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Productivity Dispersion, Entry, and Growth in U.S. Manufacturing Industries

Cindy Cunningham, Lucia Foster, Cheryl Grim, John Haltiwanger, Sabrina Wulff Pabilonia, Jay Stewart, and Zoltan Wolf*

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Abstract: Within-industry productivity dispersion is pervasive and exhibits substantial variation across countries, industries, and time. We build on prior research that explores the hypothesis that periods of innovation are initially associated with a surge in business start-ups, followed by increased experimentation that leads to rising dispersion potentially with declining aggregate productivity growth, and then a shakeout process that results in higher productivity growth and declining productivity dispersion. Using novel detailed industry-level data on total factor productivity and labor productivity dispersion from the Dispersion Statistics on Productivity along with novel measures of entry rates from the Business Dynamics Statistics and productivity growth data from the Bureau of Labor Statistics for U.S. manufacturing industries, we find support for this hypothesis, especially for the high-tech industries.

Keywords: dispersion; entry; innovation; productivity; manufacturing; high-tech industries

JEL codes: O3, O4

*Cunningham, Pabilonia, and Stewart: U.S. Bureau of Labor Statistics; Foster and Grim: Center for Economic Studies, U.S. Census Bureau; Haltiwanger: University of Maryland; Wolf: New Light Technologies. John Haltiwanger was also a Schedule A part-time employee of the U.S. Census Bureau at the time of the writing of this paper. Any opinions and conclusions expressed herein are those of the authors and do not necessarily represent the views of the U.S. Census Bureau or the U.S. Bureau of Labor Statistics. The Census Bureau has reviewed this data product for unauthorized disclosure of confidential information and has approved the disclosure avoidance practices applied to this release (Approval ID: CBDRB-FY21-261). The authors would like to thank T. Kirk White, Lucy Eldridge, Joe Piacentini, and participants at the Sixth World KLEMS Conference in 2021 for comments. Corresponding author: Pabilonia.Sabrina@bls.gov.

I. Introduction

Within-industry productivity dispersion is large and exhibits substantial variation across countries, industries, and time (Bartelsman and Doms, 2000; Syverson, 2011). Many factors have been shown to be related to this dispersion, including frictions and distortions that vary across these same dimensions (e.g., Decker, Haltiwanger, Jarmin, and Miranda, 2020). These frictions and distortions, such as barriers to entry, costs of adjusting factors of production, establishment-specific markups, and regulations preventing the equalization of marginal products, may inhibit productivity-enhancing reallocation. This would suggest that increasing within-industry dispersion is associated with slower productivity growth. An alternative hypothesis is that periods of rising within-industry dispersion may reflect innovation and experimentation. This hypothesis is based on seminal research by Gort and Klepper (1982) and Jovanovic (1982). These papers hypothesize that periods of innovation are initially associated with a surge in firm entry, followed by increased experimentation that yields rising dispersion potentially with declining aggregate productivity growth and then a shakeout process, where successful businesses grow and unsuccessful ones exit, which eventually results in higher productivity growth and declining productivity dispersion.

To explore this latter hypothesis, Foster, Grim, Haltiwanger, and Wolf (2021) looked at the dynamic relationship between entry rates (an indirect measure of innovation), within-industry labor productivity (LP) dispersion, and LP growth using firm-level data for the entire U.S. private sector, where LP is defined as output per job. They find that a surge in firm entry in a four-digit NAICS industry during a three-year period is followed by an increase in within-industry dispersion and a temporary slowdown in industry-level LP growth in the next period. In the subsequent period, there is a fall in dispersion and a rise in LP growth. These relationships are stronger in high-tech industries, where the pace of innovation is presumably faster.

In this paper, we build on Foster et al. (2021) by exploiting novel, detailed industry-level data on within-industry total factor productivity (TFP) and LP dispersion from the Dispersion Statistics on Productivity (DiSP) data, along with new measures of establishment and firm entry rates from the Business Dynamics Statistics (BDS) data for U.S. manufacturing industries. We combine these data with the official U.S. TFP and LP growth measures from the Bureau of Labor Statistics (BLS) to examine the relationships between entry, dispersion, and productivity.[1] To abstract from business cycle dynamics and to focus on the hypothesis, we examine low-frequency variation (average annual growth rates over two-year periods) and include industry and period effects. Relative to Foster et al. (2021), a primary contribution of this paper is the use of dispersion and growth measures of TFP, which are better metrics for examining the innovation hypothesis.

