DECLINING BUSINESS DYNAMISM: IMPLICATIONS FOR PRODUCTIVITY?

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SUMMARY

The last few decades have seen a decline in business dynamism, as measured by indicators such as new firm formations, worker flows, and job creation and destruction. This is a potentially worrisome trend because an important driver of productivity growth is the reallocation of resources from less productive to more productive firms. Using firm-level data for the entire U.S. economy, the authors explore whether a fall in business dynamism has resulted in a decline in productivity growth.

They first review the significant fall in business dynamism over time. For example, there is a clear downward trend in the rate of startups (new firms), and a slower decline in the rate of firm exits. Similarly, over the last several decades, the share of employment at young firms has dropped from 20 percent to 10 percent. They also review recent evidence on declining high-growth firm activity (especially by young firms).

The authors explore the potential causes and consequences of this declining dynamism, and have two main findings. First, using revenue per employee as a measure of productivity, the authors show that the gap in productivity between the most and least productive firms has widened over time. This widening is most apparent in the information sector, a sector that has historically been an important source of productivity growth. Widening dispersion in productivity is potentially a sign that firms are facing increasing frictions in adjusting to their appropriate size, or that the least productive firms are not catching up to the most productive firms as quickly as they used to.

Second, they show that the link between a firm's level of labor productivity and its rate of employment growth has been getting weaker over time. Whereas in the past more productive firms in the same industry expanded employment while less productive firms contracted, today this is less true. This decline in reallocation from less productive to more productive firms is likely holding down overall productivity growth.

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I. INTRODUCTION

A growing body of research documents that various indicators of business dynamism have been in secular decline in the U.S. since the 1980s. This trend is evident in data on new firm formations, gross job creation and destruction, and worker flows.[1] Canonical models of firm dynamics and empirical evidence indicate that there is a tight link between business dynamism and productivity growth. That is, theory and evidence suggests a substantial fraction of aggregate productivity growth is accounted for by the reallocation of resources away from lower-productivity to higher-productivity firms. In particular, firm entry and exit are an especially critical component of these productivity enhancing reallocation dynamics. Thus, a *prima facie* concern arising from these trends is that they may have had adverse effects on aggregate productivity growth.

However, a more careful review of theory and evidence suggests the observed fluctuations in the pace of productivity growth, business formation and reallocation dynamics are not inconsistent. During the 1980s and 1990s, the decline in entrepreneurship and reallocation dynamics is dominated by the Retail Trade sector. In that sector, the declines in the pace of business formation and reallocation arguably do not reflect adverse developments but rather benign factors consistent with rising productivity in the Retail Trade sector observed over that period. The patterns in the Retail Trade sector remind us that a high pace of startups and reallocation is not inherently positively correlated with economic performance. Moreover, patterns of declining job reallocation in other sectors in the 1980s and 1990s are not characterized by a loss of high-growth firm activity but reflect a symmetric narrowing of the employment growth rate distribution (Decker et al. (2016b)).[2]

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 the pace of reallocation over the first period and a sharp decline in the post-2000 period.[3]

In this paper, we explore the possible connection between the changing dynamics of business formation and reallocation—evident in sources of business microdata—and aggregate patterns in productivity growth. This exploration is in two distinct but related steps. First, we take stock of what we know about the changing patterns of business formation and business dynamism, and the possible connections with productivity, by describing recent research using detailed business microdata on productivity and employment. We summarize the recent findings in this burgeoning literature and discuss open questions. Second, we exploit a newly developed economy-wide longitudinal firm database that tracks real revenue growth, employment growth, and the connection of employment growth to labor productivity dynamics at the firm level. Consistent with previous, more narrowly focused research, we uncover compelling connections between firm-level

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1 See Davis et al. (2007); Davis, Faberman and Haltiwanger (2012); Hyatt and Spletzer (2013); Decker et al. (2014); Haltiwanger, Hathaway and Miranda (2014); Decker et al. (2016a,b).

2 As shown by Decker et al. (2016b), 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.

3 For this purpose, we follow Hecker (2005) and construct a High Tech sector based on the 14 four-digit NAICS sectors with the largest shares of STEM workers. The 14 sectors are listed in Table A.1 in the appendix of Decker et al. (2016a).

growth dynamics, economy-wide trends in job reallocation, and aggregate productivity growth. High-productivity firms are more likely to grow while low-productivity firms are more likely to contract. This productivity/growth covariance weakens over the post- 2000 period. This weakening is especially noticeable in the High Tech sector. We conduct a diff-in-diff counterfactual exercise that implies there have been substantial reductions in industry-level productivity growth from this weakening relationship. Our analysis is still exploratory but suggests that business microdata may be important for understanding the striking changes in U.S. productivity growth.

The next section summarizes recent microdata-based research on dynamism, its relationship with productivity, and its evolution in recent years. We outline what is currently known then explore specific outstanding questions and summarize recent and current efforts at answering those questions. The third section describes the rich new data source we are using. Section IV presents new evidence on the changing nature of business dynamism as measured by changes in the growth rate distribution of real revenue (as opposed to employment) across firms. Section V uses this newly developed data source to characterize the changing patterns of within- industry dispersion in productivity along with changes in the covariance between employment growth and productivity, followed by exercises quantifying the declining contribution of reallocation to aggregate productivity growth. We conclude by summarizing our main findings and highlighting avenues for future research that will contribute to our understanding of this issue.

II. TAKING STOCK AND OPEN QUESTIONS

A. Taking Stock

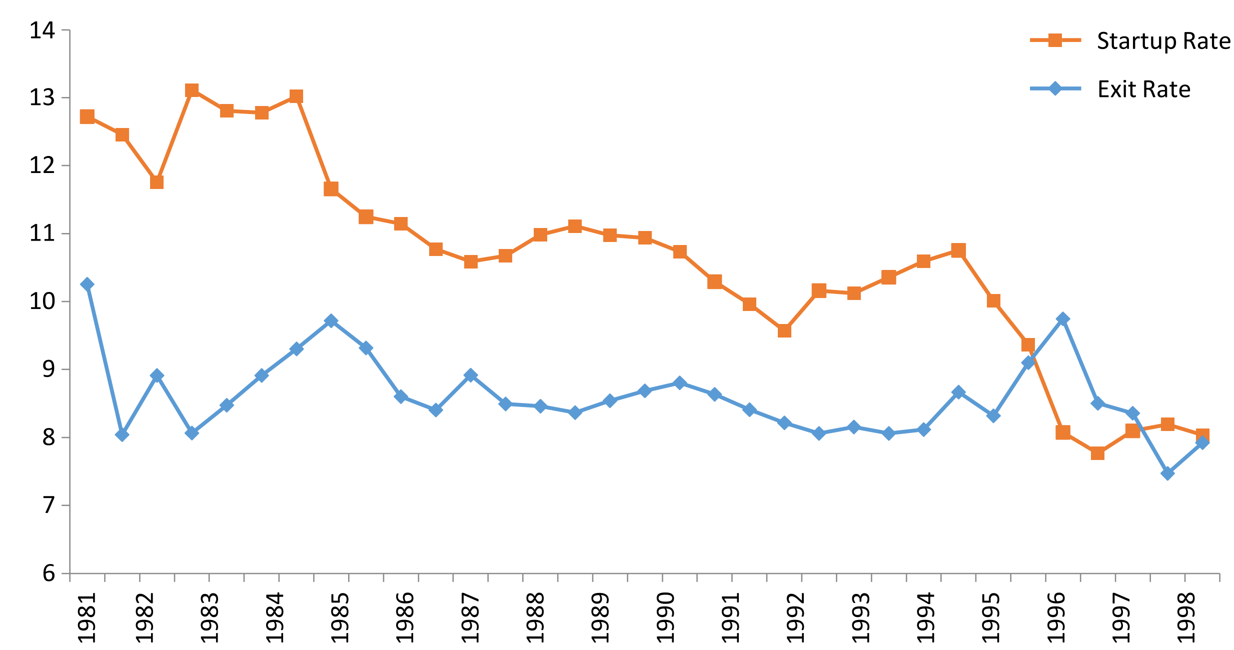
a. Changing Patterns of Business Formations, Dispersion and Skewness in Firm Employment Growth Rate Distributions

Using measures such as the pace of job reallocation, the dispersion of growth rates across businesses and within-business volatility, the decline in business dynamism for the U.S. private non-farm sector dates at least to the mid-1980s (see Davis, Haltiwanger, Jarmin and Miranda (2007), Davis and Haltiwanger (2014), Decker et. al. (2014, 2016a, 2016b), Hyatt and Spletzer (2013) and Molloy et al. (2016)). The remainder of this section provides a brief synopsis of the findings from this recent literature.

The declining firm startup rate is one of the most often cited artifacts of overall declining business dynamism.[4] This is illustrated in Figure 1, which reports national startup and exit rates based on aggregated Census Bureau microdata. The decline has been substantial enough that the net entry rate has been negative in some of the last few years. The decline in firm startup rates and the accompanying decline in the share of activity accounted for by young firms is a core component of the overall decline in dynamism. Young businesses are the most volatile businesses, so a decline in the share of activity accounted for by young businesses yields a decline in the pace of reallocation. This shift away from young firms accounts for about 30 percent of the decline in gross job flows (Decker et al. (2014)).

4 See Haltiwanger, Jarmin and Miranda (2013), Decker et al. (2014, 2016a, 2016b), Davis and Haltiwanger (2014) for more detailed discussion. A firm startup is a new legal entity with at least one employee where all the establishments are new. A firm exit occurs when a legal entity ceases to exist and all establishments shut down. These definitions abstract from firm entry and exit generated from ownership change and M&A activity.

Figure 1: Annual Firm Startup and Exit Rates, U.S. Private Non-Farm Sector, 1981-2013



Note: Startup rate is the number of new firms divided by all firms. Exit rate is number of exiting firms divided by all firms. Startups are new legal entities with all new establishments. Exits are legal entities that cease to exist with all establishments shutting down. Data from Business Dynamics Statistics.

These structural changes imply that the typical worker is increasingly more likely to work at a large, mature, national (or global) firm. The share of employment at young firms has dropped from around 20 to 10 percent over the last several decades while the share of employment at large, mature firms has risen from about 40 to 50 percent of employment. Large, mature firms account for less than 1 percent of total firms but a very large and increasing fraction of activity. This shift to large, mature firms is also accompanied by a shift toward national firms (with activity in all regions of the country). This shift to large, mature firms has been more pronounced in some sectors than others.[5, 6]

The pace of the decline in job reallocation exhibits a notable acceleration in the post-2000 period. Decker et al. (2016b) show that the acceleration of the trend decline is associated with a change in the character of the decline in the post-2000 period. Prior to 2000, the decline in indicators of business dynamism was dominated by sectors such as Retail Trade and Services. In the Retail Trade sector, the decline in entrepreneurship and dynamism has arguably been driven by benign factors reflecting a shift in the business model in Retail Trade. The shift has been away from single unit establishment firms ("Mom and Pop" firms) to large national and multi- national chains. The latter have taken advantage of IT[7] and globalization[8] to build efficient distribution and supply chain networks. Establishments in Retail Trade that are part of large, national firms are both more productive and more stable.[9]

5 Retail Trade, Wholesale Trade, and Services have each seen substantial increases in large firm activity. Measured as the share of employment accounted for by firms with more than 250 employees, these sectors have risen from 49 to 57 percent, 38 to 49 percent, and 48 to 56 percent, respectively, since 1990. The large firm share has fallen slightly in Manufacturing (from 69 to 66 percent) and risen slightly in Transportation and Utilities (from 68 to 71 percent). Similar patterns hold using a 10,000-employee cutoff (data from Business Dynamics Statistics). Using a revenue concept instead of employment yields similar results as well; see Council of Economic Advisers (2016).

6 See Figures 1a and 1b of Decker et al. (2016b).

7 See Doms, Jarmin and Klimek (2004).

8 See Basker and Hoang Van (2010).

9 See Foster, Haltiwanger and Krizan (2006) and Jarmin, Klimek and Miranda (2009) for further discussion. In terms of the rubric of the current paper, the change in the business model yielded a change to firms with higher mean productivity and lower variance and associated dynamism.

In contrast, the High Tech sector exhibited increasing indicators of business dynamism prior to 2000.[10] The evidence suggests that in High Tech, high-growth young firms play an especially critical role in job creation and productivity growth. Likewise, newly listed publicly traded firms (IPOs) exhibit particularly high job creation and productivity growth. In the robust period of aggregate productivity and job growth in the 1990s, the High Tech sector and newly listed public companies (there is considerable overlap here) exhibited increases in indicators in dynamism and entrepreneurship. However, since 2000 the High Tech sector and publicly traded firms have exhibited a decline in dynamism. The number of IPOs has fallen in the post-2000 period, and those that have entered have not exhibited the same rapid growth as earlier cohorts.[11]

The changing nature of the decline in indicators of business dynamism is mimicked in the changing nature of the decline in business startups. Prior to 2000, the decline in the firm startup rate is disproportionately accounted for by sectors such as Retail Trade and Services. After 2000 the High Tech sector exhibits a more pronounced decline in the firm startup rate than these sectors.

The acceleration and changing character of the decline in indicators of business dynamism in the post-2000 period is also evident in changing patterns of skewness in the firm employment growth rate distribution, a key focus of Decker et al. (2016b). High-growth firms (especially high-growth young firms) generate positive right skewness in the firm growth rate distribution. Prior to 2000, the decline in the pace of job reallocation and other measures of the dispersion in the firm and establishment employment growth rate distribution reflects a roughly equal decline in the 90-50 and 50-10 differentials.[12] However, after 2000 the 90-50 differential in the firm growth rate distribution falls much more dramatically than the 50-10 differential. Several factors underlie this change in the shape of the distribution of firm growth rates since 2000. First, young firms exhibit more positive right skewness than mature firms, and the share of young firms has declined. Second, sectors like Information (and the broader High Tech sector that includes most of Information) exhibited a high degree of positive right skewness in the 1990s but exhibited a sharp decline in skewness in the post-2000 period. The post-2000 decline in skewness in these sectors is accounted for by a smaller share of young firms in these sectors but also a reduction in high-growth activity amongst young firms in these sectors over this period of time. Thus, the High Tech sector exhibited not only a decline in dispersion in firm growth rates but also a decline in skewness in the post-2000 period.

b. Implications for Productivity?

