Declining Dynamism, Allocative Efficiency, and the Productivity Slowdown

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Abstract

A large literature documents declining measures of business dynamism including high-growth young firm activity and job reallocation. A distinct literature describes a slowdown in the pace of aggregate labor productivity growth. We relate these patterns by studying changes in productivity growth from the late 1990s to the mid 2000s using firm-level data. We find that diminished allocative efficiency gains can account for the productivity slowdown in a manner that interacts with the within-firm productivity growth distribution. The evidence suggests that the decline in dynamism is reason for concern and sheds light on debates about the causes of slowing productivity growth.

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Evidence of declining entrepreneurship and labor market fluidity has captured wide interest among researchers and policymakers. Startup rates and other measures of young firm activity have declined since the 1980s, with accelerated slowdowns in high-growth young firm activity since 2000. Gross job and worker flows have declined over the same period including marked drops since the early 2000s. These patterns are particularly notable in the High Tech sector, which saw rising dynamism during the 1990s before declining sharply after 2000 (Decker et al. (2016)).

A distinct literature describes a decline in the growth rate of aggregate productivity since the early 2000s (Byrne, Fernald and Reinsdorf (2016); Gordon (2016); Syverson (2016)). An important omission from much of the productivity slowdown literature is the notion that aggregate productivity depends not only on technology but also on allocative efficiency—the continual movement of resources to their most productive uses. Decker et al. (2017) document declining establishment-level responsiveness of growth to productivity and show that a weakening of the growth-productivity relationship at the business level has had potentially large implications for aggregate productivity growth while also helping explain falling rates of job reallocation. Moreover, within-industry dispersion of labor productivity—a popular (if limited) indicator of efficiency frictions—has risen since the late 1990s. In the present study, we provide further evidence linking the problem of slowing productivity growth to declining business dynamism.

Using firm-level data on labor productivity, we construct accounting decompositions to show that dampened growth in allocative efficiency can account for much of the decline in aggregate productivity growth between the late 1990s and the mid 2000s; more specifically, the slowdown reflects inefficient allocation of productive resources as well as the interaction between allocation and slowing within-firm productivity growth. Our findings imply that, consistent with the conclusions of Decker et al. (2017), declining business dynamism since 2000 is likely a drag on American living standards. Moreover, our findings suggest a reevaluation of the productivity slowdown debate, which has until now focused on technological versus measurement explanations.

1 A microdata approach

Our dataset, the RE-LBD, combines the industry and employment data of the Census Bureau's Longitudinal Business Database (LBD) with revenue data from tax records (Haltiwanger et al. (2016)). The integrated data allow us to measure gross revenue labor productivity at the firm level for virtually the entire U.S. private nonfarm economy; we apply propensity score weights to account for imperfect match rates between revenue and employment (LBD) data.

We construct aggregate labor productivity numbers that come reasonably close to official figures published by the BLS, which rely on different methodology and source data. BLS numbers are based on value added per worker, while we are limited to gross revenue per worker (deflated with BEA deflators, typically at the 3-digit or 4-digit NAICS level). Earlier research (e.g., Foster, Haltiwanger and Krizan (2001)) shows that gross output per worker tracks value added per worker reasonably well within industries but poorly across industries. We therefore focus on variation within detailed (6-digit NAICS) industries. We construct industry-level indices by aggregating the firm-level data using the employment-weighted average of log labor productivity: $P_{it} = \sum_{f \in i} \theta_{ft} p_{ft}$, where P_{it} is industry-level productivity for industry i in year t, θ_{ft} is the share of employment for firm f in year t, and p_{ft} is log labor productivity for firm f in year t. We aggregate our industry-level computations to an economywide level using fixed industry weights (reflecting each industry's average weight for the entire time sample), thereby avoiding inferences based on cross-industry variation in gross output per worker.