We find support for the hypothesis that innovation is an important driver of within-industry TFP dispersion and growth, especially for high-tech industries. A surge in entry into a high-tech industry over a two-year period results in an increase in within-industry TFP dispersion in the next two-year period, followed by an increase in within-industry TFP growth in the two subsequent two-year periods. We also find evidence that the increase in dispersion in the first two-year period following a surge in entry is accompanied by negative TFP growth. Relatedly, we find evidence of the reverse, declining TFP dispersion and faster TFP growth in

[1] The DiSP (developed jointly by BLS and the Census Bureau) is public-use data available at https://www.bls.gov/lpc/productivity-dispersion.htm and https://www.census.gov/disp. Restricted-use microdata is available for qualified researchers on approved projects in the Federal Statistical Research Data Centers (FSRDCs) (http://www.census.gov/fsrdc). The BDS is available at https://www.census.gov/programs-surveys/bds.html. Industry productivity growth data are available at https://www.bls.gov/lpc/tables_by_sector_and_industry.htm.

the second two-year period. In addition, we find the relationships between entry and TFP dispersion are stronger when we focus on high-tech industries. For non-tech industries, we find a small decrease in TFP, but with an additional lag and no subsequent increase in the following period. We find broadly similar results for LP measures of dispersion and growth.

The paper proceeds as follows. In section II, we describe the data and present descriptive statistics. The main results are in section III. Concluding remarks are in section IV.

II. Data and Descriptive Statistics

This paper uses detailed industry-level data on productivity growth, establishment and firm entry rates, and productivity dispersion from three public-use data sources: BLS Industry Productivity Statistics, BDS, and DiSP. In addition, we construct additional dispersion measures from the restricted-use data underlying DiSP.[2] Throughout the paper, we use industry-level measures for all four-digit NAICS industries in the manufacturing sector. To mitigate business cycle influences, we construct our measures for non-overlapping two-year periods to examine the longer-term relationships between entry, productivity dispersion growth, and productivity growth.

The BLS produces the official U.S. measures of LP and TFP growth for 4-digit NAICS manufacturing industries.[3] The industry LP measures compare real sectoral output—the total value of goods and services sold outside the industry—to the number of hours worked by all

[2] The experimental data product DiSP was first released in September 2019. Industry-level BDS data were first released in September 2020.
[3] BLS produces LP statistics for all 3- and 4-digit NAICS industries in mining, manufacturing, trade, and food services industries and an extensive selection of other service-providing industries. The BLS also develops labor productivity measures for 50 states and the District of Columbia at the private nonfarm business sector level. TFP measures are produced for all 4-digit NAICS manufacturing industries, as well as for air transportation and the line-haul railroad industry. See Bureau of Labor Statistics (2020).

persons in the industry.[4] For most industries, real output is derived by deflating nominal sales revenue using industry-level BLS implicit price indexes. Output is also adjusted to remove resales and to account for changes in finished goods and work-in-process inventories. Data for industry output measures are primarily from economic censuses and annual surveys of the U.S. Census Bureau. Data on hours worked come from BLS surveys.[5]

Although the BLS productivity data for detailed industries in the manufacturing sector are available annually beginning in 1987, we restrict our main analyses to growth in productivity and dispersion over the 1997–2017 period, because the DiSP data start in 1997.[6] The BLS productivity growth rates exhibit considerable year-over-year variation for many manufacturing industries (see Appendix Table A1 for four-digit NAICS industry productivity means and coefficients of variation). For this reason, we use the BLS industry productivity indexes to construct non-overlapping average annual growth rates for two-year subperiods from 1997 to 2017 (1997–1999, 1999–2001,…, 2015–2017).[7]

DiSP is a newly developed public-use dataset from the Bureau of Labor Statistics and the Census Bureau (2020). This dataset, which is constructed primarily from establishment-level data, includes several measures of within-industry dispersion in LP and TFP—the interquartile range (IQR), interdecile (90–10) range, and standard deviation for all 86 four-digit NAICS industries in the manufacturing sector from 1997 to 2016. LP is the log of real output per hour, while TFP is the log of real output per unit of all factor input costs, where the factors are capital, labor hours, energy, and materials.[8] These measures are available with and without activity-

[4] For more details on the importance of removing intrasectoral transactions for aggregate industry productivity measurement, see Kovarik and Varghese (2019).
[5] For more information on the construction of hours measures, see https://www.bls.gov/lpc/iprhours.htm.
[6] The dispersion series will be expanded backward to 1976 as well as forward in future releases.
[7] For example, $LP_{1999-1997} = (index_{1999}/index_{1997})^{0.5} - 1) \times 100$.
[8] Output is based on the value of shipments adjusted for resales and changes in inventories. Each establishment's productivity is normalized to the industry's mean productivity.

weighting, where the activity weights for LP are an establishment's hours share (the share of a plant's hours of the total hours in its industry) and for TFP are an establishment's share of combined inputs.[9] In addition, we use 90–50, 50–10, 75–50, and 50–25 measures of dispersion from the restricted-use data underlying the DiSP product to consider skewness in the within-industry distribution of productivity.