The present question is about the causes of the slowing of aggregate productivity growth in the U.S. since the early 2000s. Economic theory and a large empirical literature link firm- and establishment-level productivity and growth to economy-wide patterns, and business microdata have played a key role in shedding light on the drivers of aggregate productivity (see Syverson (2011) for a review). In this subsection, we describe the theoretical framework linking business- level dynamics to both recent

10 See Comin and Philippon (2005), Davis, Haltiwanger, Jarmin and Miranda (2007), Haltiwanger, Hathaway and Miranda (2014), Decker et al. (2016b).

11 See Davis and Haltiwanger (2014).

12 The 90-50 and 50-10 differentials are the gap between the 90th and 50th percentiles and the gap between the 50th and 10th percentiles, respectively, of the employment-weighted distribution of firm growth rates. The difference between the 90-50 and the 50-10 can be thought of as a measure of skewness.

empirical patterns of business dynamism and aggregate productivity. In short, economic theory posits that aggregate dynamism measures (such as gross job reallocation) reflect business-level responses to idiosyncratic productivity and profitability conditions (or "shocks"). Looking at the trends for responses versus shocks recent empirical evidence for the manufacturing sector suggests that changes in the nature of those shocks cannot explain recent patterns in business dynamism in manufacturing; rather, businesses have become less responsive to productivity shocks, which may have negative implications for aggregate productivity growth.

Whether declining trends in business dynamism have negative implications for aggregate productivity depends upon the underlying causes of the decline in business formation rates, job reallocation and other related indicators. According to economic theory, a high pace of dynamism is part of a healthy economy if that dynamism reflects the movement of resources— such as jobs—away from less-productive uses and toward more-productive uses. However, changes in the business model within sectors may imply less need for a high pace of business formation and reallocation dynamics to achieve productivity growth. As discussed above, the shift toward large, national and multi-national chain stores in Retail Trade, particularly during the 1990s, likely fits this pattern. The key question, then, is whether the slowing post-2000 pace of reallocation described above reflects less of the productivity-enhancing movement of resources or simply less unnecessary movement due to improvements in business organization and processes. Detailed business-level data are required for answering this question.

Recent research has made some progress on the nature of slowing business dynamism and its link to aggregate productivity. Decker et al. (2016a) argue that insights into the question can be obtained by distinguishing between changes in the dispersion of the within-industry productivity shock distribution and changes in the responsiveness of firms to their productivity realizations from that distribution. This insight follows from canonical models of firm dynamics in which economy- or sector-wide patterns of gross job reallocation reflect the aggregation of firm-level behavior in response to the idiosyncratic conditions they face. Broadly speaking, these models yield the prediction that firm-level growth in a given period will be an increasing function of firm-level realizations of productivity or profitability shocks conditional on initial endogenous state variables (e.g., initial employment) in each period. This model prediction has been well supported by the evidence. Syverson (2011) highlights that one of the most ubiquitous findings in the firm dynamics literature is that firms with high realizations of measured productivity are more likely to survive and grow.

Canonical models thus offer a promising avenue for finding the sources of changes in the distribution of firm growth rates (inclusive of firm exit). Specifically, basic theory implies that changes in the distribution of firm-level growth rates 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 shocks.

Changes in the dispersion of realizations of productivity shocks will yield changes in the dispersion of firm growth rates in canonical firm dynamics models. That is, the dispersion of realizations of productivity within a sector is a proxy for the distribution of idiosyncratic shocks impacting firms. A change in the dispersion of idiosyncratic shocks might stem from several sources. Jovanovic (1982) emphasizes that entering firms do not know their type prior to entry so that young firms exhibit substantial dispersion in both productivity and outcomes. Acemoglu et al. (2013) emphasize that young firms are more likely to be engaged in experimental innovation activity that also yields substantial dispersion in productivity and outcomes.

Changes in the role of learning or experimentation by young firms that yield changes in the dispersion of idiosyncratic productivity shocks could be from benign factors. For example, improved pre-entry information may lead to less need for costly entry, learning and experimentation. Alternatively, the relative importance of young firms vs. mature incumbent firms for technological innovation may change. The shift toward large, national chains in Retail Trade might be interpreted in this fashion. Globalization and information technology favored a subset of large incumbents who could take advantage of improved supply chains and distribution networks in ways that young, smaller firms could not.

Alternatively, changes in adjustment frictions or uncertainty may yield changes in the responsiveness of firms to a given process of idiosyncratic shocks. As Hopenhayn and Rogerson (1993) emphasize, an increase in the frictions for any margin of adjustment will impact all margins of adjustments. Increased barriers to post-entry growth will reduce not only job creation by young incumbents but also entry as the present discounted value of entry declines. In turn, reduced job creation by incumbents and entry will yield reduced job destruction by incumbents and exit as competitive pressures will be reduced.

Using these insights, Decker et al. (2016a) explore the changing pattern of the differences in productivity across plants within the U.S. Manufacturing sector along with the changing pattern of responsiveness to those differences. The remainder of this subsection summarizes the findings from this analysis.

The dispersion of TFP differences between plants rose from the early 1980s to the recent period. This holds overall in Manufacturing but also in the critical High Tech components of Manufacturing (e.g., computers and semiconductors). This rise in dispersion in TFP is consistent with a rising dispersion in the volatility of idiosyncratic productivity shocks impacting businesses.[13] Based on the above discussion, this implies that there should have been a rise in the pace of reallocation throughout the last several decades as there are increased incentives for reallocation, but the evidence shows a decline in reallocation—especially in the post-2000 period. In other words, the time series pattern of the establishment-level productivity distribution, observed in detailed microdata, is inconsistent with the hypothesis that declining reallocation has been driven by changes in the distribution of productivity or profitability conditions faced by individual businesses.

To reconcile the observed facts, Decker et al. (2016a) show there has been a changing pattern of *responsiveness* of Manufacturing plants, in terms of employment growth and survival, to TFP shocks. They do this by estimating establishment-level regressions of employment growth on measured productivity, corresponding with the policy functions implied by firm dynamics theory. In the High Tech sector, responsiveness first increased through the 1990s and then sharply decreased in the post-2000 period.

13 As discussed in Decker et al. (2016a) the evolution of the dispersion in TFP may reflect endogenous factors including changes in the selection margin. For example, if the selection margin is reduced (i.e., low-productivity establishments are less likely to exit) then dispersion in TFP will rise. They show that for High Tech manufacturing, dispersion in TFP increased in the 1990s even when the selection margin became more strict (in the 1990s they find that low productivity plants were more likely to exit). This suggests the increase in dispersion in TFP in high tech more likely reflects a change in the dispersion of shocks. Note that this issue of endogenous changes in measured dispersion in productivity looms large in the analysis in section V of this paper. For labor productivity, not only are changes in the selection margin relevant but so are changes in adjustment frictions for continuing firms.

That is, the evidence shows that establishments with high realizations of productivity were more likely to survive and grow in the 1990s but became less responsive to productivity differences after 2000. The rise and decline in responsiveness in High Tech is especially pronounced for young firms. This pattern helps reconcile the rising and then declining pace of reallocation in the High Tech sector described previously.

The declining responsiveness to idiosyncratic productivity shocks implies the contribution of reallocation to productivity growth has declined: high-productivity businesses have become less likely to grow than they were before, and low-productivity businesses have become less likely to contract or exit than they were before, and the result is that movement of resources from lower- to higher-productivity businesses has slowed. The estimated changes in productivity responsiveness imply a decline in the contribution of reallocation to productivity growth in the High Tech sector exceeding more than 1 log point per year after the mid-2000s. That is, patterns of declining business dynamism are likely linked to slowing aggregate productivity growth, at least in the Manufacturing sector.

Many questions remain regarding the changing patterns of indicators of business dynamism and the implications for productivity. To start, most of the evidence of changes in business dynamism is based on the pace of job and worker reallocation. That is, the focus is employment as the margin of adjustment. It may be that the observed patterns reflect changes in the nature of the role of workers in the dynamics of businesses. For example, outsourcing and globalization may have changed the way that productive firms are expanding. It may be, for example, that it used to be the case that a highly productive young firm expanded domestically by hiring workers. Instead, it may be that expansion is now on other margins. Expansion may be via production overseas. Alternatively, expansion may be by machines rather than workers. Finally, expansion of a highly productive and innovative young firm may increasingly be via the young firm being acquired by a large firm who takes advantage of the innovation for its own operations.

Decker et al. (2016a), summarized in the previous subsection, make progress on some of these open questions for the Manufacturing sector. They find that the decline in productivity responsiveness in the post-2000 period is concentrated in sectors with the largest increase in the import penetration ratio from low-wage countries like China, particularly for High Tech firms. They also find that the decline in responsiveness of employment growth since 2000 is matched by a decline in the responsiveness in the rate of equipment investment, indicating that businesses have not simply substituted employment adjustment with machine adjustment.

B. Open Questions

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While these findings do not resolve the source of the rise and decline in the pace of business dynamism in the High Tech sector, the findings do rule out some hypotheses for this sector. First, the evidence does not support the hypothesis that the decline in the observed indicators of dynamism is the result of a change in the shock processes driving dynamism. Productivity differences in TFP across firms within detailed industries in High Tech are rising and not declining over the last several decades.

Second, the rise and decline of responsiveness of both employment growth and investment within firm age groups does not support the hypothesis that the patterns simply reflect a rise and decline in the pace of technological change in High Tech (see, e.g., Gordon (2016)). A rise and decline in the latter can potentially account for some aspects of the changing patterns of business dynamism and business formation rates.[14] However, a rise and then slowdown in the pace of technological change is difficult to reconcile with a changing pattern of responsiveness for young firms to a given or rising dispersion in productivity differentials across young firms. Differential growth between young firms that are high vs. low in the within- industry productivity distribution should presumably not change even if the overall pace of technological change has declined.[15]

If it is not a changing pattern of shocks or a changing pattern of industry-wide technological change then how should we interpret this evidence? This remains an open question, but it is consistent with some type of increase in firm-level adjustment frictions or potentially changing margins of adjustment as we have discussed above. An active area of research is to document and explore the possible sources of changes in frictions or margins of adjustment.[16]

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14 Jovanovic (1982) and Gort and Klepper (1982) both highlight that as mean expected profitability in a sector increases then entry rates should increase. In their models, mean expected profitability is positively related to the first moment of productivity within a sector. With a rise in entry rates, the share of young firms will increase and, in these models, young firms are the most volatile firms as they experiment and learn about their profitability. This class of models is consistent with rising dispersion in idiosyncratic profitability shocks accompanying an increase in the pace of technological change. Moreover, this class of models is consistent with an increase in overall responsiveness accompanying an increase in the pace of technological change as young firms respond more to productivity differences than mature firms in these models (given the high pace of learning for young firms). However, for a given dispersion in profitability shocks, these models cannot account for a changing pattern of responsiveness among young firms.

15 Decker et al. (2016a) also find that there is no change in the persistence of idiosyncratic shocks.

16 As mentioned above, Decker et al. (2016a) find suggestive evidence that patterns of globalization may hold clues to changing responsiveness, at least within the manufacturing sector. 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.

While the existing research described above sheds light on dynamism patterns in High Tech Manufacturing, all of these open questions apply to an even greater extent to the non- manufacturing economy. Much of the innovation that characterizes the U.S. economy, especially after 2000, has been in the Information sector (e.g., software publishing, internet portals and the like). Moreover, the patterns of changes in business formation and in the dispersion and skewness of firm growth rates are even more dramatic in the non-manufacturing components of High Tech. Relatively little is known about the connection between reallocation dynamics and productivity growth outside of Manufacturing.[17] In this paper, we make further progress on these open questions by exploiting a newly developed longitudinal firm microdata database that cover the entire U.S. private, non-farm economy. The data permit tracking both revenue growth and employment growth distributions. In addition, measures of labor productivity can be constructed so that the evolution of the dispersion in productivity across firms within narrow sectors can be analyzed. In turn, the changing patterns of responsiveness of growth and survival can be tracked in the context of the evolving firm-level productivity distribution.

We exploit these newly developed data in the remainder of the paper. A strength of the data is the comprehensive coverage of the U.S. private, non-farm sector from the mid-1990s to 2013. A weakness of the data is that the only measure of productivity that is feasible is labor productivity. This makes methodological approaches and interpretation of results more complex but, we think, still insightful. In this study, we show that the decline in dynamism and high- growth activity that is evident in employment data is also apparent in revenue data. We then document rising within-industry dispersion in firm-level labor productivity throughout the U.S. economy, consistent with evidence from Decker et al. (2016a) on TFP dispersion within Manufacturing industries described above. Finally, we estimate regressions, using data for the entire U.S. economy (and the High Tech sector specifically), relating firm-level employment growth with labor productivity, finding a weakening productivity/growth relationship that is consistent with the TFP evidence of Decker et al. (2016a) already discussed. We then exploit these model estimates to construct a series of counterfactuals to roughly quantify the implications of the weakening productivity/growth relationship for aggregate productivity. These exercises are made possible through the use of newly enhanced microdata that we describe next.