Despite differences from BLS methodology and source data, we obtain similar patterns of aggregate labor productivity growth. In Figure A1 of the appendix we report average annual log differences of aggregate productivity from both the RE-LBD and BLS data for three periods: 1997-1999, 2004-2006, and 2011-2013. We report business cycle peaks to avoid cyclical issues; we will focus on the change from 1997-99 to 2004-06, the period marking the productivity slowdown, since the 2011-13 period likely continues to reflect effects of the Great Recession. Our microdata-based approach closely matches BLS numbers for the 1997-1999 period, and we report an even larger deceleration in 2004-2006. We interpret the difference between 1997-99 and 2004-06 as reflecting the productivity slowdown and focus on decomposing it into changes in within-firm growth and changes in allocative components of aggregate growth.

2 Decomposing productivity

There is a large literature on methods for decomposing aggregate productivity. We focus primarily on the Dynamic Olley Pakes method (hereafter DOP) of Melitz and Polanec (2015). Olley and Pakes (1996) showed that aggregate productivity can be decomposed into the unweighted average of firm-level productivity and a term that is proportional to the covariance between firm size and firm productivity (where we suppress time subscripts for convenience):

$$P_i = \bar{p}_i + cov\left(\theta_f, p_f\right) \tag{1}$$

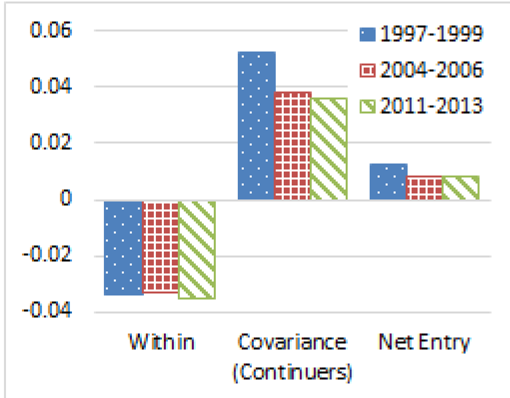

Figure 1: Dynamic Olley Pakes Decomposition
Author calculations from RE-LBD

where P_i is industry aggregate productivity, $\bar{p}_i$ is the unweighted average of (log) firm-level productivity for firms in industry i, θ_f is the share of industry employment accounted for by firm f, and p_f is the (log) labor productivity of firm f. The covariance term has been interpreted as a measure of allocative efficiency, or the degree to which higher-productivity firms have access to more resources. While this interpretation is more natural with a TFP productivity measure, Bartelsman, Haltiwanger and Scarpetta (2013) show both theoretically and empirically that the Olley-Pakes decomposition applied to labor productivity yields similar inferences. They note that this inference is model dependent, but we adopt this interpretation in this short paper.

Melitz and Polanec (2015) extends the Olley Pakes method to include entry and exit in a way that allows for careful tracking of within-firm changes:

$$\Delta P_i = \Delta \bar{p}_{i,C} + \Delta cov_C \left(\theta_f, p_f\right) + \theta_{E2} \left(P_{E2} - P_{C2}\right) + \theta_{X1} \left(P_{C1} - P_{X1}\right) \tag{2}$$

where Δ indicates year-over-year log difference, C denotes continuer firms (those with employment in both years), $E2$ denotes entrants in the second year of the calculation, $X1$ denotes firms that exit after the first year, and $C1$ and $C2$ denote continuers in the first and second years, respectively. The first term in the expression, $\Delta \bar{p}_{i,C}$, represents average within-firm productivity growth for continuing firms; the second term, $\Delta cov_C \left(\theta_f, p_f\right)$, represents the change in allocative efficiency among continuing firms; and the remaining terms represent the aggregate contribution of net entry. We calculate (2) for each industry in each year and aggregate the annual components to the economywide level using fixed industry shares as described above. Figure 1 reports the resulting components of aggregate productivity growth.

