the main text

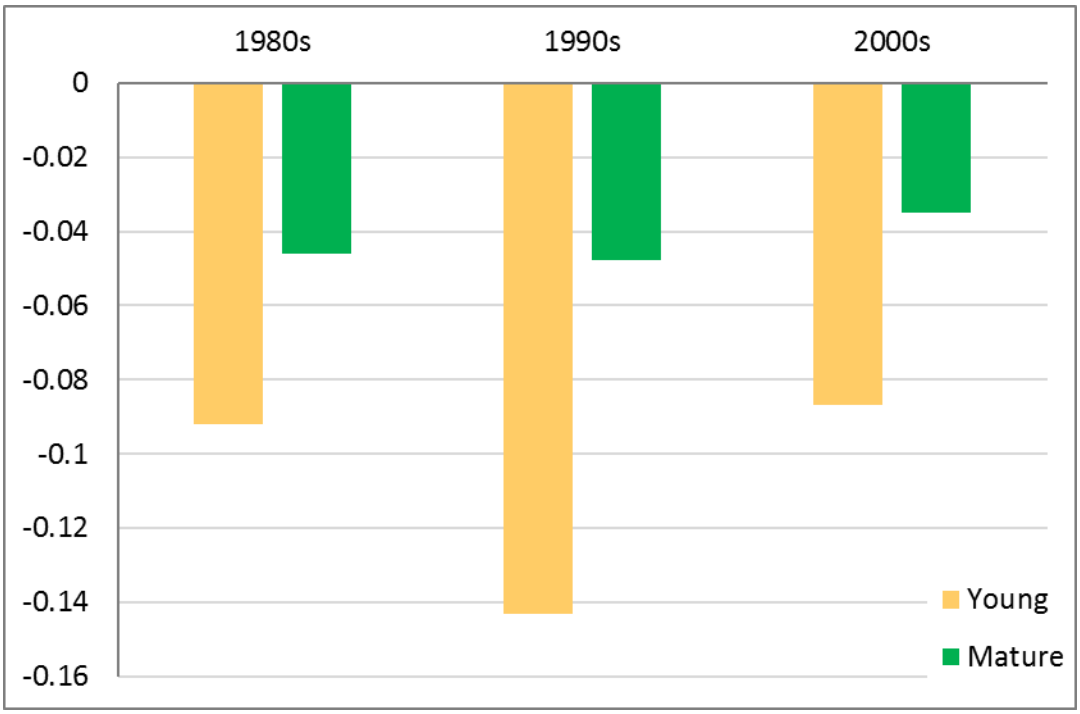
**Figure A1:** Within-industry TFP dispersion (std deviation) in Manufacturing, High-Tech Manufacturing and Non-Tech Manufacturing (HP Trends)



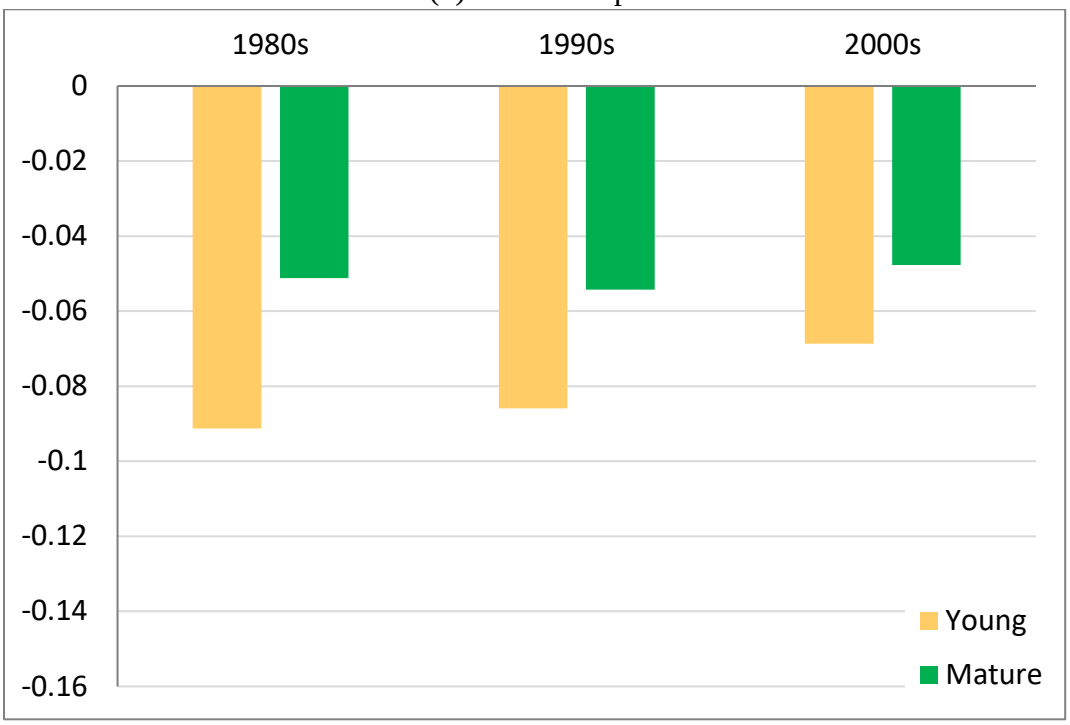

Note: The standard deviation is the based on within-detailed industry log TFP. High-Tech is defined as in Hecker (2005). Manufacturing is defined on a consistent NAICS basis. Author calculations from the Longitudinal Business Database, the Annual Survey of Manufacturers, and the Census of Manufacturers.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