III. DATA

For our purposes we make use of a new revenue-enhanced version of the Longitudinal Business Database (RE-LBD). The RE-LBD integrates employment measures from the Longitudinal Business Database (LBD) with revenue 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 LBD is a longitudinal database of establishments and firms in the U.S. with paid employees. It is sourced from the Census Bureau Business Register (BR), which is the enumeration list for the Economic Census and the frame for business surveys (see Jarmin and Miranda (2002) for details of the LBD's

17 Exceptions include the numerous studies of Retail Trade cited above that highlight the shift in the business model towards large, national chains that has been productivity enhancing. See, e.g., Foster, Haltiwanger and Krizan (2006), Jarmin, Klimek and Miranda (2009) and Foster et al. (2015).

construction). LBD coverage begins in 1976 (and currently runs through 2013) and includes the private non-farm economy.

The RE-LBD incorporates the current version of the LBD. In the LBD, business establishments under common ownership are linked via a common firm identifier, the FIRMID. Longitudinal establishment identifiers allow us to track establishment opening and closings, firm startups and shutdowns, the acquisitions and divestitures of establishments as well as merger and acquisition activity at the firm level. Economic information featured in the LBD includes employment, payroll, detailed industry, and establishment location (county) among other items. Missing from the LBD are measures of output. Revenue is available in the Business Register but only at the tax unit level.

Enhancing the LBD with revenue measures is not trivial. The LBD is an establishment- level dataset whereas the annual revenue data are only available at the tax unit level, the Employer Identification Number (EIN).[18] For single location businesses, the EIN and the establishment units coincide. However, this is not necessarily the case for firms with multiple establishments.[19] For these firms we only have annual revenue at the higher EIN-level of aggregation. Not only will an EIN unit cover multiple establishments for a large firm, the firm may report under multiple EINs. The mapping of employment reports at the establishment and annual revenue reported at the EIN level is not always straight forward and can vary over time within a firm. Thus, given our interest in exploring employment and productivity dynamics this requires that we use a revenue-enhanced LBD that integrates measures of both employment and revenue at some minimum common level of aggregation, the firm. 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 (for details about the construction and integration of the revenue field into the LBD see the data appendix to Haltiwanger, Jarmin, Kulick and Miranda (2016)).

The RE-LBD allows us to track firm employment and revenue dynamics including job creation, job destruction and net employment and revenue growth by detailed firm characteristics including firm age, firm size, detailed industry and state. Revenue coverage begins in 1996 and runs through the end of the current LBD time frame (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). Haltiwanger, Jarmin, and Miranda (2013) provide a detailed description of the procedure applied to net out the results of merger activity in firm-level employment growth. Consistent with that approach (which is also used to construct the public-use Business Dynamics Statistics), startups are identified in the data by the entry of new firm identifiers (FIRMIDs) where all the establishments are new. New firms that are the result of M&A activity are assigned the age of the oldest establishment of the firm at the time of inception. Consistent with these criteria firm acquisitions are not considered deaths. A firm death takes place when the firm ceases to exist and all establishments shut down.

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18 The Economic Census conducted in years ending in “2” and “7” collects revenue data from a large sample of establishments although the revenue concept varies across industries.

19 Firms choose how to report their income and payroll activities to the IRS according to multiple criteria including geographic boundaries, tax status, type of activity, division or subsidiary. Often this results in multiple filings for different components of the firm with each filing possibly encompassing multiple establishments.

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.[20] This results in employment observations with missing revenue data. The RE-LBD sample excludes observations with missing revenue.[21] In addition revenue outliers are removed to ensure that the observations are suitable for analysis. This includes observations with unusually high or low labor productivity (real revenue per worker), revenue levels, or revenue growth/decline (different rules are used for different revenue segments). 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)).

Finally, firms can operate across multiple industries as reflected by establishment-level activity codes. The RE-LBD assigns a dominant activity for the firm (measured by employment) using consistent NAICS codes as constructed in Fort and Klimek (2016). We allow the firm NAICS code to change over time if the dominant activity of the firm changes.

In the analysis below, revenue measures are deflated with 3-digit NAICS gross output price deflators from BEA to generate a real revenue measure. This is the measure used in section IV below, where our interest is to compare and contrast patterns in the distribution of firm-level real revenue growth rates with the patterns for employment growth rates we have detected in prior work. This measure of real revenue growth can be interpreted as real gross output growth, but variation across firms does include firm and detailed industry (within 3-digit NAICS) changes in relative prices.

In section V, our objective is to construct a relative measure of firm-level labor productivity within detailed industries. Specifically, the measure we use is (the log of) real revenue per worker deviated from detailed (6-digit NAICS) industry-by-year means. 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. The use of a measure of relative gross output per worker within detailed industries mitigates but does not obviate the concerns of using this measure of productivity relative to using the more appropriate measure, TFP.

One potential limitation of our relative labor productivity measure is that large multi-unit establishment firms may be operating in multiple 6-digit NAICS industries. Our assignment of a firm to a single industry implies

20 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.
21 Approximately 20 percent of the firm-year observations do not have output measures.

a potential source of measurement error especially for such firms.[22] We note, however, 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. In turn our quantification of relative within-industry productivity dispersion and the growth/productivity relationship is very similar to findings that restrict attention to single unit establishment firms only. Multi-unit firms constitute a small share of firms but more than 50 percent of employment, so they are important for some of the counterfactual analysis below when we explore aggregate implications. We provide some further perspective on their role in our discussion of the counterfactual analysis below.

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. DECLINING DYNAMISM AND SKEWNESS IN THE GROWTH RATE DISTRIBUTION OF REAL REVENUE

An important question raised by the Decker et al. (2016b) study of employment growth rate distributions (summarized in section II.A.a) is whether post-2000 declines in gross job flows and the dispersion and skewness of firm employment growth rates have been accompanied by similar patterns in other measures of business dynamism. In particular, a key question is whether the decline of high-employment-growth activity at the firm level has been matched by adjustment on other margins, such as stronger high-growth activity when measured by real revenue. Declining high-employment-growth activity matched by stable or rising high-output- growth activity might suggest that observed changes in labor market dynamism are benign for productivity or reflect changes in business models that reduce labor demand while preserving profitability.[23]

The addition of real revenue to economy-wide business microdata allows us to shed light on this question; we find that patterns of real revenue growth dispersion and skewness have seen declines over the same period during which employment growth dispersion and skewness fell. We study the distribution of real revenue growth rates across firms for the period 1997 to 2013, the years for which we have real revenue data at the firm level.

For the analysis that follows, we employ a real revenue growth rate concept that is analogous to the employment growth rate developed by Davis, Haltiwanger and Schuh (1996) (hereafter DHS) which can accommodate entry and exit. That is, we define real revenue growth as follows:

$$g_{f,t+1}^{Y} = \frac{Y_{f,t+1} - Y_{f,t}}{0.5\left(Y_{f,t+1} + Y_{f,t}\right)} \qquad (1)$$

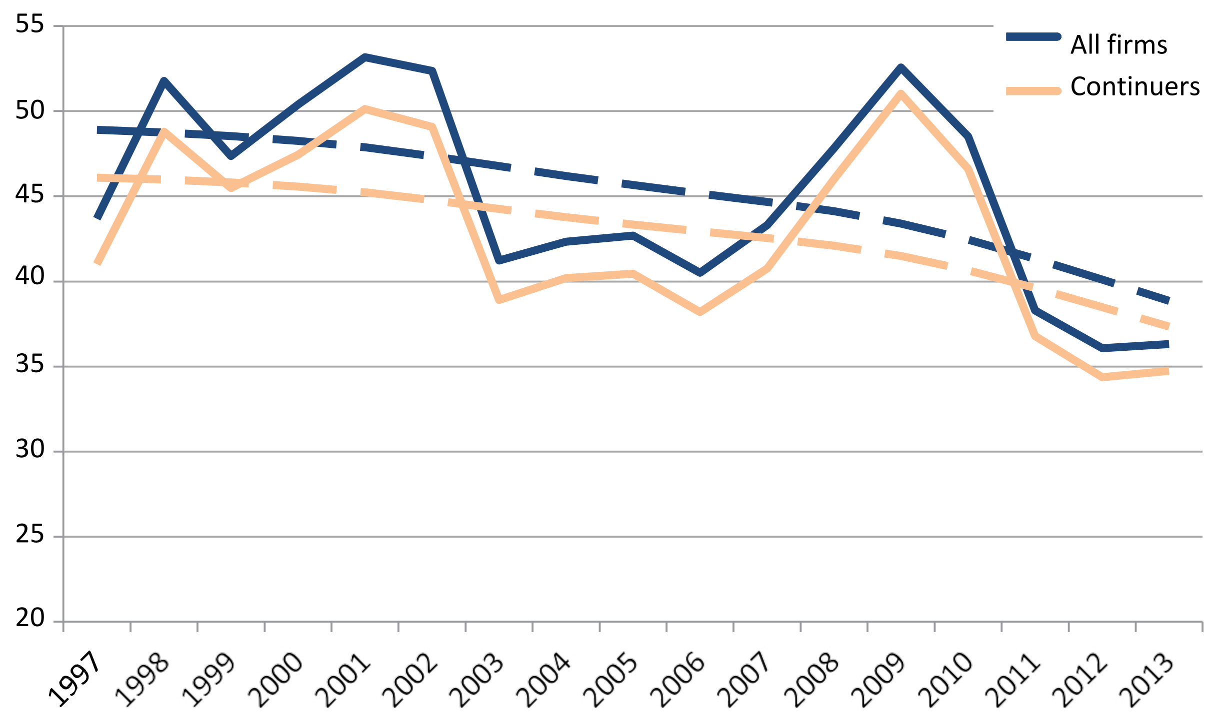
22 This limitation of assigning a single industry to firm-level observations is a common limitation of using firm-level data (e.g., COMPUTSTAT or ORBIS). We have the advantage that we have the underlying establishment-level data with detailed industries assigned at the establishment level and we know the employment distribution by industry across establishments in the same firm every year. We also have information in the Economic Census years about the sales distribution across establishments within the same firm. We can, in principle, exploit this information to construct measures of relative productivity that take into account the multi-industry activity of large, multi-unit firms. We plan to explore this in future drafts of the paper.

23 Guzman and Stern (2015) find a post-2000 decline in high-quality entrepreneurial outcomes such as high-dollar acquisition and initial public offering.

where $Y_{f,t+1}$ and $Y_{f,t}$ are the real revenue of firm f in years t+1 and t, respectively. The revenue growth measure $g^{Y}_{f,t+1}$ is bounded in the set [−2,2] and is a second-order approximation of the log difference for growth rates around zero. Its advantage relative to the log difference is that it can accommodate entry and exit (i.e., zeros in t or t+1).[24] For ease of exposition, we refer to real revenue as "revenue" in what follows.

Figure 2 shows the interdecile range (the difference between the 90th and the 10th percentiles) of the revenue-weighted distribution of firm-level annual revenue growth rates from 1997 to 2013 (note that the Y axis does not begin at zero).[25] We report this measure of dispersion separately for all firms and for continuing firms only (i.e., firms with positive activity in t and t+1). The solid lines show that this measure exhibits considerable cyclicality, but we also report Hodrick-Prescott (HP) trends since our aim is to understand longer-term developments in business dynamism.

Figure 2: Dispersion in firm real revenue growth rates



Note: Y axis does not begin at zero. Solid lines indicate the interdecile range (i.e., the difference between the 90th and the 10th percentiles) of the revenue-weighted distribution of firm revenue growth rates. Dashed lines reflect HP trends with parameter set to 100. Author calculations from the RE-LBD.

Measured by percentage points, the dispersion of revenue growth rates is considerable. Among continuing firms only, the 90th percentile firm had a growth rate more than 40 percentage points higher than the 10th percentile firm in 1997.[26] But a clear downward trend can be seen in this measure of revenue growth dispersion: from 1997 to 2013 the HP trend falls by about 10 percentage points for both continuers and all

24 Observe that this setup accommodates entry and exit by allowing $Y_{f,t} = 0$ (entry) and $Y_{f,t+1} = 0$ (exit), with $g^{Y}_{f,t+1} = 2$ and $g^{Y}_{f,t+1} = -2$, respectively.

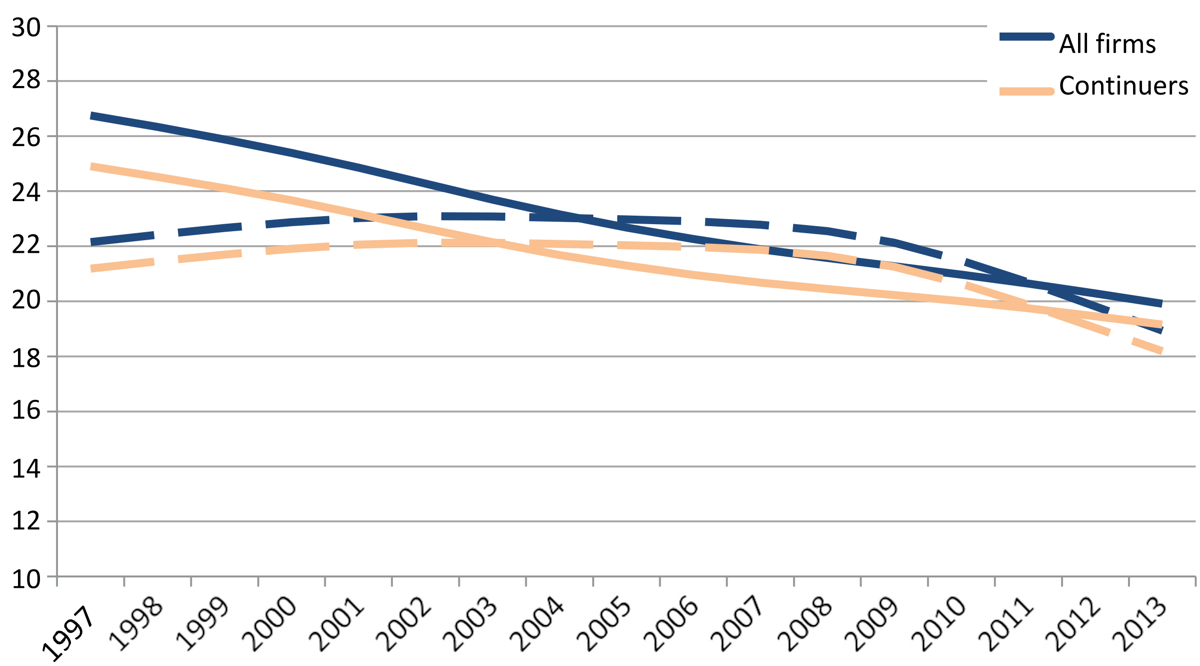
25 All results reported in the paper use RE-LBD propensity score weights as described in Section III. Also, all differences in percentiles use fuzzy percentiles where, for example, the 90th percentile is the average of 89th, 90th and 91st percentile.