On Figure 1, the first set of bars reports the average annual change in productivity within continuing firms for each noted time period, the second set reports the change in allocative efficiency among continuing firms, and the third set reports the contribution of net entry (see equation 2). Notably, the within-firm contribution is consistently below zero; surviving firms see negative productivity growth on average. This negative contribution is roughly constant over time, suggesting that the productivity slowdown was not driven by reduced within-firm productivity growth on average. The covariance terms, reflecting the aggregate improvement in allocative efficiency among continuing firms, consistently account for the bulk of aggregate productivity growth; a step down is apparent between 1997-99 and 2004-06. Likewise, net entry makes a positive contribution to growth but steps down between 1997-99 and 2004-06 consistent with work by Alon et al. (2017); these authors show that declining entry has a significant cumulative effect on productivity over the 2000s. Strikingly, from an Olley-Pakes perspective the productivity slowdown between the late 1990s and the mid 2000s is accounted for by decelerating allocative efficiency, primarily among continuing firms but also in terms of net entry, rather than slowing improvements within firms.

It is notable that within-firm productivity growth is negative on average, but recall that this term is an unweighted average in the DOP framework. About 90 percent of firms have fewer than 20 workers, so the unweighted "within" term largely reflects the contribution of very small firms. These small firms account for only about 10 percent of total employment, so it is instructive to also examine weighted within-firm productivity growth. Indeed, in some dynamic decompositions from the literature (e.g., Foster, Haltiwanger and Krizan (2001), hereafter FHK) it is typical to compute a "within" term that is the weighted average of firm-level productivity growth among continuers, $\sum_f \theta_{f1} \Delta p_f$, where the weights θ_{f1} are equal to each firm's initial employment as a share of initial aggregate employment. The difference between this weighted approach and the unweighted DOP "within" term is given by

$$\sum_f \theta_{f1} \Delta p_f - \Delta \bar{p} = \sum_f \left(\theta_{f1} - 1/N\right) \Delta p_f \qquad (3)$$

where N is the number of firms. This difference will be positive only if within-firm productivity growth and the initial employment share (size) of the firm covary positively.

On Figure 2 we again report the "within" term from our DOP exercise and, in addition, we report the FHK weighted within-firm method. The FHK "within" term is always positive, but the unweighted (DOP) "within" term is negative and consistently less than its weighted counterpart (FHK); so larger firms must have higher within-firm productivity growth on average. Rather than reflecting pure within-firm effects, then, the weighted (FHK) "within" term arguably also draws on allocative efficiency mechanics that, in the DOP framework, are instead counted in the changes in the covariance term. A comparison of the DOP and FHK

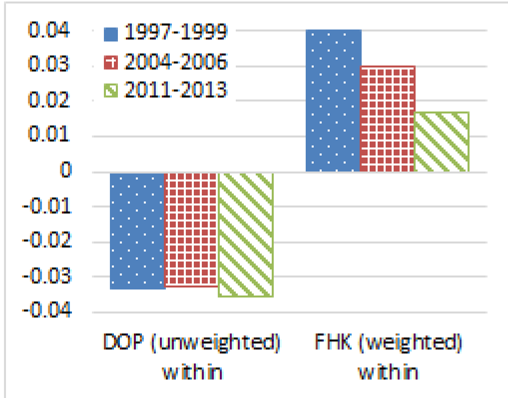

Figure 2: Within-Firm Productivity Growth
Author calculations from RE-LBD

terms on Figure 2 therefore reveals that (a) firms with higher productivity growth tend to be larger on average, (b) this positive correlation has fallen over time and, in an FHK-type framework, accounts for some portion of the productivity slowdown, and (c) differences in the changes of unweighted and weighted averages involve the interaction of allocative efficiency mechanics and within-firm productivity changes.