**Figure A2:** Marginal effect of TFP on plant exit: young vs. mature

(a) High-Tech plants

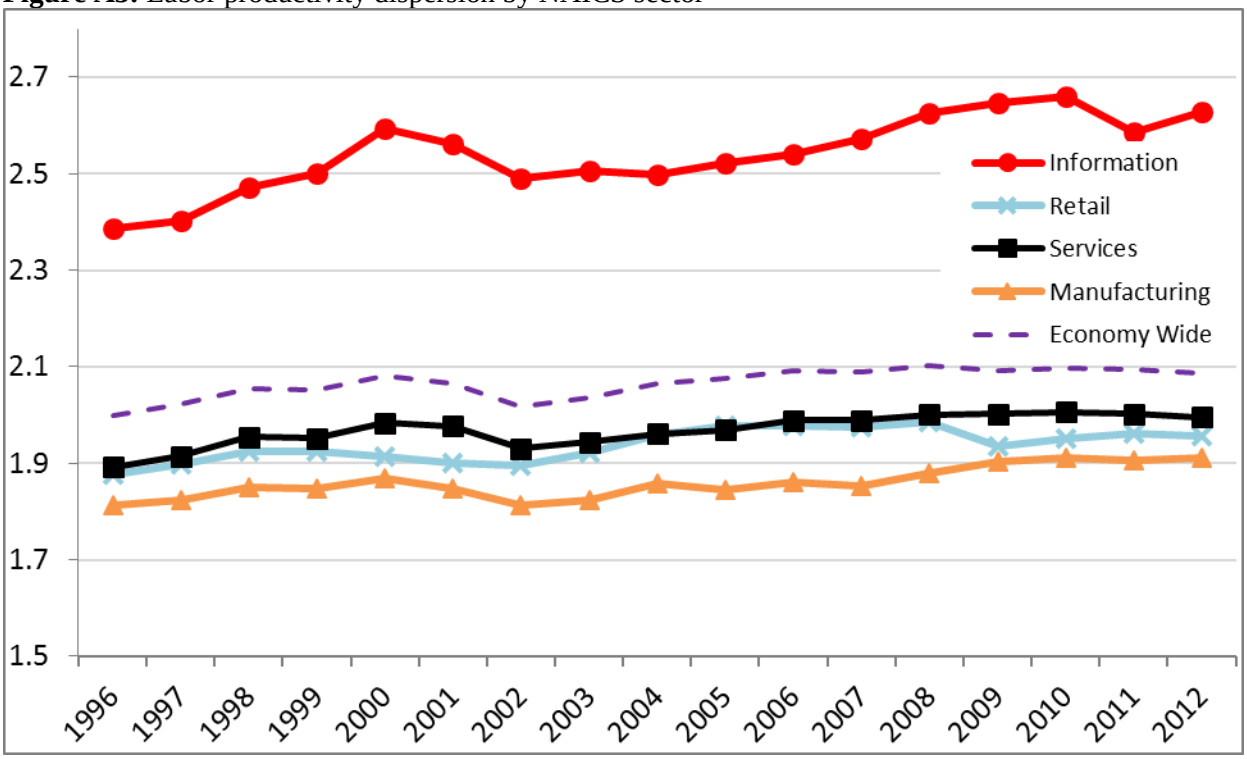



(b) Non-Tech plants



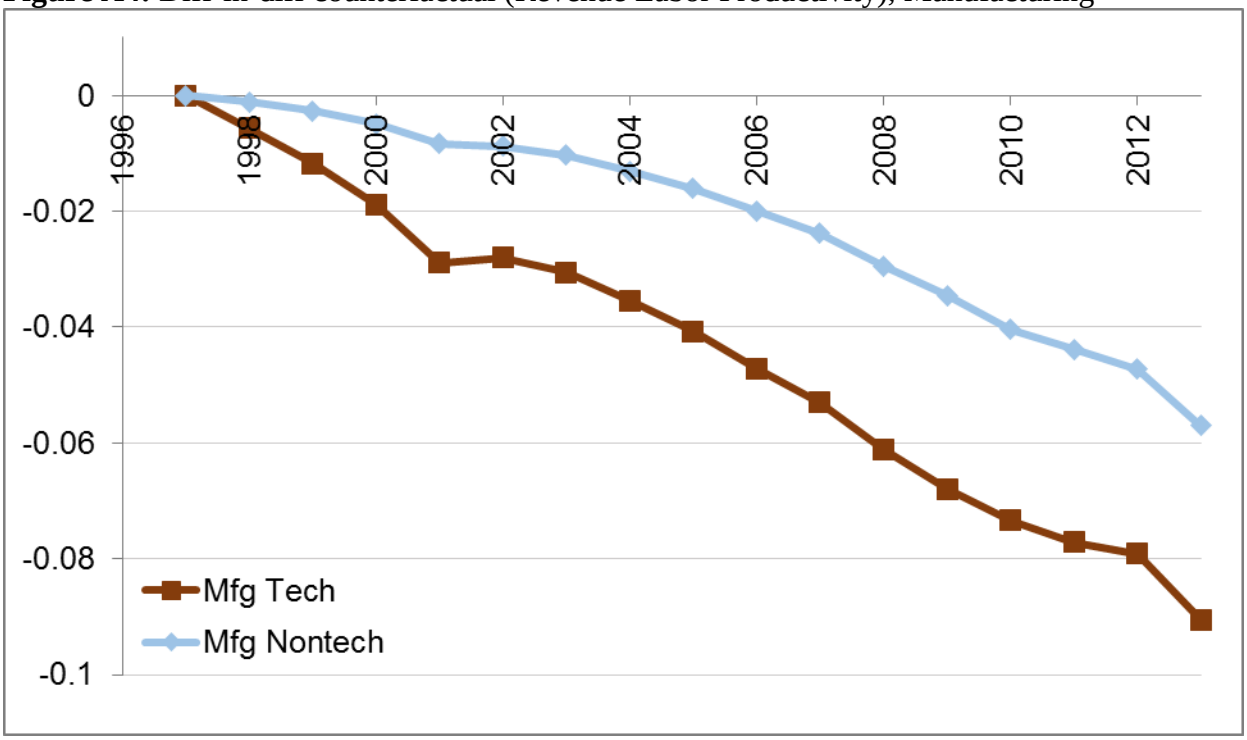

Note: Young firms have age less than 5. High-Tech is defined as in Hecker (2005). Author calculations from the Longitudinal Business Database, the Annual Survey of Manufacturers, and the Census of Manufacturers.

**Figure A3:** Labor productivity dispersion by NAICS sector



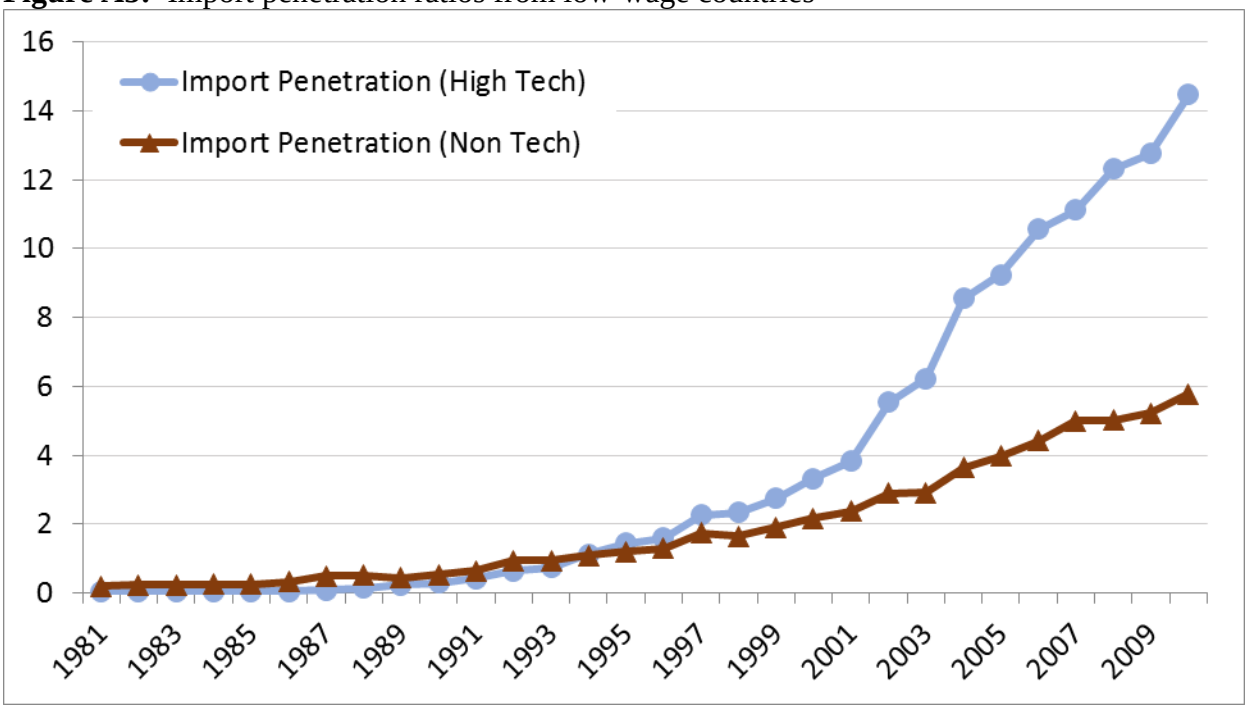

Note: Y axis does not begin at zero. Data reflect interdecile range of log labor productivity deviated from industry by year means. Sectors are defined on a consistent NAICS basis. Author calculations from the RE-LBD.

**Figure A4:** Diff-in-diff counterfactual (Revenue Labor Productivity), Manufacturing




Note: Figure depicts counterfactual change in reallocation contribution to aggregate labor productivity growth. High-Tech is defined as in Hecker (2005). Author calculations from the RE-LBD.

**Figure A5:** Import penetration ratios from low-wage countries




Source: Extended versions of Import Penetration Ratios from Bernard, Jensen and Schott (2006) and Schott (2008). Reported statistics are averages across 6-digit NAICS industries for High-Tech and Non Tech industries.