For our main analysis, we calculate average annual growth rates for each variable in each of the two-year subperiods in our sample using activity-weighted IQR dispersion measures. (In the last period, we use a one-year growth rate, because the series ends in 2016.) The within-industry IQR dispersion measure describes how much more productive an establishment at the 75th percentile of the productivity distribution is than one at the 25th percentile. Activity-weighted measures should more closely correspond to the BLS aggregate productivity measures. BLS published productivity growth rates can be thought of as changes in the first moment of the underlying distribution of productivity among establishments, where the weights are appropriately defined, while changes in dispersion from DiSP measure changes in the second moments of that distribution.[10]

On average, throughout this period and using the unweighted measures, Cunningham et al. (2021) find that establishments at the 75th percentile are 2.4 times more productive than establishments at the 25th percentile when looking at LP and 1.7 times as productive when looking at TFP.[11] However, they also find significant variability in the IQR dispersion measure across industries and a slight increase in dispersion over time. We use the IQR measures for our

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[9] See Cunningham et al. (2021) for a detailed description of these new dispersion measures.
[10] Recall, activity weights are applied at the establishment level. They give a higher weight to establishments with more activity when calculating productivity dispersion for an industry.
[11] As described in Cunningham et al. (2021), unweighted measures use inverse propensity score weights at the establishment-level to correct for sample selection issues for the ASM. Activity-weighting is the product of the inverse propensity weight and an activity weight.

main analyses because they are less sensitive to outliers; however, we also include a robustness check using the interdecile dispersion measure.

The Census Bureau (2020) significantly redesigned and expanded the BDS with the release of the 2018 BDS in September 2020. This novel public-use dataset compiled from the Longitudinal Business Database includes the distribution of firms and establishments by age (based on when they first report positive employment) within detailed industries, allowing us to identify the number of establishment births or firm startups.[12] We construct entry rates (both establishment-based and firm-based) for each four-digit NAICS industry as the simple average of annual entry rates for each two-year subperiod, where the entry rate is the number of establishments aged zero (births) divided by the average count of active establishments in year t and year t-1.[13] Our hypothesis is that increases in entry rates lead to growth in dispersion but with a lag. We construct entry rates for three lagged two-year subperiods. For example, the first-period lagged entry rates corresponding to the average annual growth rates for the 1997–1999 subperiod are the average of entry rates in 1996 and 1997. Thus, our entry rate data cover the 1992–2015 period.

Table 1 shows summary statistics for our data. The average value of the two-year average annual BLS industry LP growth rates was 1.6 percent for the 1997–2017 period. Over the same period, TFP grew on average 0.4 percent per year. The LP dispersion growth rate was 0.6 percent on average, while the TFP dispersion growth rate was 1.5 percent on average; however, there was considerable variation in aggregate productivity and productivity dispersion growth across

[12] In instances where the number of births in an age bin is not disclosed because there were only 1–2 firm births, we set the number of births equal to 1. Results are essentially the same if we were to set births at 2 firms in the undisclosed age bins.
[13] See https://www.census.gov/programs-surveys/bds/documentation/faq.html for more details on construction of entry rates.

industries and time. Entry rates were 6.1 percent on average (establishment and firm). The negative means of the changes in entry rates indicate that, on average, entry rates were falling in the manufacturing sector.

In our analysis, we differentiate between high-tech and non-tech industries, because the former has been an engine of productivity growth, especially over the earlier years in our sample period (Brill, Chansky, and Kim, 2018). We classify 16 of the 86 industries in our sample as high-tech. In these high-tech industries, the share of jobs held by STEM workers, including engineers, IT workers, scientists, and managers of these workers, exceeded 2.5 times the national average (Wolf and Terrell, 2016).[14] For our main regressions, we use establishment entry rates, which are consistent with our establishment-based dispersion measures. However, both establishment and firm entry rates are relevant in this context because the Gort and Klepper (1982) experimentation stage arguably involves both establishment and firm-level entry. Importantly, establishment-entry rates include the contribution of both firm-level entry and new establishments of existing firms.