This last point suggests that it is wrong to conclude from Figure 1 that changes in within-firm productivity growth play no role in the productivity slowdown. While the unweighted "within" mean exhibits little change, underlying this unweighted mean is wide dispersion in within-firm productivity growth rates: we find that the interdecile range of within-firm productivity growth rates is about 100 log points. Based on equation 3, this dispersion combines with positive correlation between within-firm productivity growth and initial size to drive the positive difference between the weighted and unweighted means of within-firm productivity growth illustrated by Figure 2. To shed further light on this dispersion, Figure A2 of the appendix reports (unweighted) within-industry 90th percentile productivity growth rates, averaged across industries (using our usual time-invariant employment weights), by firm size class. The 90th percentile of within-firm productivity growth rates is high but declining for all firms and for every size class. Notably, the largest declines are seen among the largest size classes. In Figure A3 of the appendix, we conduct the same exercise using employment-weighted 90th percentiles and find that the weighted percentiles are only slightly smaller in magnitude and exhibit the same pattern of declines over time.

Taken together with Figure 2, Figures A2 and A3 imply that the productivity slowdown is partly driven by declines in the upper tail of the within-firm productivity growth distribution. Interestingly, there is a decline in the upper tail of the productivity growth distribution in every size class and in both unweighted and weighted terms. On figures A4-A6 of the appendix we also find that all size classes exhibit a large, positive difference between the weighted and unweighted "within" terms, and in all cases this gap declines from 1997-99 to 2004-06. These patterns manifest themselves partly in allocative efficiency terms since they both reduce the correlation between size and productivity growth and limit opportunities for further productivity-enhancing reallocation.

3 Conclusion

The evidence presented here advances the literature in three ways. First, decompositions of aggregate labor productivity growth suggest that impaired growth in allocative efficiency can account for the bulk of the productivity slowdown from the late 1990s to the mid 2000s. Current debates about the productivity slowdown focus on whether it reflects slowing technological improvement or increasingly imperfect measurement, but allocative efficiency is crucial for transmitting advances in technology and management practices into aggregate productivity growth. Decelerating allocative efficiency can constrain productivity growth even in the midst of rapid technological progress; alternatively, changes in technology may be influencing the pace of reallocation and possibly allocative efficiency measures. We also observe wide variation in within-firm productivity growth and growth slowdowns by firm size. This evidence should inspire a reevaluation of the productivity slowdown debate.[1]

Second, there are complex interactions between within-firm productivity growth and measures of allocative efficiency. The covariance between within-firm productivity growth and initial size has weakened, and the 90th percentile of the within-firm productivity growth distribution has fallen. The decline in the latter is more substantial for the largest firms, so in this respect it is difficult to draw clear distinctions between allocative efficiency and technological stagnation mechanisms.

Third, the evidence is consistent with the notion that post-2000 declining business dynamism has not been benign for American living standards but, instead, is closely related to slowing productivity growth. These results complement Decker et al. (2017), which finds that declining reallocation reflects a decline in the responsiveness of individual businesses to their productivity.

While the discovery of strong causal factors behind these patterns has thus far proven elusive in this literature, the accumulating evidence has narrowed the possibilities considerably while emphasizing the importance of the topic.

[1] See Andrews, Gal and Criscuolo (2015) for another firm dynamics approach to the productvity slowdown.

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Appendix

Figure A1 reports average annual aggregate labor productivity growth, for three different time periods, from official BLS data and from RE-LBD microdata. As noted in the main text, our RE-LBD numbers are constructed using different source data and methodology from BLS statistics. In particular, we construct labor productivity by detailed 6-digit NAICS industry as total industry revenue divided by total industry employment, where revenue is deflated using BEA deflators (typically at the 3-digit or 4-digit level). We construct an economywide aggregate by taking the weighted average of industry productivity, where weights are calculated based on each industry's share of aggregate employment, averaged over the 1997-2013 period. Hence, industry weights are held constant to abstract from cross-industry variation in gross output per worker.

Figure A1 shows that our microdata-based productivity numbers are reasonably similar to official BLS data. We closely match average annual productivity growth for the 1997-1999 period, and we find a somewhat stronger decline in average growth from this initial period to the 2004-2006 period than is reported by BLS. Generally, though, we obtain figures that are remarkably consistent with official statistics.