## 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)

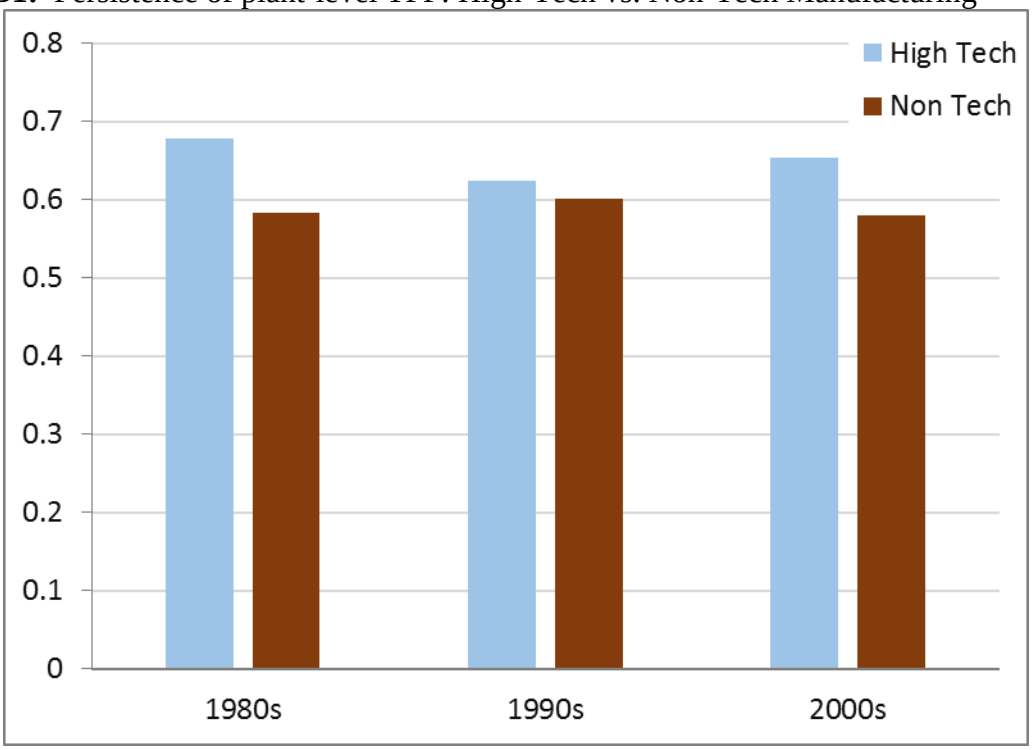
## Appendix B. Persistence and Innovation in TFP in Manufacturing

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 $t$ and $t+1$ 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.[49] With these caveats in mind, we estimate an AR(1) model of TFP applied to continuing plants. Figure B1 reports these AR(1) coefficients, averaged by decade, separately for plants in High-Tech Manufacturing and plants in Non-Tech Manufacturing. The estimates for both categories are in the 0.6 to 0.7 range and are reasonably stable over time. For High-Tech Manufacturing, there is a slight decrease in the persistence of plant-level TFP from the 1980s to the 1990s, but it rebounds in the 2000s.[50]

For the set of years where we can estimate the AR(1) process, we can also recover the distribution of innovations to plant-level TFP for continuing plants. Since this is for selected years we report averages of standard deviation of innovations to TFP by decade as we did with persistence; these are reported on Figure B2. 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, but the magnitude is reasonably stable over time.

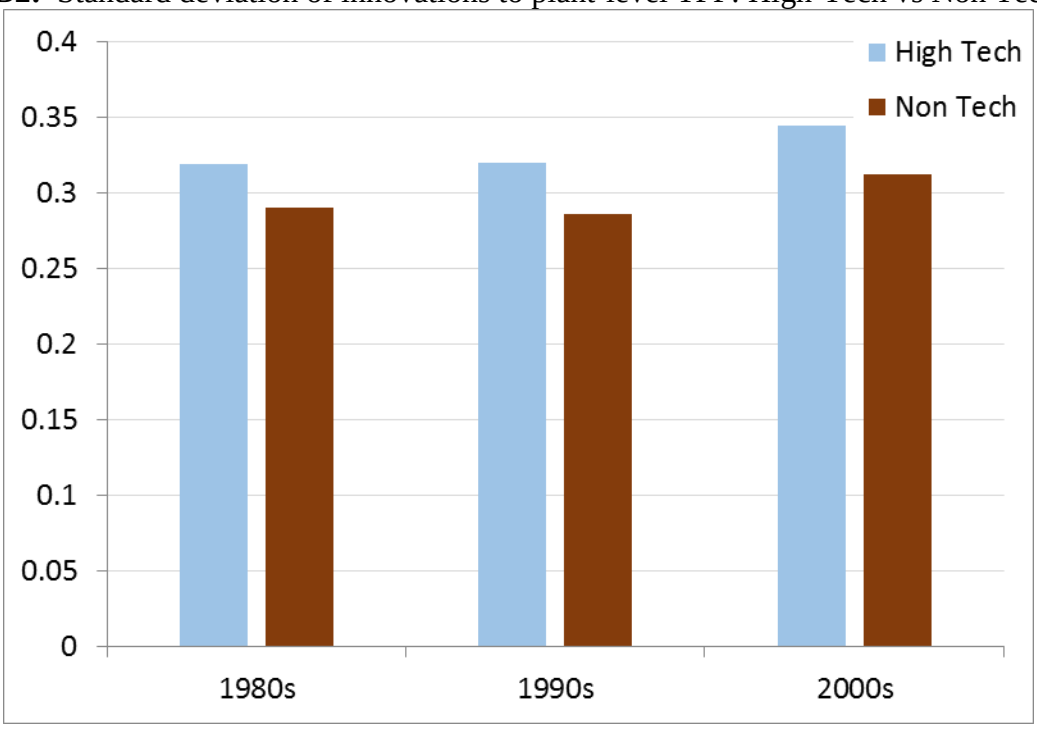
[49] Even for other years, our propensity score weights are not ideally suited for making the sample of continuers representative. In principle, we can develop separate propensity score weights for this restricted sample of continuing plants. Doing so is more of a challenge, but we plan to investigate this in future drafts of the paper.
[50] We conduct this persistence exercise using the Wooldridge (2009) revenue productivity residual (RSR) estimation method. The RSR persistence pattern is generally consistent with the TFPR result.

**Figure B1:** Persistence of plant-level TFP: High-Tech vs. Non-Tech Manufacturing




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 B2:** Standard deviation of innovations to plant-level TFP: 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.

## Appendix C. Alternative TFP calculation

Here we consider an alternative revenue productivity residual measure that explicitly incorporates potentially endogenous plant-level prices. Let $P_{et} = D_{et}Q_{et}^{\rho-1}$ where $D_{et}$ is an idiosyncratic demand shock and $\rho - 1$ is the inverse demand elasticity. Then plant-level revenue is given by (lower case variables are in logs):

$$p_{et} + q_{et} = \beta_k k_{et} + \beta_l l_{et} + \beta_m m_{et} + \beta_e e_{et} + \rho a_{et} + d_{et} \tag{C1}$$

where $\beta_i = \rho\alpha_i$ for factor $i$. That is, the $\beta_i$ coefficients are the revenue elasticities that reflect both demand parameters and the production function factor elasticities. The revenue elasticities can be estimated consistently using the Wooldridge (2009) one-step GMM method. The latter builds on the proxy methodology of Olley and Pakes (1996) and Levinsohn and Petrin (2001). With estimates of the revenue function elasticities, the revenue productivity residual can be recovered which is given by:

$$RPR_{et} = \rho a_{et} + d_{et} \tag{C2}$$

The revenue productivity residual is a function of idiosyncratic demand and TFPQ shocks. We note that the $RPR_{et}$ is distinct conceptually from $TFPR_{et}$. The former is based on revenue per unit input using revenue elasticities that incorporate demand parameters while the latter is revenue per unit input using factor elasticities from cost shares. This implies that even with endogenous prices in the face of plants facing downward sloping demand functions that RPR will exhibit dispersion regardless of any frictions or distortions.