We begin our analysis by illustrating graphically the relationships between establishment entry rates, TFP dispersion growth, and TFP growth for the two high-tech industries that were the top contributors to the marked TFP slowdown that occurred around 2005: semiconductor and other electronic component manufacturing and computers and peripheral equipment manufacturing (Brill, Chansky, and Kim, 2018). We then consider a non-tech industry, grain and oilseed manufacturing, where we do not necessarily expect to see innovations that lead to entry.

[14] The high-tech industries include: petroleum and coal products; basic chemical; resin, synthetic rubber, and artificial and synthetic fibers and filaments; pharmaceutical and medicine; industrial machinery; commercial and service industry machinery; engine, turbine, and power transmission equipment; other general purpose machinery; computer and peripheral equipment; communications equipment; audio and video equipment; semiconductor and other electronic components; navigational, measuring, electromedical, and control instruments; manufacturing and reproducing magnetic and optical media; electrical equipment manufacturing; aerospace products and parts.

In Figure 1, we see high entry rates in semiconductor and other electronic component manufacturing in the early 1990s followed by high growth in dispersion between 1997 and 2003, especially in 2001–2003, when dispersion grew by 37 percent. Around 2003, entry rates became relatively stable at around 4 to 5 percent, with little change in dispersion from one period to the next after that. We see TFP grew from 1997 to 2007 and was especially high in 1997–1999, several periods after a surge in entry. Growth was modest but still positive in 2003–2005 and 2005–2007, following a large spike in dispersion in 2001–2003. In three out of the four periods following the Great Recession, TFP growth was negative.

Figure 2 shows the relationships for computer and peripheral equipment manufacturing. Again, we see that entry rates are initially very high through 2001, exceeding 10 percent. Thereafter, entry rates are consistently below 8 percent, except during the Great Recession when the entry rate rose to about 8.7 percent. Dispersion rises and falls with a large increase during the Great Recession, but there is no obvious pattern that it follows changes in entry; however, TFP growth is very high until the Great Recession, following several periods of relatively high entry rates by a lag.

Figure 3 illustrates the relationships for grain and oilseed manufacturing. Here, we see much lower entry rates that hover between 4 and 6 percent. Movements in dispersion do not appear to be tied to movements in entry, and there is little growth in productivity.

III. Empirical Model and Results

We explore the relationships between entry, productivity dispersion, and aggregate productivity growth by estimating panel models of the following form:

$$Y_{i.t} = \alpha + \lambda_t + \lambda_i + \sum_{k=1}^{3}\left[\beta_k Entry_{i,t-k} + \delta_k Entry_{i,t-k} * Tech_i\right] + \varepsilon_{i,t} \quad (1)$$

where $Y_{i.t}$ is either average annual within-industry productivity dispersion growth or aggregate industry productivity growth where productivity is measured as LP or TFP. The subscript i denotes the industry, while the subscript t denotes time in two-year subperiods. $Entry$ is either the establishment or firm entry rate, which enters the equation with one-, two-, and three-period lags, thus covering a total of six years. $Tech$ is a binary variable equal to one if the industry is high tech and zero otherwise. The parameters of interest, β_k and δ_k, represent the associations between entry and growth, allowing for differences by industry type (high tech or not). α is a constant term. The model also includes period effects (λ_t) and industry effects (λ_i). The parameter ε is a random error term. We estimate the models by ordinary least squares and cluster the standard errors at the industry level.

Our main results are presented in Table 2. We begin with the discussion of the results using TFP dispersion (measured as the IQR) and growth, as these reflect our more important and novel results. These results are in columns 3 and 4 of Table 2. For high-tech industries, a one-percentage-point increase in the establishment entry rate is associated with a 2.9-percentage-point increase in TFP dispersion growth in the next period (column 3). In contrast, a one-percentage-point increase in the establishment entry rate is associated with a 0.7 of a percentage point decrease in TFP growth in the next period (column 4).[15] In the second period after entry, dispersion growth falls dramatically (a 4.6-percentage-point decrease) while TFP growth rises (a 0.6 of a percentage point increase). The latter estimate is not statistically significant at conventional levels but the difference between high-tech and non-tech industries is about 0.8 of a percentage point and is statistically significant in the second period after entry. For non-tech

[15] As a robustness check, we also examine the relationship between entry and the 90–10 dispersion statistics. The patterns are similar for TFP, although statistical significance is not as strong (Appendix Table A2). We also looked at the relationships using dispersion statistics that were not activity weighted (Appendix Table A3). Results are not as strong without activity weighting.

industries, we find little relationship between entry, dispersion, and growth (entry is associated with a small drop in TFP growth two periods later, with no subsequent growth). As a sensitivity analysis, we used the longer aggregate productivity series back to 1987, but we still did not find productivity growth for non-tech industries in the third period following an increase in entry (see Appendix Table A4).