26 Decker et al. (2016a) find even larger dispersion in employment growth rates; among continuers, the interdecile range of employment growth rates in 1997 was above 50 percent.

firms. That is, we see that declining business dynamism is reflected not just in measures of labor market dynamics, but in output-related statistics such as real revenue growth as well.

We further investigate this decline in revenue growth rate dispersion by decomposing the interdecile range into the 90-50 differential (the difference between the 90th and the 50th percentile) and the 50-10 differential (the difference between the 50th and the 10th percentile), reported on Figure 3. The relative magnitudes of the 90-50 and the 50-10 differentials provide an indicator of skewness or high-growth activity (note that the Y axis is again limited to illustrate the time series patterns). Consistent with the employment-based evidence of Decker et al. (2016b), we find a decline in the skewness of the revenue growth rate distribution. By 2004 and 2005 the skewness is completely gone.[27] In unreported results, we find that this decline does not only reflect the effects of the Great Recession, though the recession episode did involve a surge in the 50-10 differential. We conclude that, as in employment growth rate distributions, the decline in the dispersion of revenue growth rates reflects in part a decline in skewness and high-growth firm activity.

Figure 3: Skewness in firm real revenue growth rates



Note: Y axis does not begin at zero. Solid lines indicate 90-50 differential (i.e., the difference between the 90th and the 50th percentiles); dashed lines indicate the 50-10 differential (i.e., the difference between the 50th and the 10th percentiles). Data reflect HP trends with parameter set to 100. Author calculations from the RE-LBD.

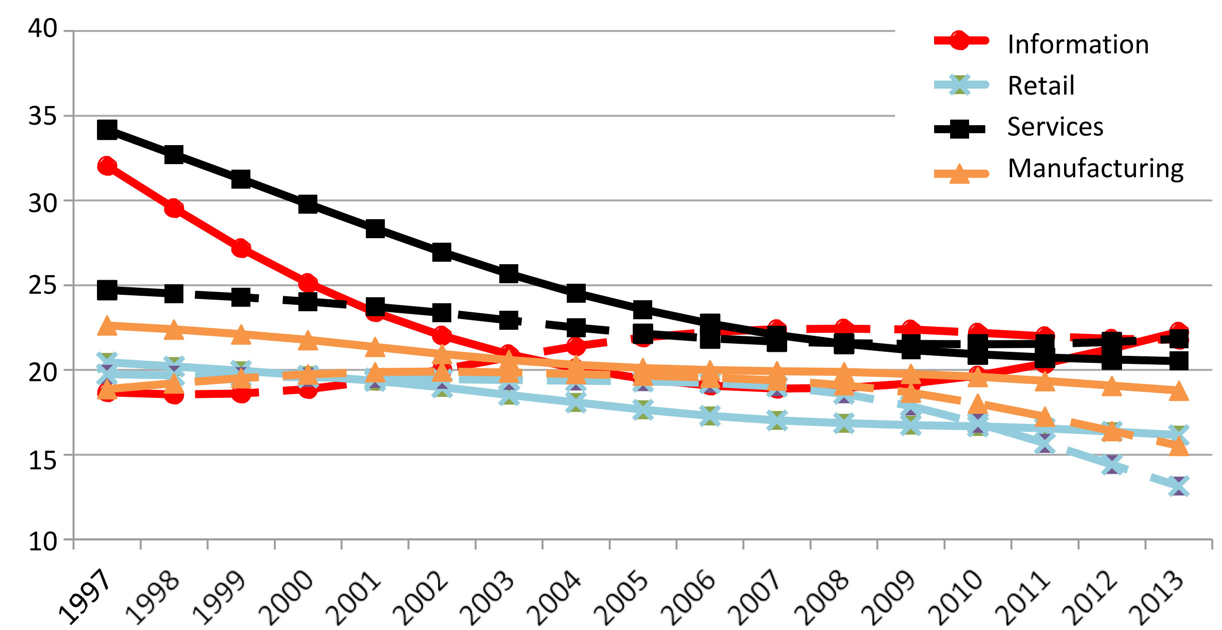
A contribution of Decker et al. (2016b) was to show substantial cross-sector variation in patterns of business dynamism over time. Figure 4 shows 90-50 and 50-10 differentials in revenue growth rates for selected sectors (Information, Retail Trade, Services, and Manufacturing). As in the employment data, sectors show considerable variation in revenue growth rate dispersion (recall that the interdecile range is the sum of the 90-50 and the 50-10 gaps); also consistent with employment data, this cross-sector variation declines over

27 This precedes the closing of the skewness in the employment growth distribution by a couple of years.

time.[28]

Figure 4 reveals substantial variation in revenue growth skewness patterns that is broadly consistent with Decker et al. (2016b) findings on employment growth. The Retail Trade sector exhibits no skewness throughout the 1997-2013 period, with Manufacturing showing only slightly more skew with a similar time series pattern. Information begins the late 1990s with significant skewness, suggesting the presence of strong high-revenue-growth firm activity, but this skewness is eliminated by 2003.[29] Services exhibits a similar pattern of initially high skewness that is absent by the mid-2000s. In general, cross-industry variation in patterns of business dynamism is present in both employment and revenue data, a potentially important fact for understanding causes behind aggregate patterns.

Figure 4: Skewness in firm real revenue growth rates, selected sectors



Note: Y axis does not begin at zero. Solid lines indicate 90-50 differential; dashed lines indicate the 50-10 differential. Data reflect HP trends with parameter set to 100. Sectors are defined on a consistent NAICS basis. Data include all firms (new entrants, continuers, and exiters). Author calculations from the RE-LBD.

Previous research established the importance of the High Tech sector for productivity and economic growth especially over the period of strong U.S. productivity growth during the 1990's. The Information sector can be a rough proxy for High Tech activity, but it also includes industries like newspapers, libraries, and book publishers that do not well capture the High Technology concept. We follow Hecker (2005) in constructing the High Tech sector based on the composition of an industry's workforce in terms of science, technology, engineering, and mathematics (STEM) workers. High Tech defined in this way includes NAICS industries in

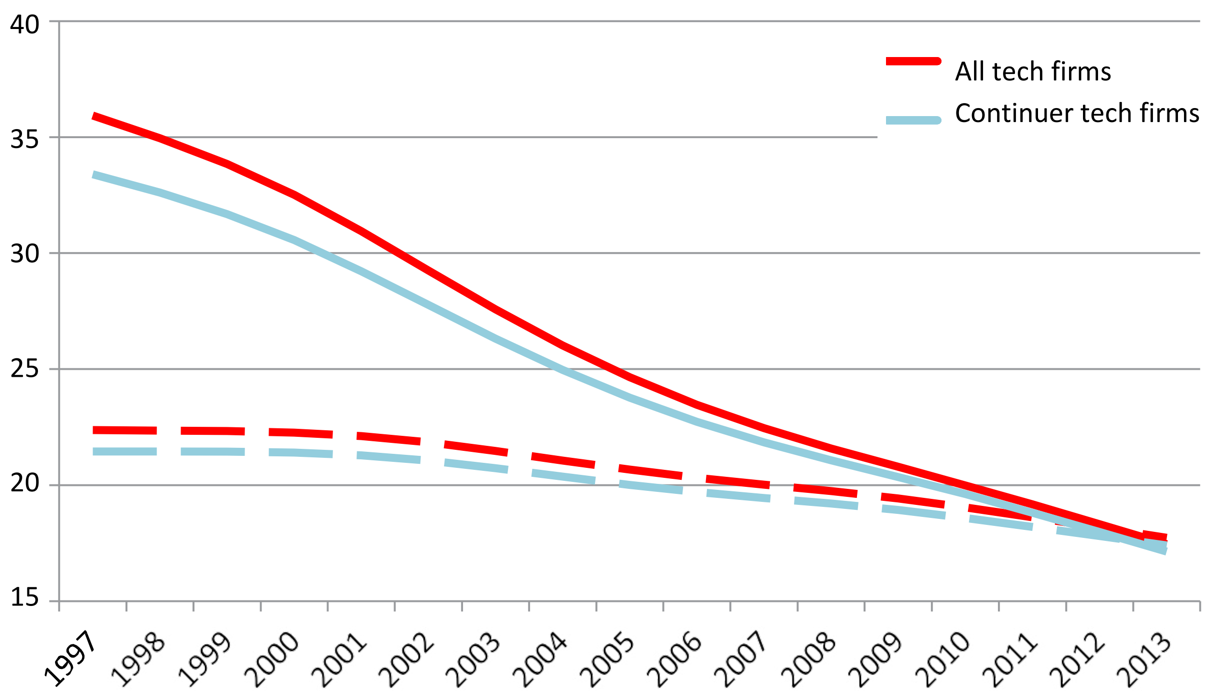
28 Decker et al. (2016b) find that the 1997 sector-level interdecile ranges of employment growth rates vary from about 40 percentage points for Manufacturing to just under 70 percentage points for Services. We find that the interdecile ranges of output growth rates vary from about 40 percentage points for both Manufacturing and Retail Trade to just under 60 percentage points for Services in 1997. That is, there is less cross-sector variation in output growth rate dispersion than there is in employment growth rate dispersion, but the former is still considerable. By 2011 (the last year for which Decker et al. (2016b) have data), output growth rate interdecile ranges vary from just over 30 percentage points (Retail Trade) to just over 40 percentage points (Services and Information), while employment growth rate interdecile ranges have a similar spread with Information at the bottom and Services at the top.

29 Notably, both dispersion and skewness of output growth in Information may be again rising by 2013.

Manufacturing, Information, and Services (see Decker et al. (2016b) for further details). We pay particular attention to High Tech even though it accounts for only about 7 percent of employment and 8 percent of gross output in the private sector. The reason is that the High Tech sector has played an outsized role in the productivity dynamics at the aggregate level (see, e.g., Fernald (2014)).

Figure 5 reports 90-50 and 50-10 differentials for both continuers and all firms in the High Tech sector. The figure reveals a striking pattern of skewness in the sector, which began the late 1990s at a very high level but diminished rapidly until disappearing entirely before 2008. High-growth activity (in terms of revenue) declined dramatically from its levels in the late 1990s and has not recovered as of 2013.

Figure 5: Skewness in firm real revenue growth rates in High Tech

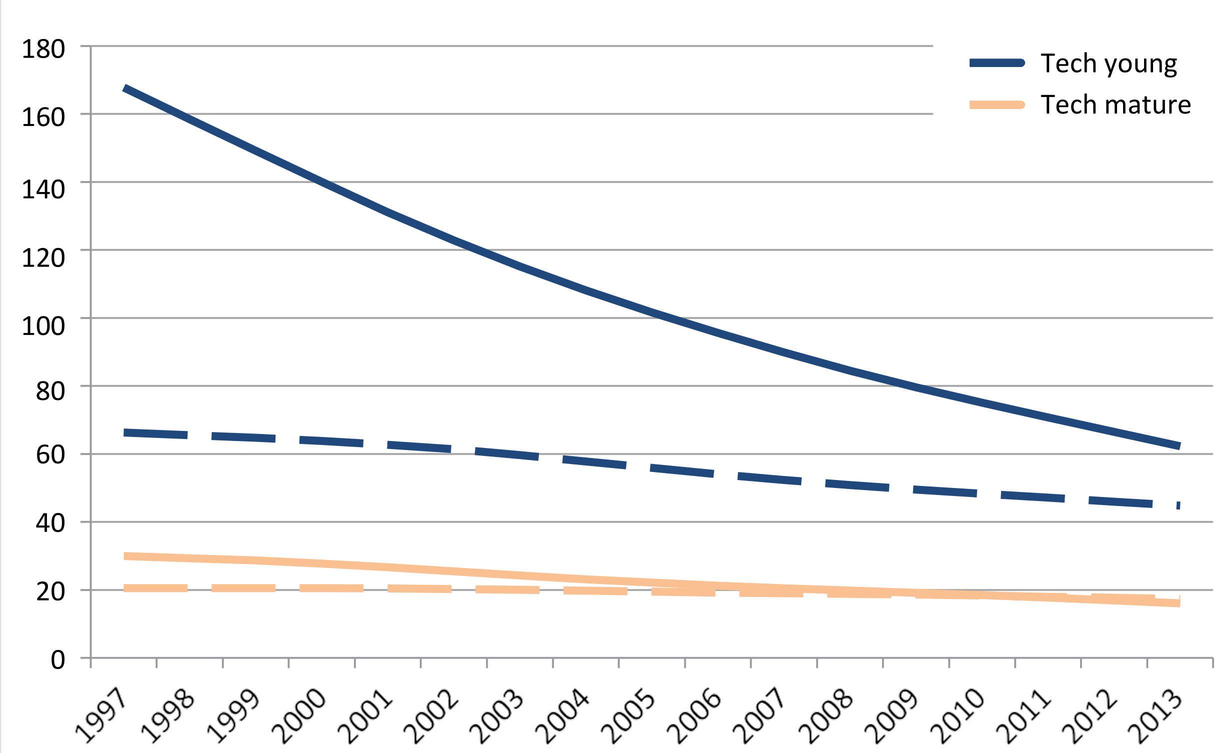


Note: Y axis does not begin at zero. Solid lines indicate 90-50 differential; dashed lines indicate the 50-10 differential. Data reflect HP trends with parameter set to 100. High Tech is defined as in Hecker (2005). Author calculations from the RE-LBD.