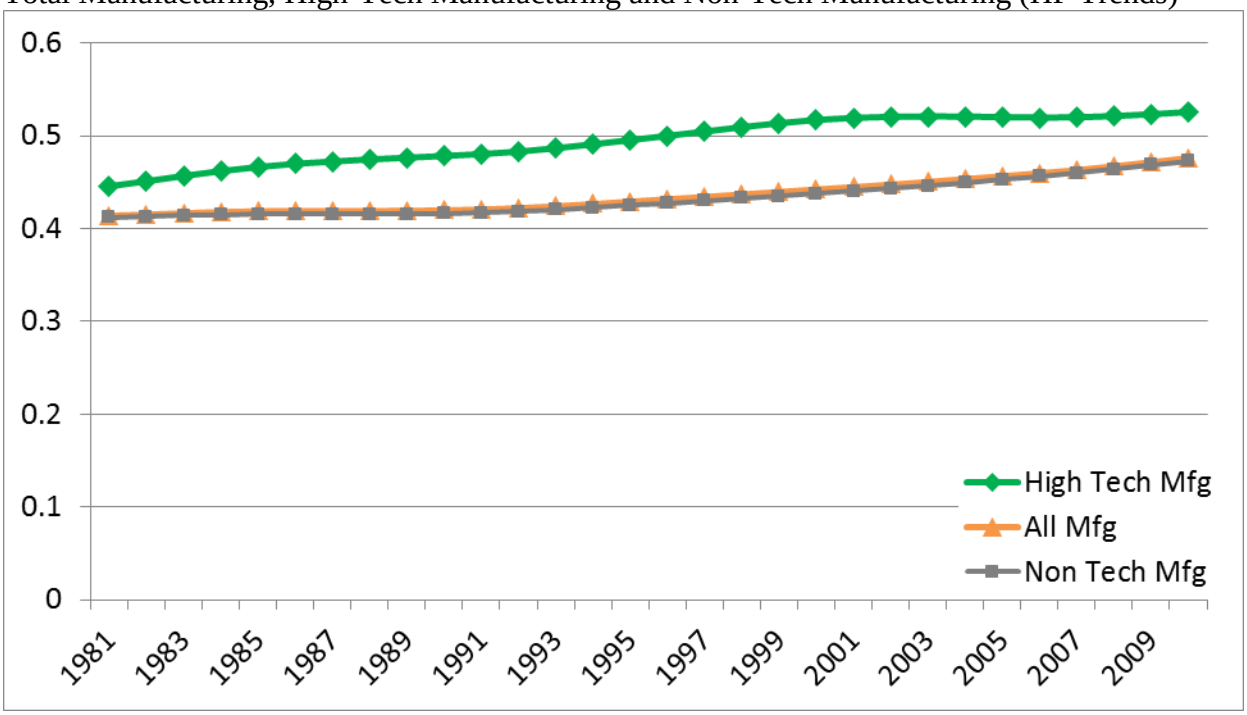
We implement this methodology following the guidance of Foster et al. (2016) in estimating the revenue elasticities to vary at the 3-digit NAICS level. They find that the proxy method estimates using the Woolridge method are sensitive to outliers and pooling across a large number of observations mitigates this sensitivity. After estimating the elasticities, we compute the revenue productivity residuals and deviate the latter from 6-digit NAICS industry by year means. We find that $RPR_{et}$ has a correlation of 0.76 with $TFPR_{et}$.

We replicate the exercises we have conducted with $TFPR_{et}$ with the alternative measure of $RPR_{et}$. Figure C1 shows the evolution of within industry dispersion in $RPR_{et}$ for all manufacturing industries, manufacturing High-Tech and non-manufacturing High-Tech. As with Figure A3 of Appendix A (which depicts analogous patterns for TFP), we observe gradually rising RPR dispersion throughout the time period, with higher dispersion in High-Tech Manufacturing than in the rest of the sector. Figure C2 reports AR(1) coefficients for plant-level RPR (see Appendix B for a discussion of this measure and its limitations in our dataset). Again, consistent with the TFP persistence results (depicted on Figure B1 of Appendix B), we find little change in productivity persistence over the time period. Taken together, the dispersion and persistence results shown here confirm our conclusions from TFP data: changes in the distributional characteristics of plant-level productivity cannot explain aggregate patterns of job reallocation.

We estimate equation (2) using RPR in place of TFP. Figure C3 reports annual regression coefficients relating productivity and growth, averaged by decade. The results are generally consistent with those reported for TFP on Figure 5 with young firm productivity responsiveness in High-Tech that rises from the 1980s to the 1990s then falls in the 2000s. Among mature firms in High-Tech, responsiveness is somewhat flat from the 1980s to the 1990s before falling markedly in the 2000s.

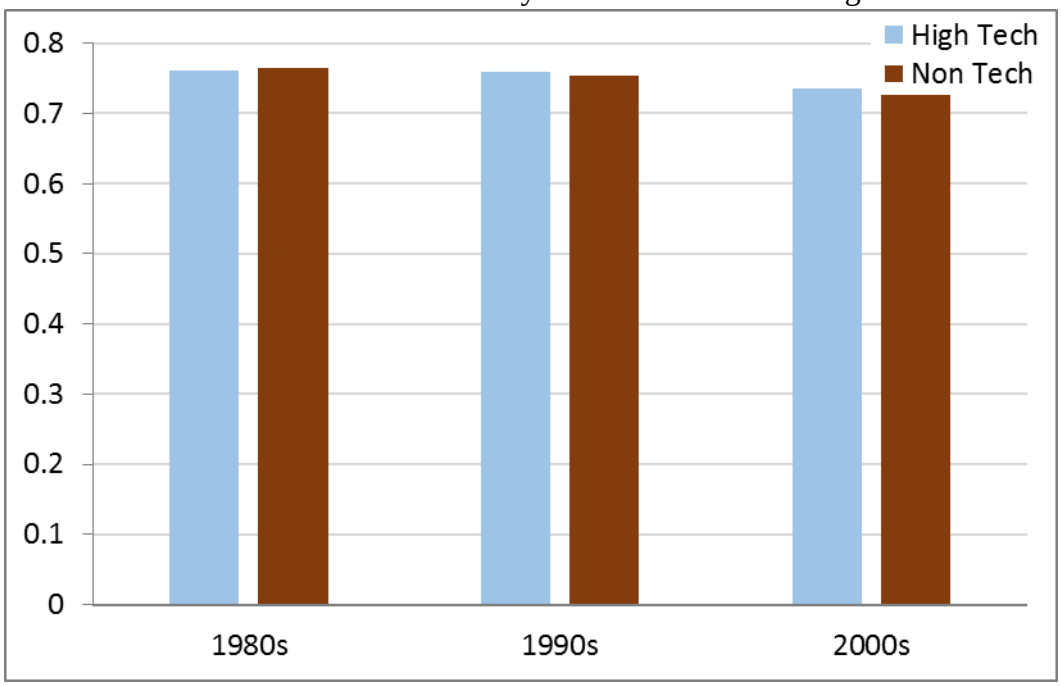
Finally, Figure C4 reports the counterfactual described by equation (5), that is, the contribution of reallocation to aggregate productivity growth as determined by the regression model with RPR productivity. Among High-Tech plants, declining responsiveness produces a counterfactual that is broadly similar—both qualitatively and quantitatively—with the TFP-based results from Figure 6, with a productivity "drag" that is only slightly smaller under RPR than under TFP. Among Non-Tech plants, the counterfactual produces somewhat different results from those reported in Figure 6, with a gap opening up early in the sample then remaining stable (and negative) after the late 1990s. In general the RPR results confirm the TFP-based findings suggesting a quantitatively significant change in the contribution of reallocation to aggregate productivity growth.

**Figure C1:** Within-Industry Dispersion in the Revenue Productivity Residual (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 revenue productivity residual. 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.

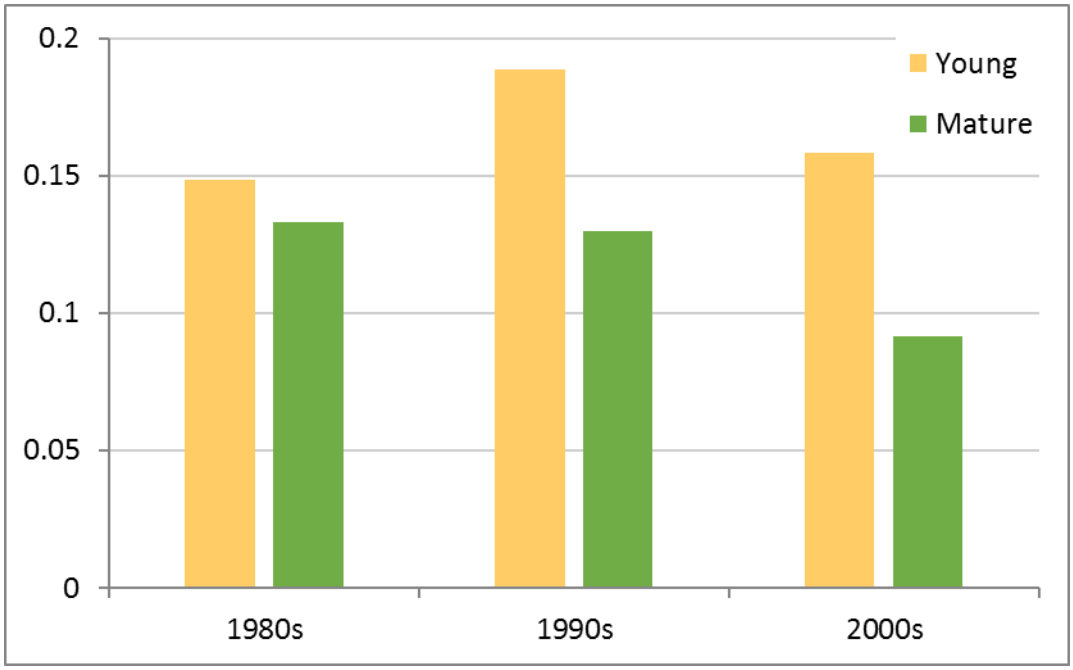
**Figure C2:** Persistence of Revenue Productivity Residual for Plants: High-Tech vs. Non Tech