Turning to LP results, column 1 shows the relationship between LP dispersion and entry, controlling for differences by industry type. For non-tech industries, we find a one percentage point increase in the establishment entry rate is associated with a one percentage point increase in the growth rate of LP dispersion in the following period. For high-tech industries, we find entry is associated with an increase in dispersion only three periods later. Column 2 shows the relationship between aggregate LP growth and entry. We find that a surge in entry is associated with a small increase in LP growth among non-tech industries in the next period. The results do not show significant changes in LP growth for higher-order lags of entry. However, in high-tech industries, a one-percentage-point increase in entry leads to a 1.1-percentage-point decrease in LP growth one period later and to over 1.2-percentage-points higher LP growth in the two subsequent periods. The differences between high-tech and non-tech are large and statistically significant. The results for LP are broadly consistent with those for TFP but less systematic.[16]

Table 3 presents results using firm entry rates instead of establishment rates, which are largely similar to those in Table 2. The coefficient estimates are consistent with the innovation hypothesis, though not always statistically significant at conventional levels. As with Table 2,

[16] The weaker results for LP are not inconsistent with the findings of Foster et al. (2021) that focused on LP dispersion, growth, and firm entry. Foster et al. (2021) used 4-digit NAICS data for the entire private sector, while the current paper is restricted to the manufacturing sector. The primary value-added of the current paper is the use of TFP dispersion and growth measures at the detailed industry level within manufacturing.

results in Table 3 are more systematic using TFP dispersion and growth measures for high-tech industries.

Lastly, we consider whether there are stronger relationships between entry and dispersion growth for different parts of the support of the productivity distribution. For example, we may expect to find larger effects of entry among establishments above the median if more productive establishments are able to benefit more from innovations or if innovation induces entry of many establishments with relatively similar productivity levels. In Table 4, we present estimates of the relationship between entry rates and dispersion growth for the 75–50 and 50–25 ranges of the productivity distribution. We focus on the TFP results for this exercise.[17] For high-tech industries, entry initially leads to an increase in dispersion among both below- and above-median establishments, but the relationship is significant only for the lower part of the support (50–25). However, dispersion falls significantly both below and above the median in the second period but more dramatically among more productive establishments. In the third period, dispersion in the upper part of the support increases significantly. For non-tech industries, we find asymmetric effects, with entry leading to lower dispersion in the 75–50 range, but higher dispersion in the 50–25 range three periods later. Again, results are similar when we consider the relationships between firm entry rates and dispersion growth. We interpret these results as providing suggestive evidence that entry yields not only changes in overall dispersion but also changes in the shape of the dispersion.

In closing this section, it is instructive to observe that underlying the dynamic relationships we have uncovered are highly persistent processes. Productivity (LP and TFP),

[17] Results for LP are presented in Table A5. Results using the 90–50 and 50–10 ranges for both TFP and LP are presented in Table A6.

dispersion (LP and TFP), and entry levels all exhibit substantial persistence within industries.[18] Our findings highlight that these persistent processes relate to each other in complex and interesting ways.

IV. Conclusion

This paper uses novel detailed industry-level data on TFP and LP dispersion from the DiSP along with new measures of establishment and firm entry rates from the BDS to examine the relationships between productivity growth, productivity dispersion, and entry for U.S. manufacturing industries. We test the hypothesis that periods of innovative activity in an industry are initially associated with a surge in entry of new firms or establishments that is followed by an increase in experimentation that leads to rising within-industry dispersion with potentially declining productivity growth. Under this hypothesis, there is then a shakeout process, where the successful businesses grow and thrive while the unsuccessful ones exit, causing productivity dispersion to decline and productivity growth to rise. We find the strongest support for this hypothesis using the high-tech industries and measures of TFP dispersion and TFP growth. An increase in entry rates is initially associated with an increase in TFP dispersion and a decline in TFP productivity growth for high-tech industries. This is followed in subsequent periods by a decline in TFP dispersion and an increase in TFP growth for high-tech industries (especially relative to TFP growth for non-tech industries). Overall, these results lend support to the hypothesis that rising within-industry dispersion at least partly reflects innovation and experimentation. Future work using the restricted-use micro-productivity data could explore the

[18] Average AR1 coefficient for LP (TFP) productivity levels is 0.61 (0.54) for high-tech and 0.57 (0.45) for non-tech. Average AR1 coefficient for LP (TFP) dispersion levels for high-tech is 0.42 (0.23) and 0.30 (0.36) for non-tech. Average AR1 coefficient for entry rates for establishments is 0.61 for high-tech and 0.56 for non-tech. Table A7 in the Appendix presents estimates from an AR1 model for establishment entry for each manufacturing industry.

reasons we observe a stronger relationship between entry and productivity dispersion for the upper half of the productivity distribution.