Figure 6a reports 90-50 and 50-10 gaps for both young (age less than 5) and mature firms in High Tech; Figure 6b does the same for continuing firms only. Consistent with evidence from employment growth data, Figure 6a shows that high revenue growth activity is primarily a characteristic of young firms (note that Figure 6a includes births and deaths). Skewness has declined among both young and old firms, among both continuers and all firms generally. The overall decline in high-growth activity in High Tech shown on Figure 5 reflects both a decline in skewness within age classes and a compositional shift toward older firms (not shown), though the entry margin appears to play a dominant role. In general the decline of high growth activity is very much present in the High Tech sector.

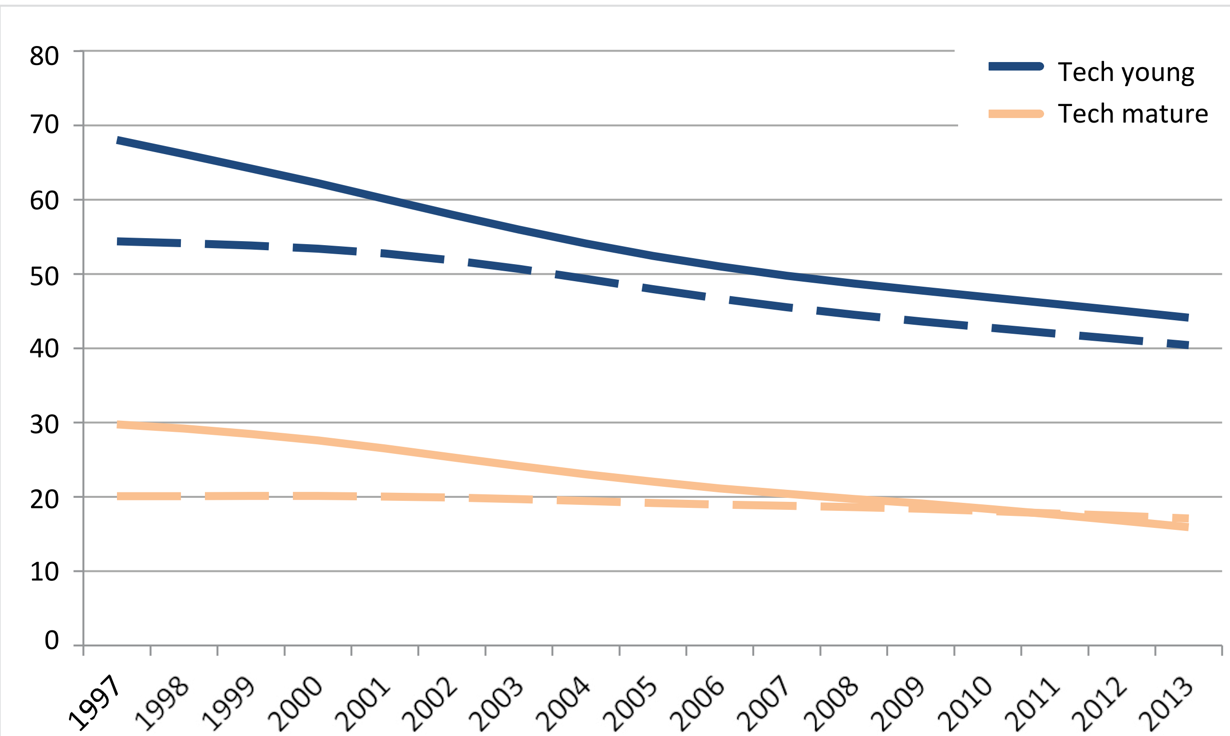
The above evidence and discussion suggest that the patterns in business dynamism seen in employment-based measures are broadly present in revenue data as well. Cross-sectional dispersion in business outcomes has narrowed, and this narrowing reflects in part a reduction in high-growth firm activity.

Figure 6a: Revenue growth skewness for the High Tech sector by firm age (all firms)



Note: Solid lines indicate 90-50 differential; dashed lines indicate the 50-10 differential. Data reflect HP trends with parameter set to 100. Young firms have age less than 5. High Tech is defined as in Hecker (2005). Author calculations from the RE-LBD.

Figure 6b: Revenue growth skewness for the High Tech sector by firm age (continuers)



Note: Solid lines indicate 90-50 differential; dashed lines indicate the 50-10 differential. Data reflect HP trends with parameter set to 100. Young firms have age less than 5. High Tech is defined as in Hecker (2005). Author calculations from the RE-LBD.

V. DECLINING DYNAMISM: IMPLICATIONS FOR PRODUCTIVITY

As discussed in Section II, we proceed with a framework guided by canonical models of firm dynamics. In short, changing patterns of job reallocation at aggregate levels can be the result of either changing patterns of "shocks" faced by firms (typically TFP shocks in model settings but could also reflect idiosyncratic demand shocks) or changing marginal responsiveness of firms to those shocks in terms of labor demand. This approach leads to simple empirical questions: have shock patterns changed, or has marginal responsiveness changed?

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: $g_{ft} = f_t(A_{ft}, n_{ft-1})$ 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. This implies that changes in the distribution of firm growth rates stem from either changes in the distribution of A_{ft} or the responsiveness of the firm to a given realization of A_{ft}. As discussed in more detail in Decker et al. (2016a) the latter can arise from changes in adjustment frictions (see, e.g., Hopenhayn and Rogerson (1993), Cooper and Haltiwanger (2006) and Elsby and Michaels (2013)).

As detailed in Section II, Decker et al. (2016a) investigate these questions in the Manufacturing sector with a particular focus on High Tech Manufacturing. The focus on that sector has the advantage of availability of the data needed to measure TFP, providing a reasonably clean mapping from the model framework discussed above to the empirical questions. However, a focus on Manufacturing leaves out the bulk of the U.S economy (and of the High Tech sector specifically, which includes industries in Information and Services in addition to Manufacturing).

In the present study, we focus on a labor productivity concept that stretches the "shocks" vs. "responses" methodology and interpretation of Decker et al. (2016a). Relative gross output per worker within industries (the measure of labor productivity we use in this section) is an endogenous object along many dimensions, reflecting not only TFP but also the endogenous intensity of other inputs such as capital. Perhaps even more importantly, changing dispersion in 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 A we provide a more formal treatment of these arguments). In any given period, firms have new realizations of TFP.[30] 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

30 As discussed in Decker et al. (2016a) empirical evidence supports treating firm-level TFP as being an AR1 process with a high variance of innovations and substantial persistence (between 0.6 to 0.8).

revenue product of labor are closely related (under Cobb-Douglas 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 in measured labor productivity.[31] 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.[32]

Investigating the responsiveness mechanism is more complex as well without direct measures of TFP, but 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 concerns, appropriate caution should be used in interpreting the results in this section. They can potentially be interpreted through the lens of the "shocks" vs. "responsiveness" perspective, but more cautiously the results here provide insights into the changing distribution of labor productivity across firms in the same industry and the changing covariance between realizations of labor productivity and firm survival and growth. Of particular relevance is that 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.[33] The advantage of the current relative to prior analysis is that we are able to study the entire High Tech sector and, indeed, the entire private nonfarm U.S. economy. With these limitations in mind, we proceed with our investigation.[34]

A. Patterns of productivity dispersion

Figure 7 reports the interdecile range (90-10 differential) of within-industry dispersion in labor

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31 It is this type of insight that have 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/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 A elaborates on these issues.

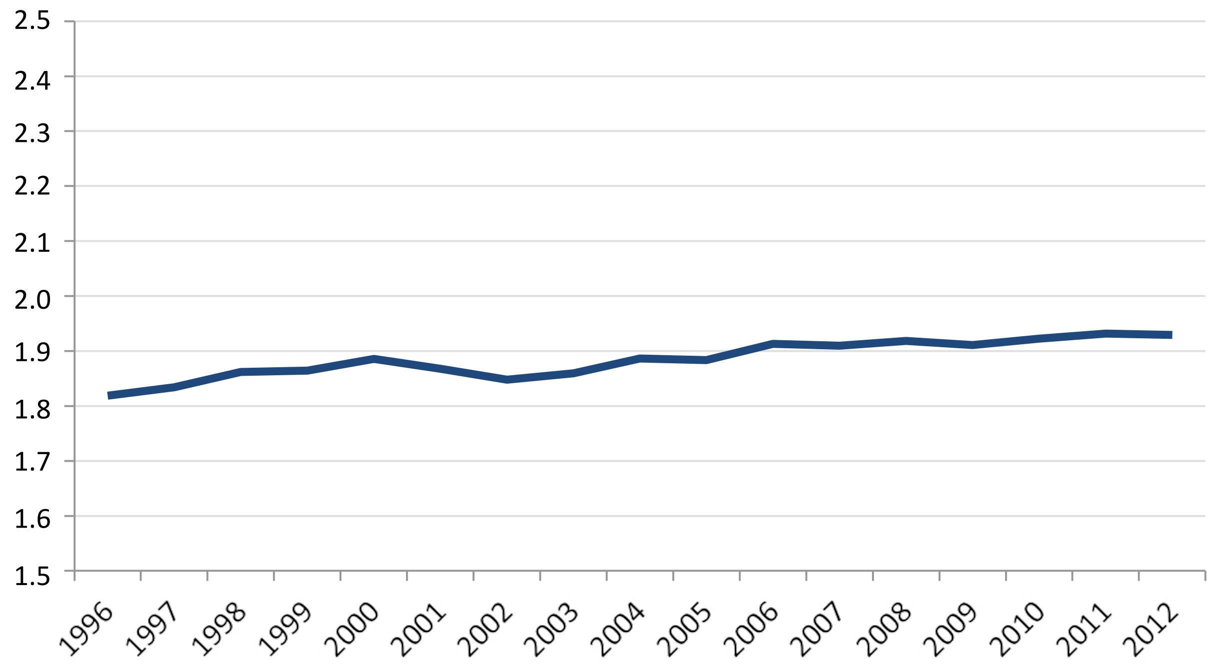
32 There may be other factors at work as well. For example, changes in the dispersion of capital intensity across firms in the same industry will yield changes in the dispersion of measured labor productivity. This could arise if there is some change in the production structure of firms. This may be relevant 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.

33 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.

34 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).

productivity.[35] It is useful to note that, as in related literature, we find considerable productivity dispersion even within detailed industries, with the productivity of the 90th percentile firm exceeding that of the 10th percentile firm by more than 180 log points in 1996.[36] Moreover, since the 1990s productivity dispersion for the U.S. economy as a whole has been rising rather than falling. The increase over the 1996 to 2012 period is substantial—the 90-10 differential increased by more than 10 log points. In 1996, the 90th percentile firm was about 6.2 times as productive as the 10th percentile firm; by 2012 that ratio was about 6.8.

Figure 7: Within-industry dispersion in labor productivity



Note: Y axis does not begin at zero. Data reflect interdecile range (i.e., the difference between the 90th percentile and the 10th percentile) of log labor productivity deviated from industry by year means. Author calculations from the RE-LBD.

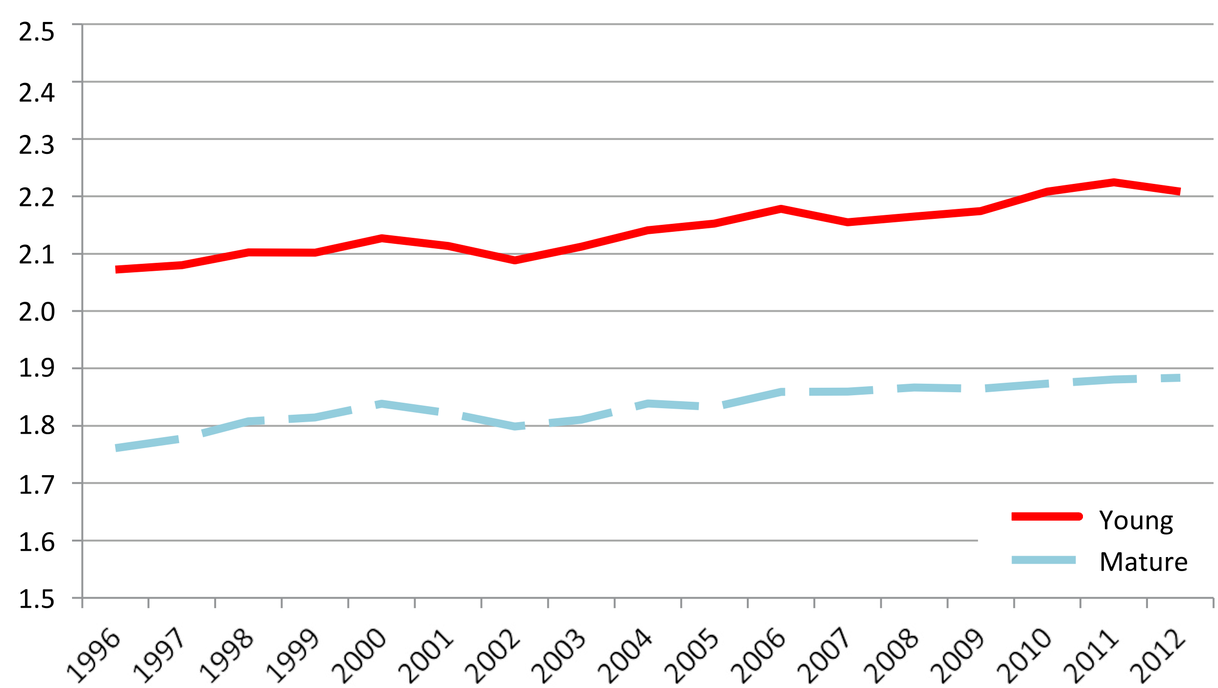
Drilling down on various slices of the data reveals a pervasive pattern of rising productivity dispersion. Figure 8 reports the productivity interdecile range for both young and mature firms. Productivity dispersion is much higher among young firms, but it is still considerable among mature firms. Dispersion rises among both age classes over the time period, with young firm dispersion reaching about 220 log points by 2012 (this suggests that young firms at the 90th percentile are an astounding nine

35 We use propensity score weights to control for the patterns of missingness in the revenue data but we don't use activity weights in the calculations of productivity dispersion. One measurement issue relates to our use of modal industry for multi-unit firms. Recall that we construct firm-level productivity as the log deviation of firm-level real revenue per worker from its industry-year mean (using 6-digit NAICS). Since over 95 percent of firms are single-unit establishment firms, the quantification of dispersion is overwhelmingly dominated by single-unit firms. In unreported results, we find that the dispersion patterns in Figure 7 are almost identical if we focus on single-unit establishment firms. We also find in unreported results that multi-unit establishment firms exhibit somewhat lower dispersion than single-units. We also note that we restrict attention to continuing firms in this section given that in the subsequent section we explore the relationship between growth and productivity for continuing firms.