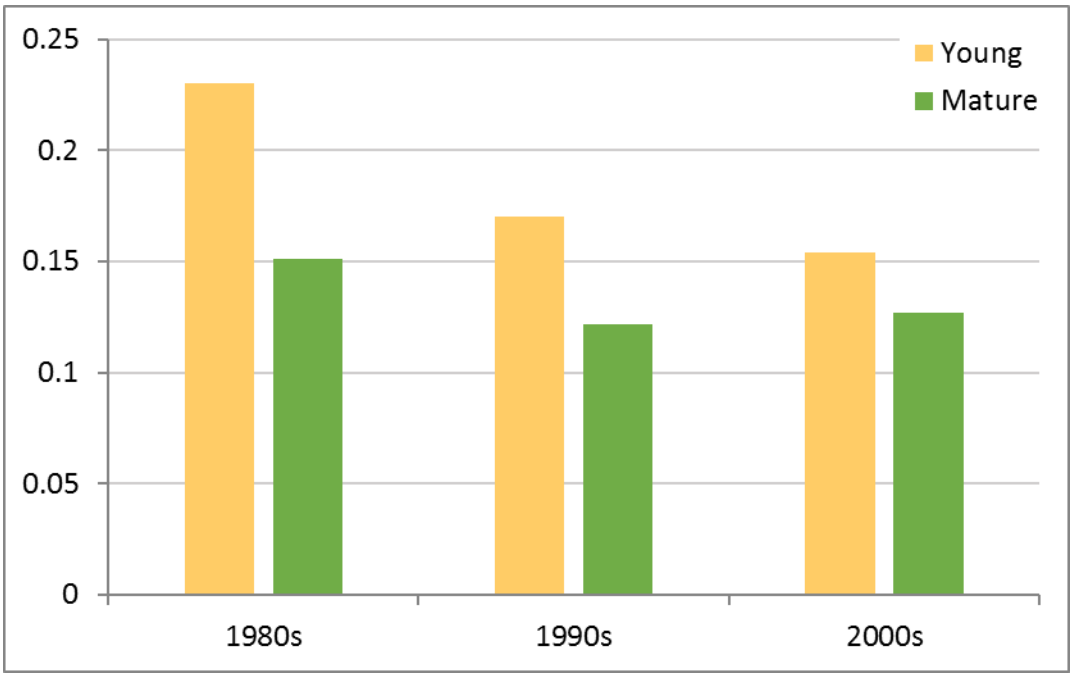

Note: High-Tech is defined as in Hecker (2005). Author calculations from the Longitudinal Business Database, the Annual Survey of Manufacturers, and the Census of Manufacturers.

**Figure C3:** Marginal effect of revenue productivity residual on plant-level net employment growth

(a) High-Tech plants

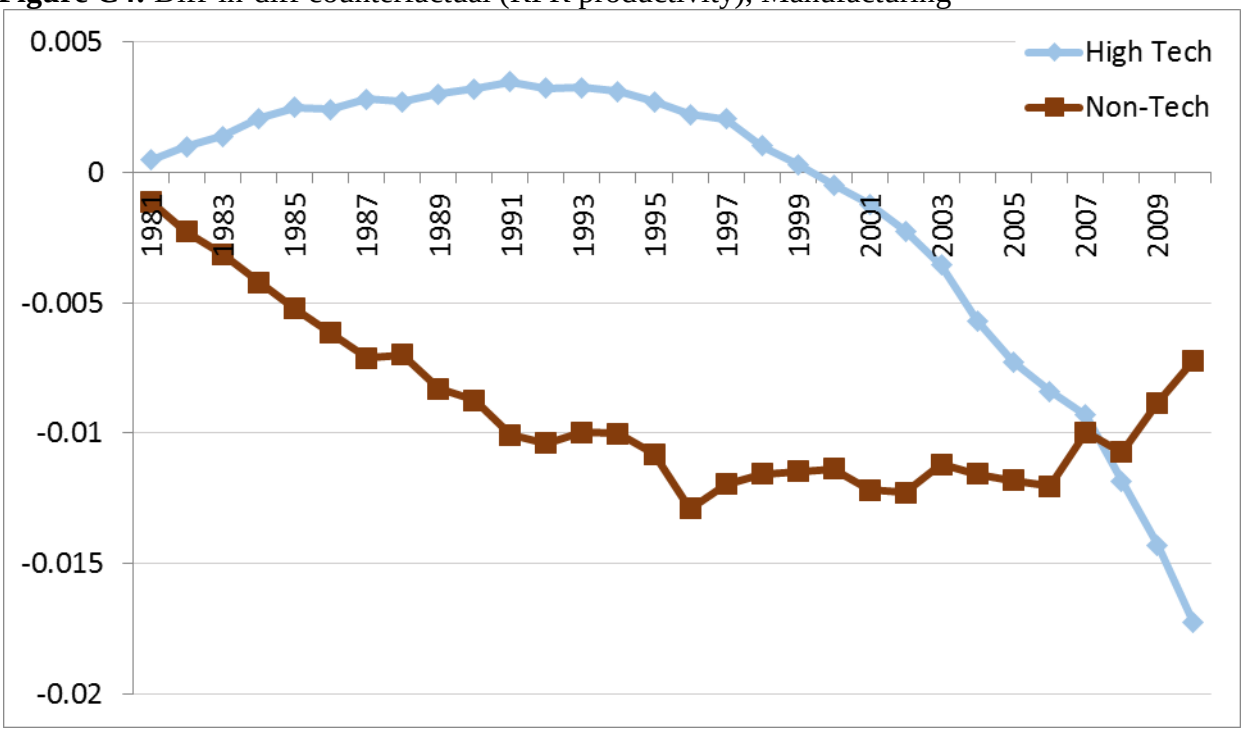



(b) Non-Tech plants




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 C4:** Diff-in-diff counterfactual (RPR productivity), Manufacturing




Note: Figure depicts counterfactual change in reallocation contribution to aggregate 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.

## Appendix D. Dispersion in labor productivity

To help understand the relationship between dispersion in labor productivity relative to dispersion in TFP, consider first a simple model where firms within a given industry maximize profits in the absence of adjustment frictions (or other distortions) given by:

$$\pi_{ft} = P_t Y_{ft} - w_t n_{ft} \text{ with } Y_{ft} = A_{ft} n_{ft}^{\alpha} \tag{D1}$$

where $Y_{ft}$ is output for firm *f* at time *t*, $n_{ft}$ is the labor input for firm *f* at time *t*, $P_t$ is the price of the output for the industry, $A_{ft}$ is TFP of firm *f* at time *t*, and $w_t$ is the wage and $\alpha < 1$. We assume the latter to put curvature in the profit function at the firm level. It might reflect fixed factors or decreasing returns to scale from for, for example, Lucas (1978) span of control reasons. We could also put curvature in the profit function from downward sloping demand coming from product differentiation and assume CRTS. We only focus on labor here for expositional ease but the arguments here easily extend to allowing multiple factors. The first order condition for labor is given by:

$$\alpha P_t A_{ft} n_{ft}^{\alpha-1} = w_t \tag{D2}$$

Firms with high TFP will be larger so that, in turn, dispersion in firm-level TFP within industries will generate the size distribution of activity within an industry. This characterization of the size distribution is isomorphic to that discussed and described by Lucas (1978).