Given the recent trend of low entry rates prior to the pandemic, we may expect to see slower productivity growth in the years to come. However, the surge in new business applications in the second half of 2020 suggests the possibility of a new round of productivity growth (Dinlersoz, Dunne, Haltiwanger, and Penciakova, 2021; Haltiwanger, 2021).

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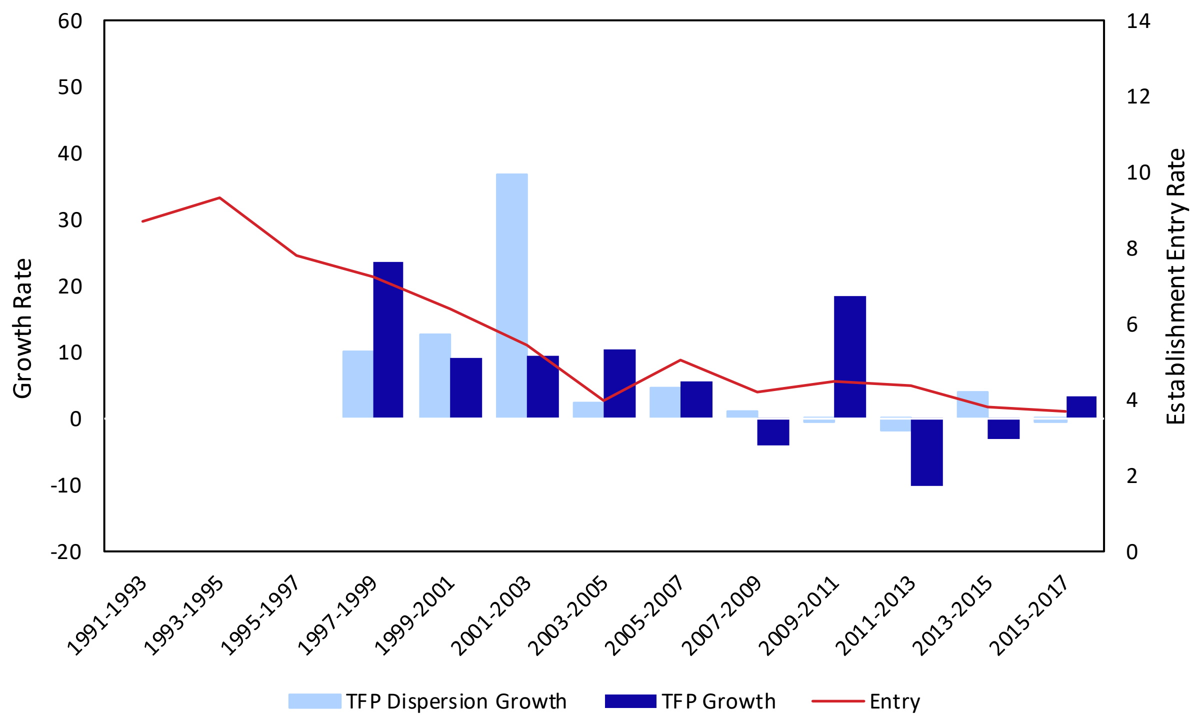

Figure 1. Semiconductor and other electronic component manufacturing, 1991–2017

Notes: Productivity and dispersion growth are calculated as non-overlapping two-year-average annual growth rates. Entry rates are two-year-average rates. Dispersion is the interquartile range of within-industry log revenue per hour, activity weighted.

Source: Authors' tabulations based on BLS Industry Productivity Statistics, Dispersion Statistics on Productivity, and Business Dynamic Statistics.