36 This suggests that the 90th percentile firm is about six times as productive as the 10th percentile firm. These interdecile within-industry dispersion measures are very large but in line with other findings in the literature (see, e.g., Syverson (2004)).

times as productive as the young firms at the 10th percentile). The quantitative increase in the 90-10 differential for both young and mature firms is above 10 log points—representing a substantial increase in productivity dispersion.

Figure 8: Within-industry dispersion in labor productivity by firm age



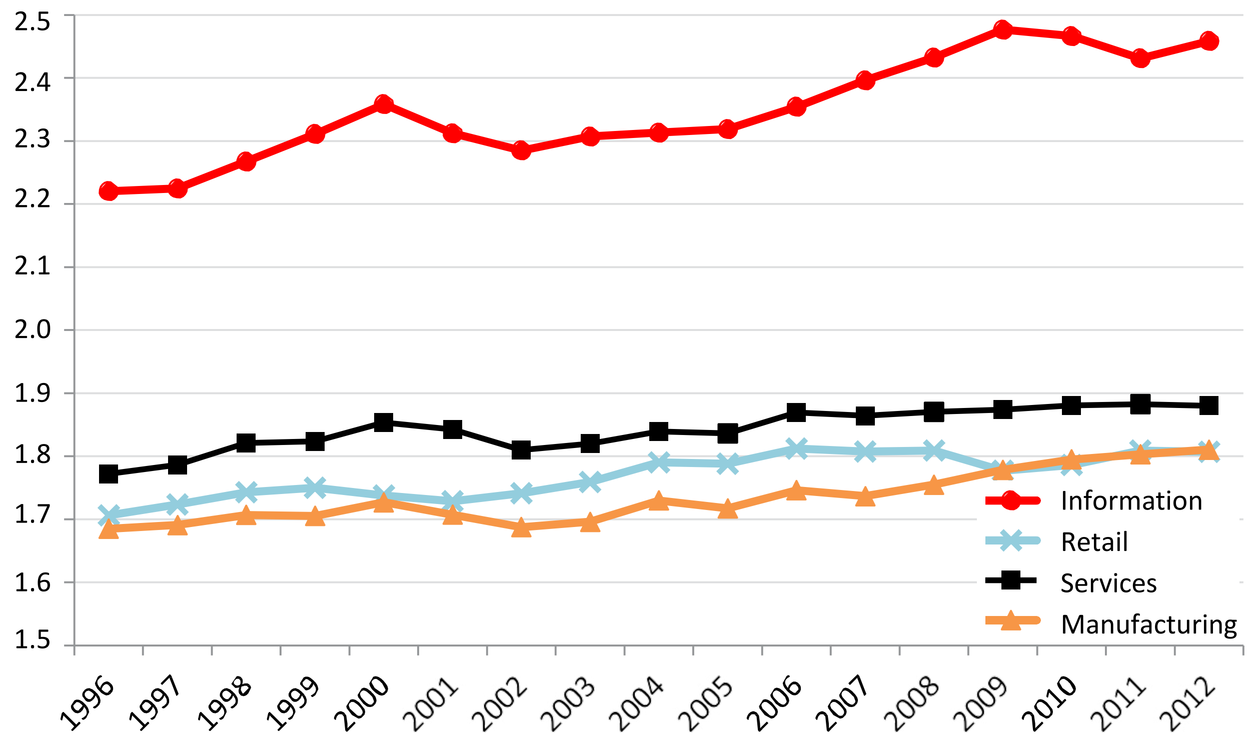
Note: Y axis does not start at zero. Data reflect interdecile range of log labor productivity deviated from industry by year means. Young firms have age less than 5. Author calculations from the RE-LBD.

In Figure 9, we report the time series of productivity dispersion broken up by broad NAICS sector. The Information sector is substantially more dispersed than other sectors; we find that this is (perhaps surprisingly) driven by the Information industries that fall outside of High Tech. The gap between the Information and the other sectors may be surprising in light of the results reported on Figure 4; that is, the Information sector is characterized by exceptionally high productivity dispersion, but the sector's revenue growth rate dispersion is not significantly higher than that of other sectors.[37] We discuss this finding in more detail below.[38]

All sectors show considerable within industry productivity dispersion, and all show an upward trend since the late 1990s. Figure 10 reports results for High Tech only, broken up by age. Again we see that young firms are more dispersed than mature firms. The slope of the young firm series is relatively steep, reflecting significantly increased dispersion since the 1990s. For young firms, the increase in the 90-19 differential is more than 20 log points. In unreported results, we find upward-trending dispersion in both the High Tech and Nontech portions of the U.S. economy. We also find increased dispersion among both the High Tech and Nontech components of each of Manufacturing, Services, and Information.

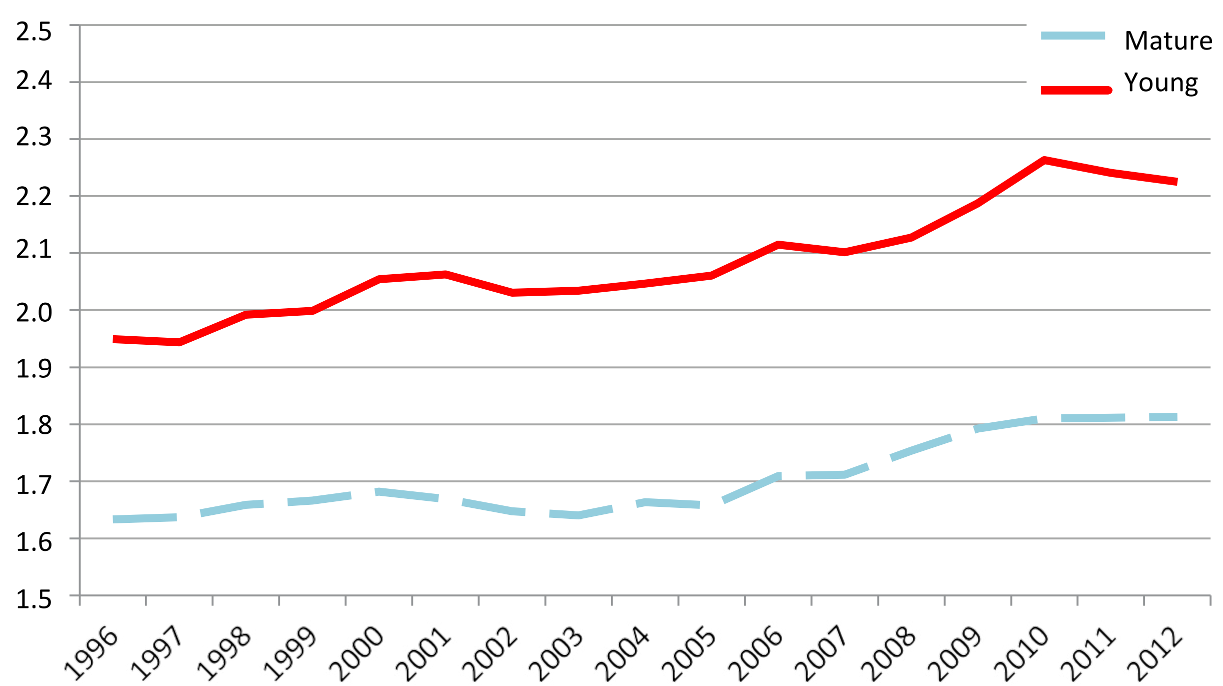
37 Decker et al. (2016b) show that Information also does not have exceptionally high employment growth rate dispersion.
38 The Information sector is characterized by a weaker relationship between productivity and growth than other sectors. This dampens the correlation between productivity dispersion and output (and employment) growth dispersion.

Figure 9: Within-industry dispersion in labor productivity, selected sectors



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 10: Within-industry dispersion in labor productivity by firm age, High Tech



Note: Y axis does 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.

Our finding of rising 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 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.[39] 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.[40] 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 Foster et al. (2004) for earlier empirical treatments of the subject).

What do we make of the findings in this subsection? The evidence does not support the hypothesis that the declining pace of reallocation is due to declining dispersion of idiosyncratic shocks. Instead, the findings are consistent with either an increase in the dispersion of idiosyncratic productivity shocks or an increase in adjustment frictions or both. In the next section, we investigate the changing covariance structure between labor productivity and growth that sheds further light on these issues.

B. The changing relationship between firm production and growth

As emphasized by Syverson (2011), one of the most ubiquitous findings in the literature is that firms with high idiosyncratic realizations of productivity are more likely to survive and grow. This basic finding has been shown to hold in a wide variety of settings including using labor productivity as the measure of productivity. In this section, we explore whether the relationship between labor productivity and growth at the firm level has changed over time. As noted above, we view this as providing new basic facts about the covariance structure between labor productivity and growth.

For this purpose, we estimate regressions relating employment growth from t to $t+1$ and measured labor productivity in period t with appropriate controls. We define employment growth for firms between

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39 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 Decker et al. (2016a), which relies on total factor productivity in manufacturing industries). 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.

40 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.

periods t and t+1 using the DHS concept (see equation (1) and surrounding discussion) that accommodates, in principle, entry and exit:

$$g^E_{f,t+1} = \frac{E_{f,t+1} - E_{f,t}}{0.5\left(E_{f,t+1} + E_{f,t}\right)} \tag{2}$$

where $E_{f,t+1}$ and $E_{f,t}$ are employment at firm f in years t+1 and t, respectively. For this analysis of changing responsiveness, we restrict our attention to continuing firms (firms with positive employment in t and t+1). In this respect, our findings on changing responsiveness reflect factors such as changes in adjustment frictions that impact the growth rate of continuing firms.[41]

Using various groupings of our data, we estimate the following regression:

$$\begin{aligned} g^E_{f,t+1} = \lambda_{t+1} &+ \beta_y * LP_{ft} * Young_{ft} + \delta_{1y} * LP_{ft} * Young_{ft} * Trend_t \\ &+ \delta_{2y} * LP_{ft} * Young_{ft} * Trend_t^2 \\ &+ \beta_m * LP_{ft} * Mature_t + \delta_{1m} * LP_{ft} * Mature_{ft} * Trend_t \\ &+ \delta_{2m} * LP_{ft} * Mature_{ft} * Trend_t^2 + X'_{ft}\Theta + \varepsilon_{f,t+1} \end{aligned} \tag{3}$$

where $g^F{}_{f,t+1}$ is the DHS employment growth rate of continuing firm f between years t and t+1 defined in (2), LP_{ft} is labor productivity for firm f at time t (recall this is log real revenue per worker for the firm deviated from a detailed 6-digit NAICS industry by year mean), $Trend_t$ is a simple linear time trend (which we also include as a quadratic term in some specifications), $Young_{ft}$ is a dummy equal to 1 if firm f is young (age less than 5) in year t, $Mature_{ft}$ is a dummy equal to 1 if firm f is mature (age 5 or greater) in year t, and X_{ft} is a set of controls. The X_{ft} vector includes firm size, year effects which capture the national cycle and trends, and the change in state unemployment rates to control for local business cycle effects. We interact the latter with our productivity measure to permit the marginal response of growth to productivity to change over the cycle (this is the focus of Foster et al. (2016)). The $Trend_t$ terms do not enter as main effects because we include a full set of year effects; these capture general trends as well as national cyclical effects. Importantly, the inclusion of the $Trend_t$ variable allows us to estimate a time-varying relationship between productivity and growth; in exercises described following our discussion of the regression analysis, we exploit this time-varying relationship to understand the changing contribution of reallocation to aggregate productivity growth.

We estimate equation (3) using our RE-LBD propensity score weights but otherwise we do not estimate activity-weighted regressions. Since over 95 percent of firms are single-unit establishment firms, we find in unreported results that all of the findings in this section are robust to restricting analysis to single unit establishment firms.[42] All of the terms involving labor productivity are fully saturated with young and mature

41 In future drafts we will also consider the exit margin as we have in Decker et al. (2016a). Preliminary results show that the exit margin also becomes less responsive to productivity so that the overall DHS growth rate inclusive of the exit margin becomes less responsive to productivity. This implies that the reduction in the contribution of reallocation is larger taking into account the less responsive exit margin as well.
42 We also find in unreported results that multi-unit establishment firms exhibit declining responsiveness.

dummies, as the evidence on the dispersion of productivity, employment, and output growth suggests systematic differences in the relevant dynamics of young and mature firms.

The regression in (3) is motivated by the policy functions that emerge from canonical models of firm dynamics discussed above. In applying this logic to annual data, we estimate the relationship between growth between t and t+1 based on the realization of productivity in period t. Using lagged productivity helps mitigate concerns about the endogeneity of labor productivity. As we have noted, we are exploiting only labor productivity differences within industry by year. Between-industry differences in indicators of productivity and profitability are likely also important, but we do not have good measures of such variation.