However, observe in the absence of frictions or distortions, marginal revenue products will be equalized so that average revenue product of labor are equalized as well:

$$APL_{ft} = \frac{P_t Y_{ft}}{n_{ft}} = P_t A_{ft} n_{ft}^{\alpha-1} = \frac{w_t}{\alpha} \tag{D3}$$

Marginal revenue products are in this case proportional to average products of labor. This stark result stems from the simple production function and demand structure assumed but is useful for us to illustrate the potential role of frictions. As discussed in Haltiwanger (2016) and

Haltiwanger, Kulick and Syverson (2016), richer demand and production structures yield dispersion in the average product of labor even in the absence of frictions. For our purposes, this simple structure is useful without such complications because it helps us illustrate that dispersion in labor productivity arguably stems in part from frictions that impede the instantaneous equalization of marginal revenue products.

Adding adjustment frictions to this model pushes us toward the standard models of adjustment frictions discussed in the main text (see, e.g., Cooper and Haltiwanger (2006), Elsby and Michaels (2013)). With either convex or non-convex adjustment costs, the policy functions for firms that emerge from such models have the general form: $g_{ft} = f_t(A_{ft}, n_{ft-1})$ where $g_{ft}$ is the growth rate of firm $f$ between $t-1$ and $t$, $n_{ft-1}$ is initial size, and $A_{ft}$ is the realization of firm (idiosyncratic) productivity. With such frictions, there will be dispersion in the average revenue product of labor (labor productivity) in equilibrium that in turn will be positively related to the dispersion in $A_{ft}$. However, dispersion in labor productivity will also be increasing in the adjustment frictions as is evident from the discussion here. In this simple illustrative example, in the absence of frictions there is no dispersion in labor productivity, but as frictions increase so will the dispersion in labor productivity.

Note as well that in the presence of adjustment frictions, increases in $A_{ft}$ will yield an increase in the marginal revenue product of labor (the LHS of (D2)) (and an increase in measured labor productivity) and in turn induce firms to increase employment over time. Increased adjustment frictions will reduce the responsiveness of the employment growth to such changes in marginal revenue products (and thus measured labor productivity). Or in the context of the empirical exercises in the paper, an increase in adjustment frictions will reduce the covariance between employment growth and labor productivity.

## Appendix E. Multi-Unit Firms Operating in Multiple Industries

In the firm-level analysis, we deviate firm-level log revenue per worker from the firm's industry-by-year mean. This requires assigning a firm to a single industry. For this purpose, we use the modal industry of the firm based upon employment. Since 95 percent of firms are single-unit establishment firms this is unlikely to have large implications for empirical exercises that pool across single-unit and multi-unit firms. Indeed, in unreported results we have repeated the exercises using labor productivity for single-unit establishment firms only and obtain very similar results. In interpreting this, it is useful to note that the dispersion of within-industry productivity and the regressions on changing responsiveness use firm-level data without activity weighting. The one exercise that might be more sensitive to this issue is the diff-in-diff counterfactual since this is an employment-weighted exercise.

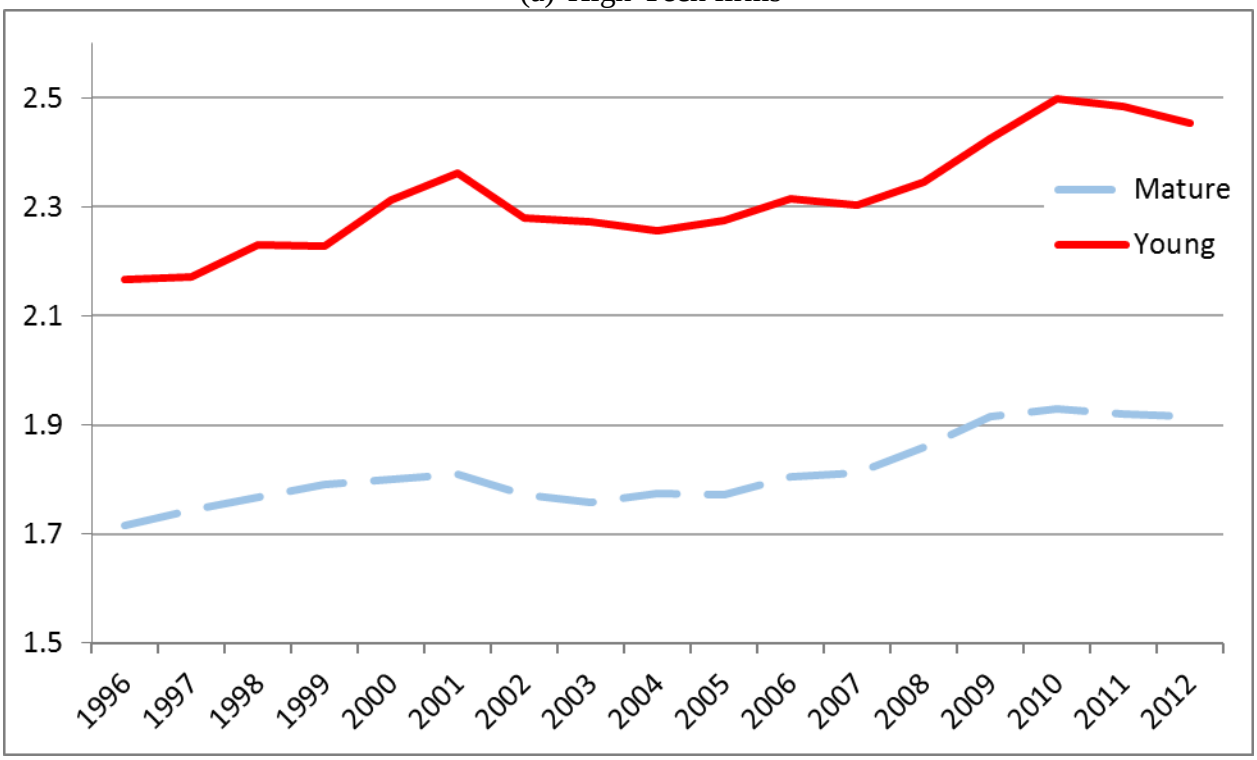
In this appendix, we consider an alternative way of treating multi-unit firms operating in multiple industries that will also potentially impact the single unit establishment firms as well. Specifically, the method used in the main text for generating the relative within-industry measure of productivity is equivalent to estimating a simple fixed effects regression of log revenue per worker on interacted industry-by-year effects and then using the residual as the relative productivity measure. As an alternative, we consider a regression of log revenue per worker on industry-by-year effects where each firm has up to five (6-digit NAICS) industry effects. Moreover, each of the (up to) five industry-by-year effects are interacted with a share variable that is equal to the share of employment within the firm for that industry. For a single unit establishment firm, only one industry effect is included, with the share variable equal to one.

Figure E1 is the analogue to Figure 7 showing within-industry dispersion for young and mature firms for tech and Non-Tech firms. For computing statistical measures by industry group we still use the predominant modal industry but note that the industry grouping in Figure E1 is much broader than a 6-digit NAICS industry. Figure E2 is the analogue to Figure 8 in the main text, reporting the time-varying coefficients relating firm-level employment growth to firm-level labor productivity, based on firm-level productivity generated with this alternative demeaning method. Finally, Figure E3 is the analogue to Figure 9 in the main text, reporting diff-in-diff counterfactual results for the changing contribution of reallocation to aggregate productivity growth, again based on the alternative demeaning method. Observe that each figure based on the