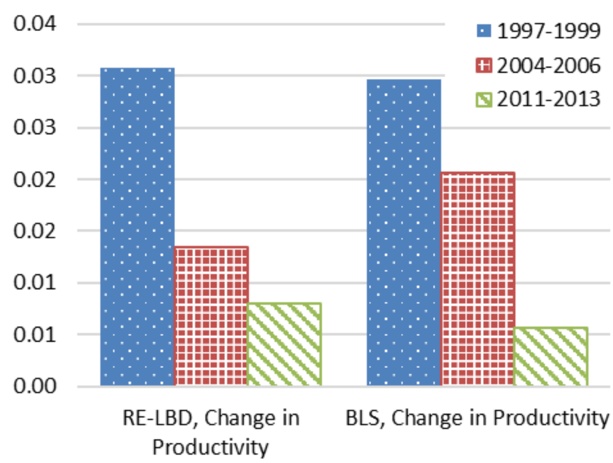

Figure A1: Annual Productivity Growth
BLS and author calculations from RE-LBD

Figure A2 reports average 90th percentile rates of within-firm productivity growth by firm employment class. We first obtain the 90th percentile of firm-level growth in labor productivity (for continuer firms) by industry, where the percentile is based on the unweighted distribution of the industry. We then average these 90th percentiles using time-invariant industry employment weights as above. We do this for each size class and for all firms. The average 90th percentile falls over time within each size class, with larger declines among

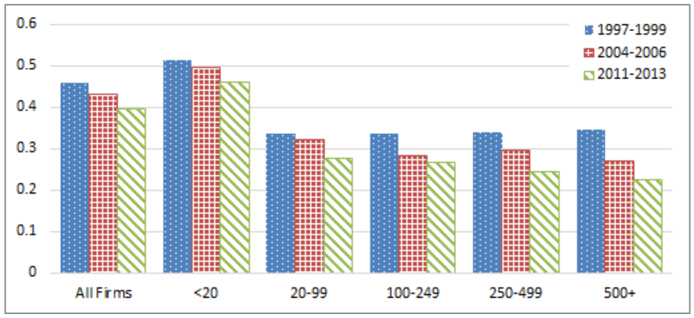

Figure A2: Average 90th Percentile Growth Rates by Firm Size (Unweighted)
Author calculations from RE-LBD

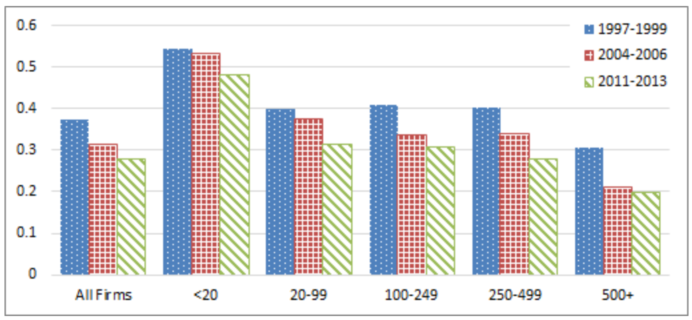

Figure A3: Average 90th Percentile Growth Rates by Firm Size (Weighted)
Author calculations from RE-LBD

larger firms. Figure A3 follows the same concept as Figure A2, but we instead take the 90th percentile of the employment-weighted distribution within industries. Weighted 90th percentiles show a downward-stepping pattern in within-firm productivity growth that is similar to unweighted 90th percentiles, again suggesting a decline in productivity growth among the highest-performing firms (even within size classes). Note that these exercises, which track only the top part of the within-firm productivity growth distribution, are mechanically reflected in the covariance term of Dynamic Olley-Pakes (DOP) decompositions described in the main text. This term is typically interpreted as a measure of allocative efficiency, but it captures these notable patterns among firms with high within-firm productivity growth.

Figure A4 reports the "within" term of the DOP decomposition constructed separately for each size class. These data add nuance to the economywide results described in the main text. Within-firm productivity growth is negative on average (unweighted) for small firms, though among the smallest firms it actually became less negative from the late 1990s to the mid 2000s. Among the largest firms, productivity growth was positive in the late 1990s but stepped down thereafter.