We focus on employment growth as the outcome since it is the only endogenous factor for which we observe changes at the firm level for the entire non-farm private sector. Decker et al. (2016a) examine both employment growth and equipment investment in a similar setting. The advantage of that prior work is that TFP is used as the indicator of productivity. The disadvantage is that the prior work is restricted to the Manufacturing sector.

The parameters β_y and β_m are important for our analysis because they reflect the relationship between productivity and firm growth (for young and mature firms, respectively). Theory and previous empirical research both suggest that these parameters should be positive and significant, indicating that high-productivity firms grow while low-productivity firms contract.[43] Aggregate (industry-level) productivity growth depends in part on these mechanisms.

Our main question of interest is whether the productivity/growth relationship has changed over time. The answer will be determined by the parameters δ_{1y} and δ_{1m}, the coefficients on the interaction between productivity and the time trend. A weakening productivity/growth relationship would be indicated by negative values of these parameters.[44] Note that we also allow for nonlinear behavior in this relationship with the quadratic terms associated with the parameters δ_{2y} and δ_{2m}.

Table 1 reports results of the regression from (3) for all firms and for the High Tech and Nontech sectors separately.[45] Columns 2, 4, and 6 include estimated quadratic terms (parameters δ_{2y} and δ_{2m}), while columns 1, 3, and 5 allow only the linear trend effect. In all specifications, 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 (as shown by the first two rows of coefficients). This finding is consistent with existing literature (e.g., Syverson (2011)). The productivity/growth relationship is stronger for young than for mature firms, though not dramatically so (Decker et al. (2016a)) find a larger difference between young and old firms for the responsiveness to TFP differences). We also find that the productivity/growth relationship is stronger among High Tech firms than for the rest of the economy.

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43 Recall that productivity is measured as the (log) deviation of firm-level labor productivity from its industry-year mean, reflecting the notion that the productivity/growth relationship should depend on the competitive environment faced by individual firms in their own industries.

44 Decker et al. (2016a) find negative values for these parameters when applied to TFP in the Manufacturing sector (with particularly notable patterns in High Tech Manufacturing).

45 All regressions include year t observations for the years 1996-2012 and, consistent with the other analyses in this paper, omit the Finance, Insurance, and Real Estate sectors (NAICS 52-53).

Table 1: The relationship between firm growth between period *t* and *t*+1 and the realization of productivity in period *t*, all firms and High Tech

	All firms	All firms	High Tech	High Tech	Nontech	Nontech
prod*young	0.1506***	0.1485***	0.1714***	0.1890***	0.1494***	0.1465***
	0.0002	0.0003	0.0009	0.0013	0.0002	0.0003
prod*mature	0.1267***	0.1267***	0.1571***	0.1648***	0.1256***	0.1253***
	0.0002	0.0002	0.0008	0.0013	0.0002	0.0002
prod*trend*young	-0.0027***	-0.0019***	-0.0055***	-0.0119***	-0.0025***	-0.0014***
	0.0000	0.0001	0.0001	0.0004	0.0000	0.0001
prod*trend*mature	-0.0018***	-0.0018***	-0.0032***	-0.0059***	-0.0018***	-0.0017***
	0.0000	0.0001	0.0001	0.0003	0.0000	0.0001
prod*trend^2*young		-0.0001***		0.0004***		-0.0001***
		0.0000		0.0000		0.0000
prod*trend^2*mature		0.0000		0.0002***		0.0000**
		0.0000		0.0000		0.0000
N	49806000	49806000	2363000	2363000	47443000	47443000
R^2	0.0878	0.0878	0.0937	0.0937	0.0877	0.0877

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

Notably, we find a negative and statistically significant declining trend in the strength of the productivity/growth relationship. This negative trend is typically stronger among young firms than among mature firms, suggesting a tendency toward convergence of the productivity/growth relationship between firms of different ages. That is, young firms increasingly resemble mature firms in terms of the degree to which firm-level growth is related to firm-level productivity. We also find that the weakening trend is more pronounced in the High Tech sector than elsewhere. Broadly speaking, the evidence suggests that the growth differential between high- and low-productivity firms in the High Tech sector is declining over time.

Table 2 reports regression results by broad sector. As indicated by the first two rows of coefficients, a significant productivity/growth relationship exists in each sector among firms of all ages; this relationship is strongest in Retail Trade and weakest in Information. The weak relationship in Information is consistent with previously discussed evidence that productivity dispersion is exceptionally high in Information but growth rate dispersion (of either output or employment) is generally within the range of other sectors. That is, the wide productivity dispersion that exists in Information does not imply wide dispersion in output or employment growth because the productivity/growth relationship is weaker in that sector. Also note that the productivity/growth relationship is weaker in Information than in the High Tech sector (reported on Table 1), again suggesting fundamental differences between the High Tech and Nontech components of Information.

Table 2: The relationship between firm growth between period *t* and *t*+1 and the realization of productivity in period *t*, selected sectors

	Manufacturing	Retail	Information	Services
prod*young	0.1607***	0.1732***	0.1452***	0.1479***
	0.0011	0.0006	0.0025	0.0005
prod*old	0.1473***	0.1354***	0.1356***	0.1245***
	0.0008	0.0005	0.0023	0.0004
prod*trend*young	-0.0034***	0.0009***	-0.0090***	-0.0025***
	0.0003	0.0002	0.0007	0.0001
prod*trend*old	-0.0013***	-0.0007***	-0.0058***	-0.0012***
	0.0002	0.0001	0.0006	0.0001
prod*trend^2*young	-0.0001***	-0.0002***	0.0002***	-0.0001***
	0.0000	0.0000	0.0000	0.0000
prod*trend^2*old	-0.0001***	-0.0001***	0.0002***	0.0000***
	0.0000	0.0000	0.0000	0.0000
N	3660000	11031000	447000	22137000
R^2	0.0987	0.1023	0.0819	0.0795

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

Again we find a declining trend in the productivity/growth relationship in most sectors. The interesting exception is Retail Trade, where the trend is actually slightly positive among young firms and negative among mature firms (though the quadratic term suggests that the positive trend among young firms is diminishing). Retail Trade is therefore characterized by an exceptionally high productivity/growth relationship but a much weaker trend in this relationship than other sectors. The trend decline is remarkably rapid in the Information sector, where the trend coefficients for both young and mature firms are more than twice as large as in any other sector.

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 decline in this relationship is particularly pronounced in the High Tech sector. Due to the limitations discussed above regarding the use of gross labor productivity, appropriate caution is needed to interpret these results. However, based on the firm dynamics model framework discussed above, our estimates suggest that declining rates of job reallocation are related to changes in the firm-level relationship between growth and idiosyncratic productivity rather than changes in patterns of productivity or profitability dispersion.

Putting the results together from the last two sub-sections, we have produced evidence that dispersion in labor productivity has increased over time while the covariance between labor productivity in period t and firm (employment) growth between t and t+1 has decreased. As discussed above, these findings are likely related as an increase in adjustment frictions is consistent with both. In the exercises that follow, we investigate the implications of these changes in firm-level behavior for aggregate productivity growth.

C. Implications for aggregate (industry-level) 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 firms. Our analysis above is very much about such shifts, a fact that we now exploit in a simple counterfactual exercise to provide some perspective on aggregate implications.

Our estimates described above suggest that there has been a statistically significant weakening in the relationship between idiosyncratic differences in firm-level productivity within industries and differences across firms in employment growth. We now attempt to roughly quantify the substantive magnitude of this estimated trend decline by analyzing what it implies for the contribution of job reallocation to aggregate (industry-level) productivity growth. Given that we estimated our growth/productivity relationship for continuing firms, the exercises in this section focus on the changing contribution of reallocation to productivity growth for continuing firms.

For each year, we compute a base year (industry-level) productivity index as follows:[46]

$$LP_t = \sum_f \theta_{ft} LP_{ft} \tag{4}$$

where θ_{ft} is the employment weight for firm f in year t, and LP_{ft} is firm-level productivity (log deviation from industry-year mean). This construction of aggregate productivity readily lends itself to shift-share counterfactuals. We use the estimated regression models described above to generate a counterfactual index given by:

$$LP_{t+1}^C = \sum_f \theta_{f,t+1}^C LP_{ft} \tag{5}$$

46 This type of productivity index has been actively used in the literature. See Baily, Bartelsman and Haltiwanger (2001) and Foster, Haltiwanger, and Krizan (2001, 2006). This yields measures of labor productivity at the industry and aggregate level that track standard labor productivity measures (e.g., those from BLS) well. In unreported results we find that the index from (4) aggregated to the economy-wide level matches BLS labor productivity patterns quite well. Much of the literature uses various types of shift share decompositions to consider within- and between-firm components of aggregate productivity growth. In this sub-section, we do something related but instead of a simple accounting decomposition, we use the estimated models of the relationship between firm growth and productivity to generate counterfactual estimates of the contribution of reallocation under different scenarios. Specifically, the difference in the contribution using the covariance relationship at the beginning of the sample vs. the contribution using the trend changes in the covariance relationship from Tables 1 and 2. We also note that in this exercise that multi-unit establishment firms play a potentially important role since this is an activity-weighted exercise. Our regression specifications control for firm size but one might want to permit the changing responsiveness to differ between single unit and multi-unit establishment firms. We will consider such specifications in future drafts. We note, however, that in unreported results we find in specifications of the regressions where estimated coefficients are permitted to vary by multi-unit status that we find that multi-unit establishment firms exhibit similar patterns of declines in responsiveness as single-units. This suggests that our current specifications are likely robust to consideration of this potential source of heterogeneity in changing responsiveness.

where $\theta^{C}{}_{f,t+1}$ is the predicted employment share for firm f in year t+1 based upon the estimated model. In other words, the regression model provides a prediction for employment growth of every firm 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 for every firm. We conduct this exercise by setting business cycle effects to zero, and we use the model specifications that include quadratic terms for the trend variable (the linear models produce nearly identical results).

Given that we use firm-level productivity measured as deviations from within industry-by-year means, this calculation yields an estimate of the implied increase in within-industry productivity from reallocation effects alone. Moreover, since the firm-level distribution of productivity is held constant (in each year) for this exercise, the change only reflects the interaction of the predicted changes in the distribution of employment with where firms sit in the within-industry productivity distribution.

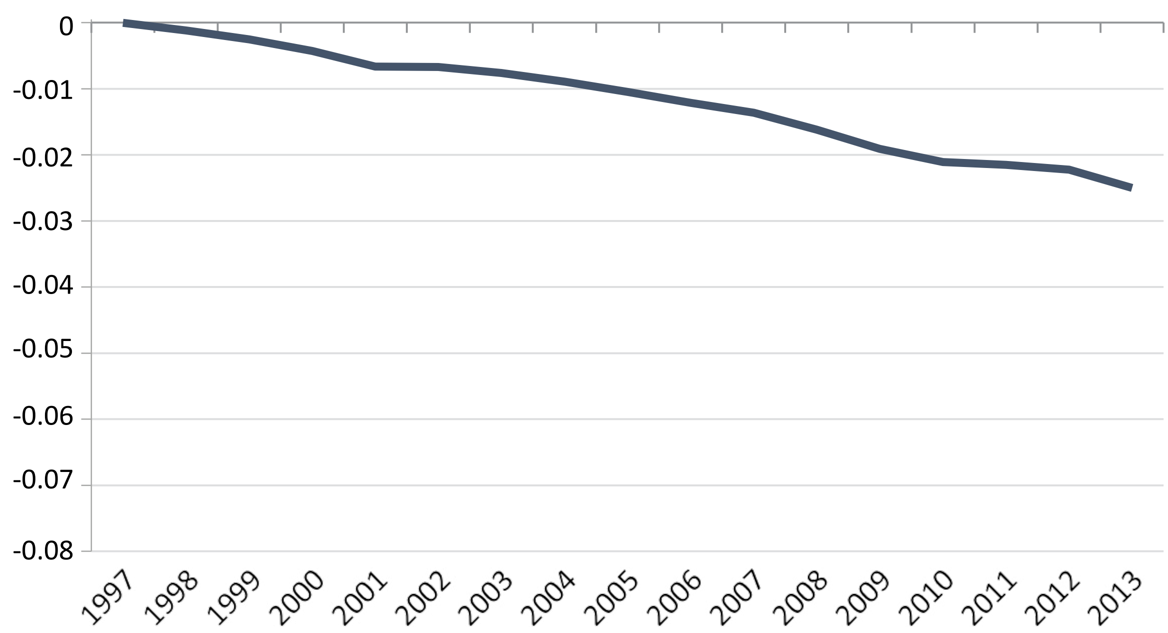
Productivity gains from model-driven reallocation are given by $LP^{C}{}_{t+1} - LP_t$, that is, the difference in aggregate productivity that results only from reallocating employment between firms of varying productivity according to model growth predictions while holding the unweighted distribution of productivity constant. We construct two different model counterfactuals to study the substantive effect of the trend decline in the productivity/growth relationship. First we construct the gains from reallocation using the full model including the estimated trend effects. Then we construct the gains from reallocation based on the model but omitting the trend effects, that is, leaving the productivity/growth relationship at its 1997 level. The difference between these two quantities reflects the gap between counterfactual aggregate productivity with and without the declining trend in the productivity/growth relationship. The exercise can be concisely described as follows:

$$\Delta_t^{t+1} = \left(LP_{t+1}^{C,trend} - LP_t\right) - \left(LP_{t+1}^{C,no\ trend} - LP_t\right) \tag{6}$$

where $LP_{t+1}^{C,\ trend}$ is the counterfactual model-based aggregate productivity that includes trend effects, and $LP_{t+1}^{C,\ no\ trend}$ is the counterfactual model-based aggregate productivity that excludes the declining trend in the strength of the growth/productivity relationship. This "diff-in-diff" counterfactual can be computed for every year and can be thought of as a rough estimate of the degree to which the weakening relationship between productivity and growth at the firm level can account for slowed productivity growth.