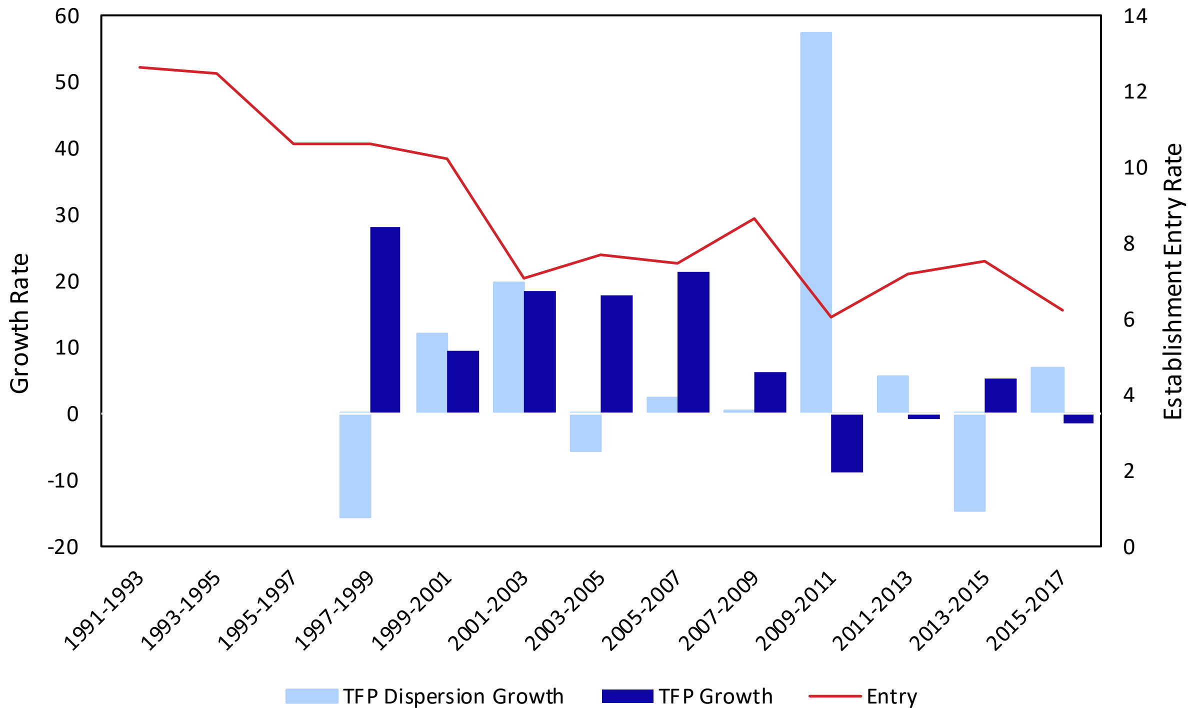

Figure 2. Computer and peripheral equipment manufacturing, 1991–2017

Notes: Productivity and dispersion growth are calculated as non-overlapping two-year-average annual growth rates. Entry rates are two-year-average rates. Dispersion is the interquartile range of within-industry log revenue per hour, activity weighted.

Source: Authors' tabulations based on BLS Industry Productivity Statistics, Dispersion Statistics on Productivity, and Business Dynamic Statistics.