Figure A5 reports the "within" term of the Foster Haltiwanger Krizan (FHK) decomposition, again performed separately for each size class. Recall that this method highlights the

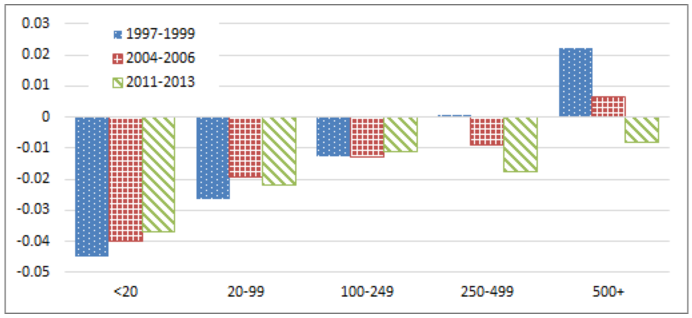

Figure A4: Within-firm Productivity Growth by Firm Size (DOP Method)
Author calculations from RE-LBD

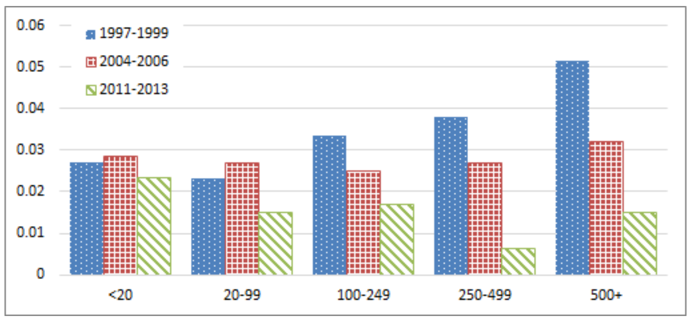

Figure A5: Within-firm Productivity Growth by Firm Size (FHK Method)
Author calculations from RE-LBD

employment-weighted average of within-firm productivity. These terms are positive across the entire firm size distribution, indicating that larger firms have higher productivity growth even within size classes. Within-firm productivity growth stepped down from the late 1990s to the mid 2000s for the larger size classes. Taken together, Figures A4 and A5 show very different productivity dynamics for small and large firms, with slight improvements among small firms but declines among larger firms during the period of the aggregate productivity slowdown. Declines in within-firm productivity growth among some firms suggest that the productivity slowdown is not entirely a story about allocative efficiency, but the size-dependent nature of changes in firm-level growth highlights the complex interaction between allocative efficiency and within-firm improvements.

Figure A6 reports the difference between the FHK and the DOP "within" terms, again by size class. This exercise is inspired by equation 3 from the text, which shows that the difference between the FHK and DOP terms depends on the correlation between firms' initial employment shares and their within-firm productivity growth. Positive covariance between initial size and productivity growth can be interpreted in allocative efficiency terms. Figure A6 shows that this difference is positive but declining for all size classes.

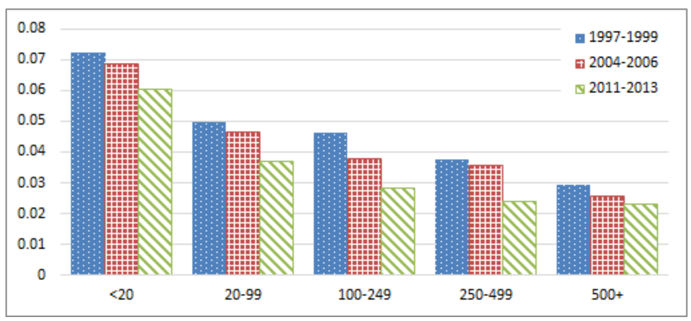

Figure A6: Difference Between FHK and DOP “Within” Terms
Author calculations from RE-LBD