Figure 11 reports this counterfactual exercise for the whole economy (excluding Finance, Insurance, and Real Estate). Each annual observation reports $\Delta_t{}^{t+1}$, or the amount by which the trend effects in the regression model have reduced reallocation-driven productivity growth from year t to t+1. For example, the observation for t+1=1997 has $\Delta_t{}^{t+1}$+1=0 because the trend variable begins then. But the 2004 observation shows that the model-generated productivity growth from 2003 to 2004 would have been about 1 log point higher ($\Delta_t{}^{t+1}$+1=−0.01) if the adjustment dynamics immediately reverted to the stronger responsiveness in 1997 given the dispersion in productivity in 2003.

Figure 11: Reduction in contribution of reallocation to productivity from reduced responsiveness



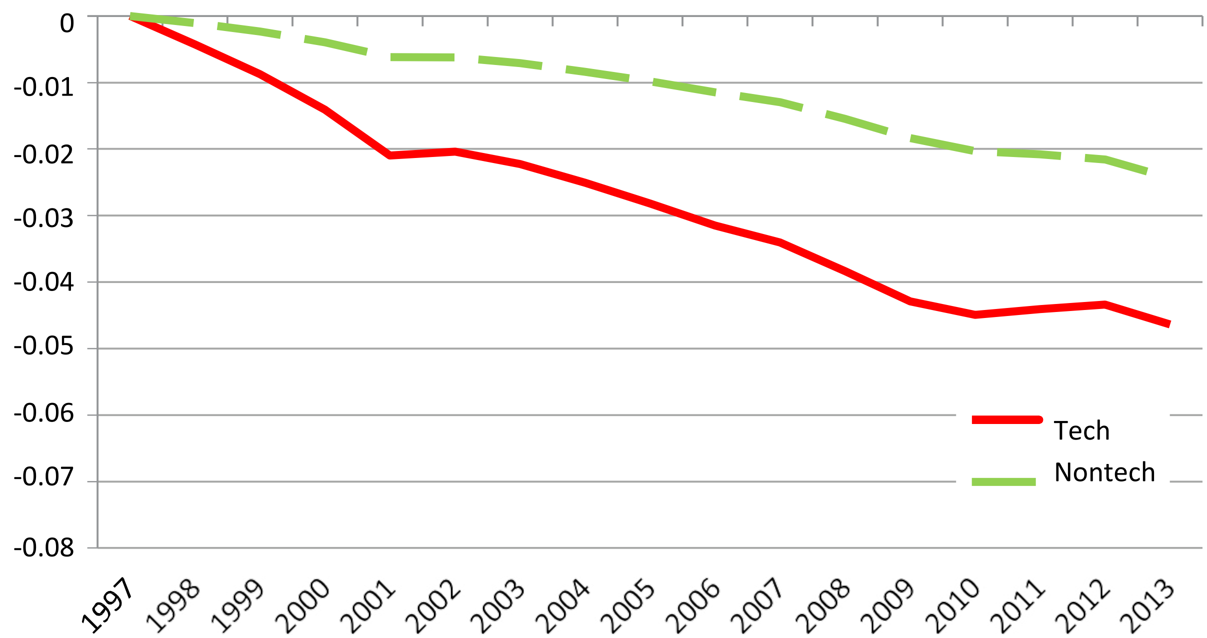
Note: Corresponds with counterfactual productivity difference-in-difference estimates based on regression reported on Table 1 column 2. Data from the RE-LBD.

This estimate potentially reflects cumulative factors. To understand this, consider an increase in adjustment frictions as the source of the reduced covariance between firm growth and the realization of productivity. As adjustment frictions increase, dispersion in labor productivity will endogenously increase over time for reasons discussed above. Such effects will cumulate over time reflecting both current and cumulative past shocks that have not been adjusted to (or have been adjusted to less than in the past). 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 labor productivity, which is in part driven by previous adjustment dynamics.

By 2013, the slower implied adjustment over time has potentially built up substantially increased dispersion in labor productivity. As such, there are large potential gains from reverting to the rapid responsiveness of the late 1990s applied to the wide dispersion of productivity in 2012. The productivity differentials generated by the counterfactual is about 2.5 log points by 2013. After taking advantage of these immediate gains, the gains would not persist as more rapid adjustment would imply a reduction in the dispersion in labor productivity. If, for example, the shock processes were the same as back in 1997 then ultimately the gains from reallocation would converge back to their 1997 level. In sum, the large magnitude of the Δ_t^{t+1}+1 productivity growth gaps follows from both the direct effect of a weaker firm-level productivity/growth relationship in that year and the indirect, cumulative effect of increased productivity dispersion that creates larger potential gains from reallocation.

Figure 12 reports the results of the counterfactual exercise for both High Tech and Nontech. As suggested by the results on Table 1, the productivity differential is exceptionally large and rapidly widening in High Tech, reaching about 5 log points annually by 2013. Again, this potentially reflects cumulative effects especially given the evidence in the prior section showing the rapidly rising dispersion in labor productivity in the High Tech sector.[47]

Figure 12: Reduction in contribution of reallocation to productivity from reduced responsiveness, Tech vs. non-Tech



Note: Corresponds with counterfactual productivity difference-in-difference estimates based Tech and Nontech regressions reported on Table 1. High Tech is defined as in Hecker (2005). Data from the RE-LBD.

There are a variety of reasons to be cautious in interpreting the magnitudes of these counterfactuals. For one, our use of linear and quadratic trends is a simple means of detecting changing covariance structure between growth and productivity over time. However, deterministic trends especially with a quadratic can yield quantitatively large predictions at the end of a sample.[48] For another, while we have included many controls to capture potential changes in the responsiveness of growth to productivity over the cycle, our trend estimates may be contaminated by the very large cyclical downturn that occurs towards the end of our sample period. Foster et al. (2016) find that the Great Recession was less cleansing than prior downturns especially among young firms. They argue this is consistent with the view that the financial crisis distorted the relationship between fundamentals and growth. It may be that we are in part capturing those effects especially to the extent that credit markets were slow to recover for young firms (see Fort et. al. (2013) and Davis and Haltiwanger (2016) for analysis supporting this hypothesis).

Finally, it is important to note that we are focusing only on the reallocation component of productivity growth. There may be within-firm productivity growth effects that either reinforce or offset the effects we have detected. Fernald (2014) and Byrne et al. (2016) highlight many factors that are likely contributing

47 In unreported results we find that the Information sector has similarly large productivity reduction from reduced responsiveness.
48 We do not consider the inclusion of the quadratic term to be a major concern. In unreported work, we calculate the productivity gap counterfactuals using the linear-only model that omits quadratic terms, and the results are nearly unchanged. In other unreported work we estimate the regression models using year indicator variables in place of the linear and quadratic trend variables. The resulting year-specific productivity/growth relationship terms show a pattern that declines nearly linearly throughout the time period.

to within firm declines in productivity growth in the post-2000 period. In addition to the factors they emphasized, 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.

VI. CONCLUDING REMARKS

The post-2000 period in the U.S. has exhibited declines both in various indicators of business dynamism and in aggregate productivity growth. The decline in both has been most dramatic in the High Tech sectors of the economy. This paper explores possible connections between these two distinct but potentially related trends by exploiting rich new microdata on firm-level productivity.

Before focusing on the post-2000 period, reconciling the patterns of dynamism and productivity growth prior to 2000 is relevant. Productivity growth surged in the U.S. from the late 1980s through the 1990s. Over this same period, overall indicators of business dynamism like business formation and job reallocation rates declined. Reconciling these disparate trends is possible by taking into account the changing nature and character of the decline in indicators of business dynamism over time. During the 1980s and 1990s, the decline in business formation rates and job reallocation was dominated by the Retail Trade sector. During this period, there was a well-documented shift away from Mom and Pop retail businesses to large, national chains. Since the evidence also shows that the productivity of large, national chains is substantially greater than that of Mom and Pop businesses, this decline in dynamism in Retail Trade arguably reflects benign changes in the business model so that the typical Retail Trade establishment has become both more productive and more stable over time. Evidence shows that much of the aggregate increase in productivity in the Retail Trade sector in the pre-2000 period is associated with this structural change within Retail Trade. Thus, rather than a source of inconsistency, the declines in indicators of business dynamism in Retail Trade in the 1980s and 1990s are consistent with surging productivity in that sector over this period.

In the 1990s, the High Tech sector exhibited increases in the pace of reallocation and business formation rates. This is the sector that led the aggregate increases in productivity. After 2000, the High Tech sector was the sector with the largest declines in the indicators of business dynamism. Thus, the pattern of a rise and then decline in indicators of business dynamism in the High Tech sector is broadly consistent with the timing of the rise and then decline in the pace of productivity growth in the High Tech sector. The consistent timing of these patterns suggests further exploration of the potential connection between them is warranted.

In our recent research and this paper, we explore the potential connections using microdata on productivity and firm growth dynamics. Theory and evidence support the view that a substantial fraction of industry-level productivity growth is associated with productivity-enhancing reallocation facilitated by growth and contraction at the establishment and firm level. Our analysis is intended to explore whether the declines in the pace of reallocation have been a drag on productivity. We know from the evidence on Retail Trade that declines in the pace of reallocation need not be.

Our approach is to exploit insights from canonical models of firm dynamics that imply that a decline in dynamism should be from one of two sources: either a change in the volatility of shocks or a change in the responsiveness to shocks. We investigate the role of these alternative sources with a focus on the High Tech sectors of the economy. Our prior work focuses on the High Tech component of Manufacturing where we can investigate this connection using the relationship between productivity as measured by TFP and firm growth dynamics in terms of both employment growth and investment from the early 1980s to 2010. The current paper extends this analysis to the entire private non-farm sector but for the period 1996 to 2013, focusing on the dynamics and connections between firm-level labor productivity and employment growth.

In our prior work, we found that the within-industry dispersion of TFP rose modestly in the 1980s and 1990s and more sharply in the post-2000 period in High Tech Manufacturing. In the current paper, we find that within-industry dispersion of labor productivity rose substantially in the High Tech sectors of the economy including both the manufacturing and the non-manufacturing components of High Tech as well as in other sectors. These findings suggest that it is not changes in the shock processes that account for the changing patterns of reallocation in the High Tech sector. The patterns of reallocation in High Tech (both manufacturing and non-manufacturing) are of rising reallocation in the 1990s and then sharply declining reallocation in the post-2000 period.

Instead, we find evidence of changing responsiveness of plant-level and firm-level growth and survival to idiosyncratic differences in productivity in the High Tech sector. This change in responsiveness is especially substantial for young firms. In our plant-level analysis of the High Tech manufacturing sector (Decker et al. (2016a)), we found that the growth rate differential between high- and low-productivity plants of young firms (where productivity is measured by TFP) increased in the 1990s and then declined sharply in the post-2000 period. In our present firm-level analysis of the High Tech sector including both manufacturing and non-manufacturing, we find that the growth rate differential between high- and low-productivity young firms (where productivity is measured by labor productivity) declined sharply in the post-2000 period. In addition, we find a pattern of rising dispersion of labor productivity in High Tech consistent with slower responsiveness.

The changing pattern of responsiveness of plant-level and firm-level growth to within-industry productivity differences has implications for aggregate (industry-level) productivity growth. Decker et al. (2016a) find that the increased responsiveness of growth 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. In the present study, the decline in responsiveness of firm-level growth to idiosyncratic productivity differences within industries yields a decline in the contribution of reallocation to industry-level productivity growth in both the manufacturing and non-manufacturing components in the post-2000 period. While primarily exploratory, our results highlight the importance of microdata and the firm dynamics framework for the study of U.S. productivity dynamics. Changes in behavior at the firm level can have quantitatively significant implications for aggregate patterns.

The open question is why firms with high realizations of productivity, especially those in the High Tech sector, do not experience the same high growth as before. In our view, it is difficult to account for the changing patterns of responsiveness and contribution of reallocation to productivity growth without appealing to some change in either adjustment frictions for business-level growth and/or changing margins of adjustments. Whatever the explanation, it must account for the changing pattern of responsiveness to be greatest for young firms.

There is suggestive evidence that globalization is playing a role for the latter. That is, within High Tech manufacturing the largest declines in responsiveness of young firms are in those detailed sectors with the largest increase in the import penetration ratio from low wage countries. While this can potentially help explain some of the patterns for High Tech manufacturing, there are even larger swings in the patterns of responsiveness and the contribution of reallocation in the overall High Tech sector (including both manufacturing and non-manufacturing). Exploring the potential role of globalization for High Tech outside of manufacturing is an interesting area for future research.

Since our results are consistent with an increase in adjustment frictions or other distortions and frictions slowing down firm responsiveness, a high priority should be to investigate and identify the potential sources of increases in adjustment frictions or other frictions and distortions. Davis and Haltiwanger (2014) and Molloy et al. (2016) discuss various potential sources of such increases in adjustment frictions. Given the outsized role the High Tech sector has played in productivity acceleration and decline understanding this changing pattern of responsiveness of firms (especially young firms) in High Tech should be a high priority.

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APPENDIX A:
DISPERSION OF 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:

$$\pi_{ft} = P_t Y_{ft} - w_t n_{ft} \text{ with } Y_{ft} = A_{ft} n_{ft}^{\alpha} \qquad \text{(A1)}$$

where 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 α <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:

$$\alpha P_t A_{ft} n_{ft}^{\alpha-1} = w_t \qquad \text{(A2)}$$

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:

$$APL_{ft} = \frac{P_t Y_{ft}}{n_{ft}} = P_t A_{ft} n_{ft}^{\alpha-1} = \frac{w_t}{\alpha} \qquad \text{(A3)}$$

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 (A2)) (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.