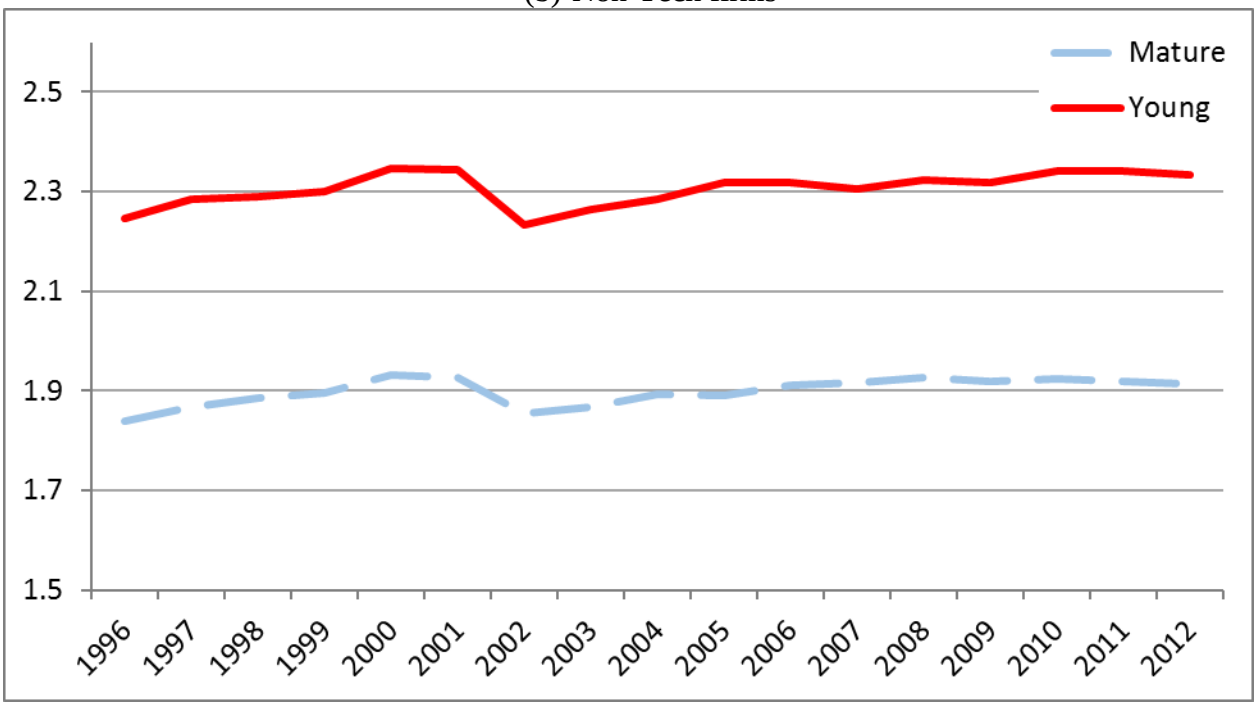
alternative demeaning method broadly confirms the results in the main text (that are based on a simple one-industry-per-firm approach). While the productivity counterfactual is modestly smaller in magnitude under the alternative approach, it still reveals large effects of the weakening relationship between productivity and growth.

**Figure E1:** Within-industry dispersion in labor productivity, young vs. mature (alternative method for demeaning)

(a) High-Tech firms

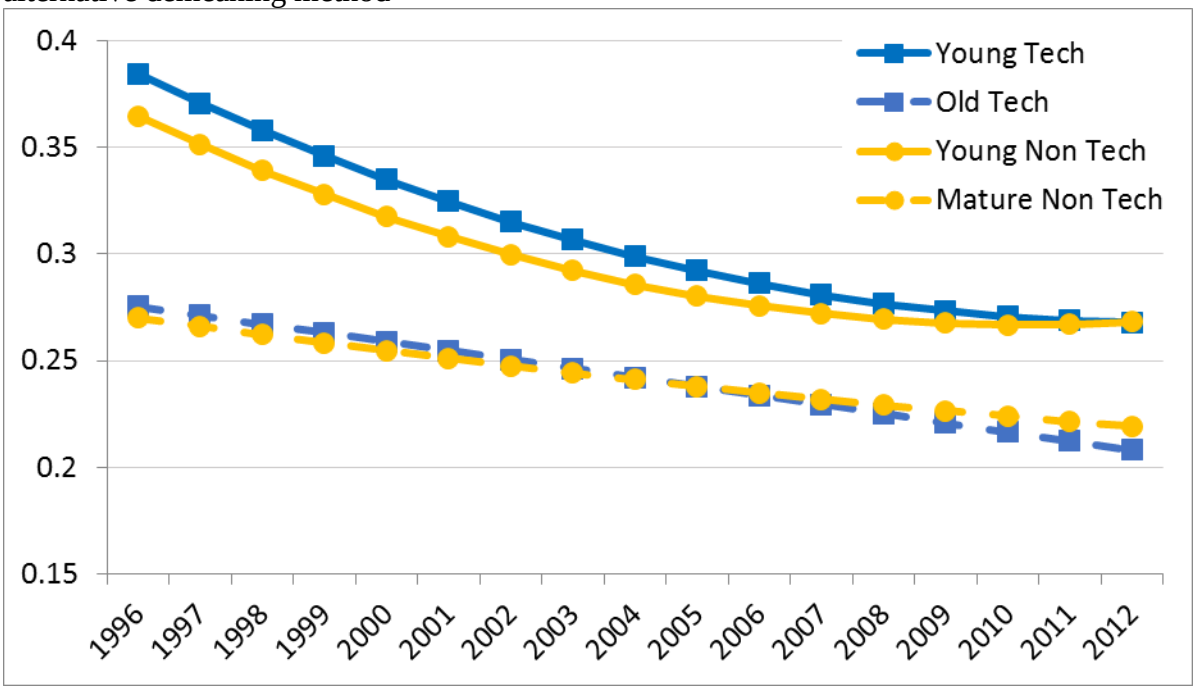



(b) Non-Tech firms



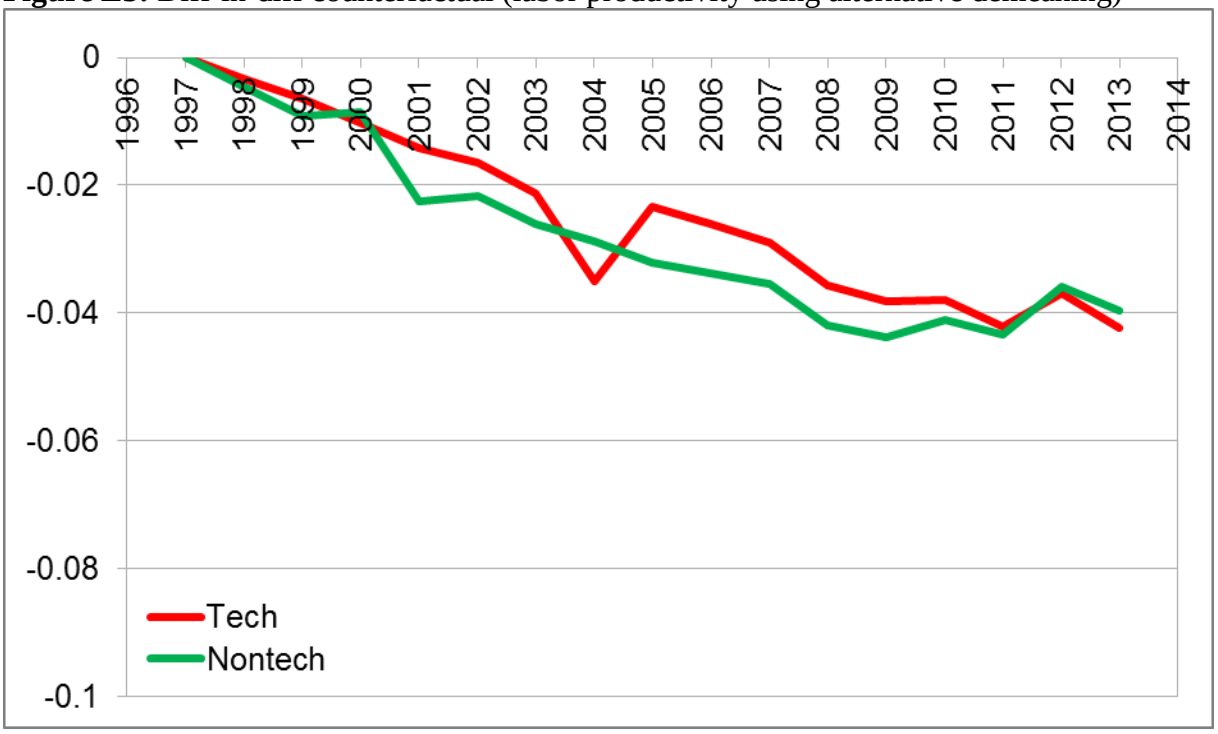

Note: Y axes do not begin at zero. Data reflect interdecile range of log labor productivity deviated from industry by year means. Young firms have age less than five. High-Tech is defined as in Hecker (2005). Author calculations from the RE-LBD.

**Figure E2:** Labor productivity and growth at the firm level (economywide, including exit), alternative demeaning method




Note: Annual coefficients from analogue of Table 2 using the alternative measure. Young firms have age less than five. High-Tech defined as in Hecker (2005). Author calculations from the RE-LBD. Finance, Insurance and Real Estate (NAICS 52-53) omitted.

**Figure E3:** Diff-in-diff counterfactual (labor productivity using alternative demeaning)




Note: Figure depicts counterfactual change in reallocation contribution to aggregate labor productivity growth. High-Tech is defined as in Hecker (2005). Author calculations from the RE-LBD

## Appendix F. The changing composition of High-Tech Manufacturing

In the High-Tech Manufacturing sector, another possible cause of declining productivity responsiveness after 2000 is the transition from "general-purpose" to "special-purpose" equipment manufacturing in the U.S documented by Byrne (2015).[51] One hypothesis is that 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 F1 shows that during the 1990s the share of employment in among general purpose technology producers grew rapidly but, consistent with Byrne (2015) (which examined revenue shares), the general purpose share has fallen substantially since the late 1990s. Given these compositional changes, it is possible that the changing responsiveness reflects differential responsiveness across industries.

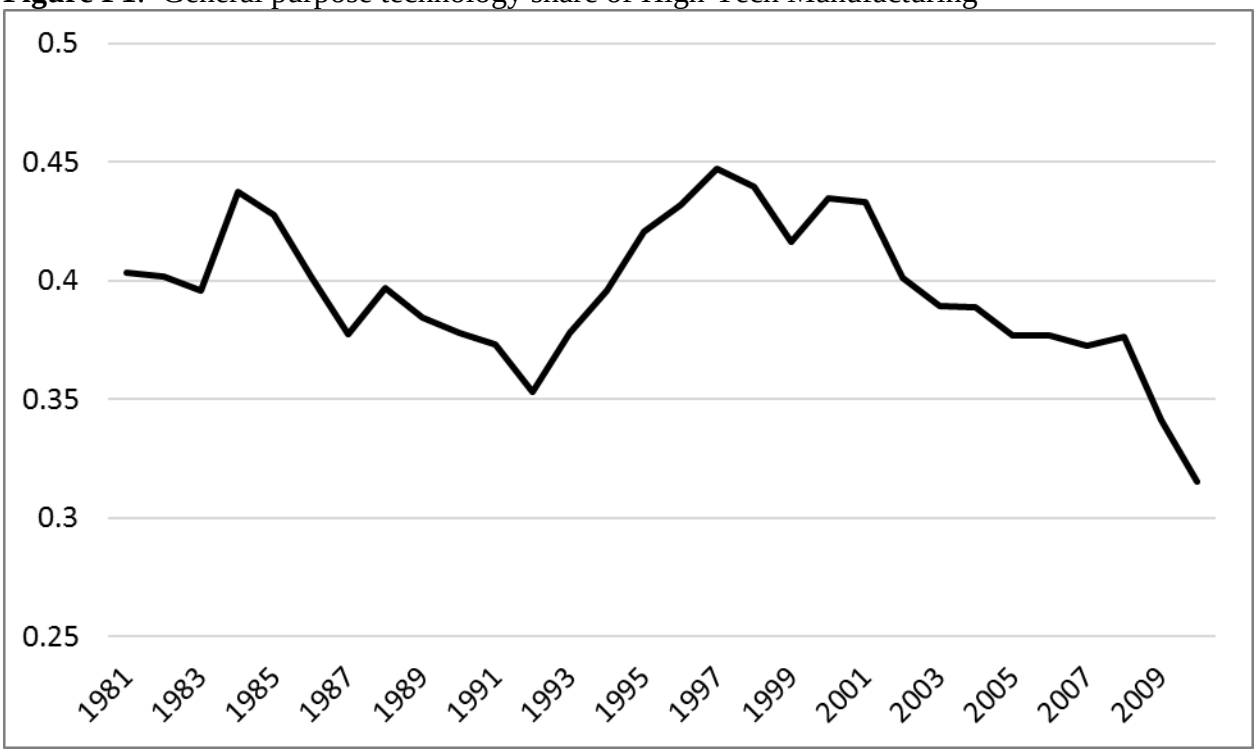
To explore the role of this composition effect, we estimate specification (3) separately for each 6-digit industry in High-Tech Manufacturing but, importantly, we omit time trend interactions from the specification. With the estimated responsiveness coefficients for each 6-digit industry, we compute the employment-weighted aggregate responsiveness in each year using the actual year 6-digit employment weights.[52] If the shift from general-purpose to special-purpose tech products is driving a decline in average productivity responsiveness, we would expect general-purpose plants to be more responsive than special-purpose plants, and this would be manifest in shift-share analyses that hold responsiveness constant but allow employment shares to shift over time as in the data.

Figure F2 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 (which would have been expected if general-purpose producers were more responsive on average), and there is actually a modest increase in responsiveness from the 1990s to the 2000s from composition effects rather than a decline. Interestingly, the average

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

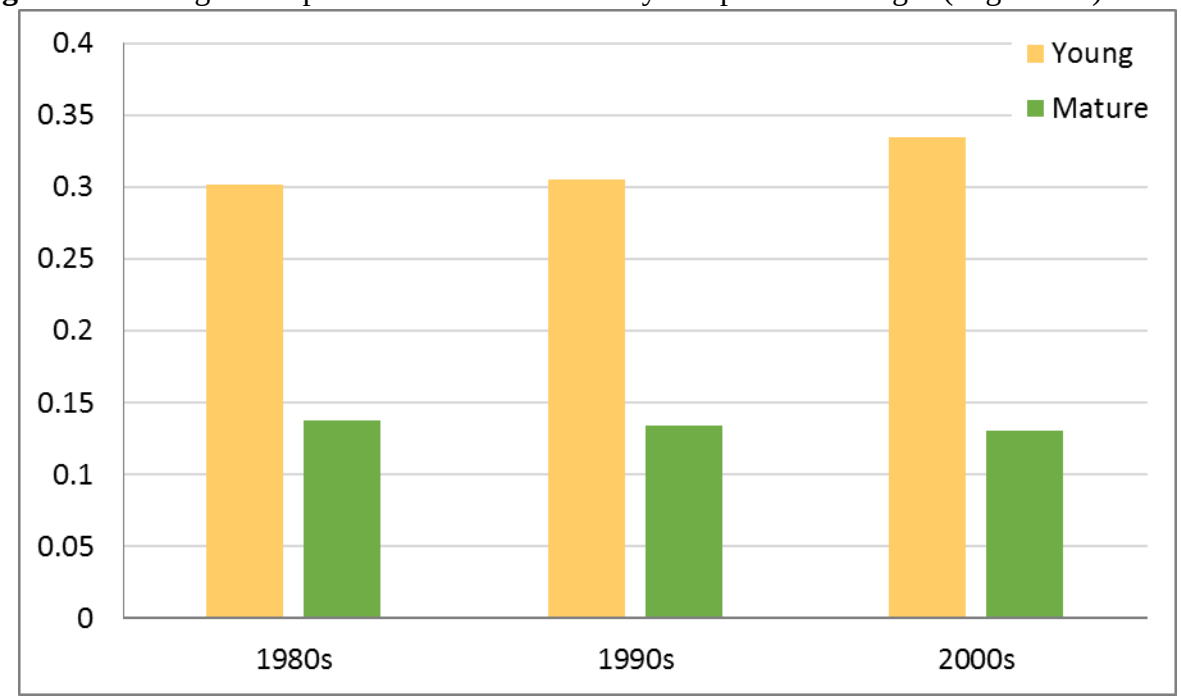
responsiveness of producers of special-purpose technologies is slightly higher than that of general-purpose technology producers, which is why the aggregate responsiveness in our shift-share analysis rises slightly from the 1990s to the 2000s. Declining responsiveness must therefore be a within-category phenomenon with respect to the general-purpose/special-purpose taxonomy. These findings suggest that the rising and then declining pace of job reallocation in High-Tech Manufacturing cannot be accounted for by the changing composition of High-Tech.

**Figure F1**: General purpose technology share of 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 F2:** Change in responsiveness due to industry composition changes (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.