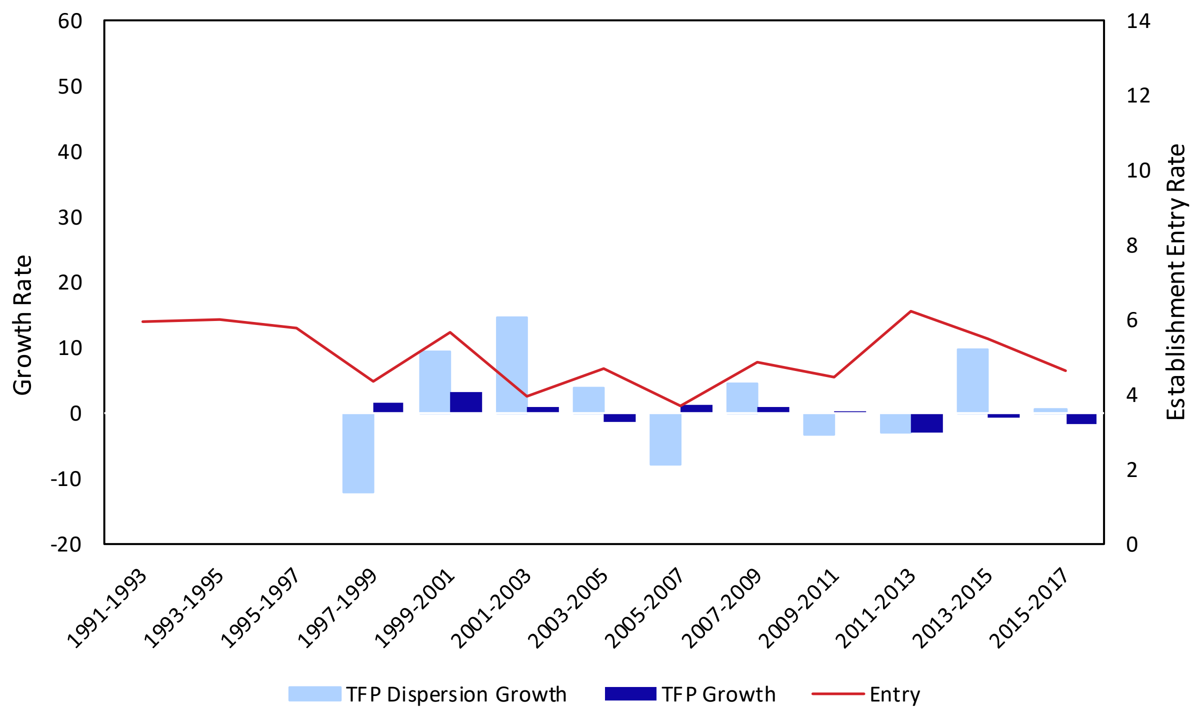

Figure 3. Grain and oilseed manufacturing, 1991–2017

Notes: Productivity and dispersion growth are calculated as non-overlapping two-year-average annual growth rates. Entry rates are two-year-average rates. Dispersion is the interquartile range of within-industry log revenue per hour, activity weighted.

Source: Authors' tabulations based on BLS Industry Productivity Statistics, Dispersion Statistics on Productivity, and Business Dynamic Statistics.

Table 1. Summary Statistics, All 4-digit NAICS Industries in the Manufacturing Sector

Variable	**Years**	**N**	**Mean**	**SD**	**Min**	**Max**
Productivity growth						
BLS labor productivity	1997–2017	860	1.6	6.0	-24.4	38.4
BLS total factor productivity	1997–2017	860	0.4	4.0	-11.1	28.0
Dispersion growth						
Labor productivity dispersion	1997–2016	860	0.6	8.6	-33.9	79.4
Total factor productivity dispersion	1997–2016	860	1.5	13.1	-63.8	118.5
Entry rate						
Establishment entry rate	1992–2015	1,032	6.1	2.5	1.5	21.1
Firm entry rate	1992–2015	1,032	6.1	2.7	1.2	23.2
Entry rate (percent change)						
Establishment entry rate	1992–2015	946	-0.5	24.7	-63.6	371.7
Firm entry rate	1992–2015	946	-0.6	27.2	-62.4	486.5

Note: Productivity and dispersion growth are calculated as non-overlapping two-year-average annual growth rates except in the last period dispersion is a one-year growth rate because this series ends in 2016, e.g., $LP_{1999–1997} = (index_{1999}/index_{1997})^{0.5} - 1) \times 100$. Entry rates are two-year-average rates, i.e., $entry_{1999–1998} = (entry_{1999} + entry_{1998})/2$. Dispersion is the interquartile range of within-industry log revenue per hour, activity weighted.

Source: Authors' tabulations based on BLS Industry Productivity Statistics, Dispersion Statistics on Productivity, and Business Dynamic Statistics.

Table 2. Productivity Growth, IQR Dispersion Growth, and Establishment Entry Rates (1997–2017)

	Labor Productivity		Total Factor Productivity	
	Dispersion (1)	**Productivity (2)**	**Dispersion (3)**	**Productivity (4)**
Lag 1 Entry	1.00***	0.45**	0.00	0.01
	(0.33)	(0.21)	(0.44)	(0.07)
Lag 2 Entry	-0.36	-0.20	-0.35	-0.20**
	(0.27)	(0.24)	(0.42)	(0.09)
Lag 3 Entry	-0.31	-0.15	0.33	-0.05
	(0.37)	(0.17)	(0.40)	(0.09)
Lag 1 Entry x Tech	-1.60	-1.59***	2.90*	-0.67**
	(1.24)	(0.51)	(1.49)	(0.30)
Lag 2 Entry x Tech	0.91	1.30*	-4.24**	0.78*
	(1.27)	(0.70)	(1.63)	(0.46)
Lag 3 Entry x Tech	1.33**	1.39**	0.85	0.83
	(0.57)	(0.69)	(1.94)	(0.57)
Joint Hypothesis Tests:				
Lag 1 Entry + Lag 1 Entry x Tech	-0.60	-1.14**	2.91**	-0.66**
	(1.21)	(0.49)	(1.41)	(0.31)
Lag 2 Entry + Lag 2 Entry x Tech	0.55	1.10	-4.59***	0.58
	(1.25)	(0.66)	(1.60)	(0.45)
Lag 3 Entry + Lag 3 Entry x Tech	1.02**	1.24*	1.18	0.79
	(0.51)	(0.69)	(1.90)	(0.58)
Observations	860	860	860	860
R-squared	0.08	0.28	0.09	0.34

Notes: Robust standard errors in parentheses are clustered at the industry level. Controls also include a constant, period effects, and industry effects. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Source: Authors' analysis based on BLS Industry Productivity Statistics, Dispersion Statistics on Productivity, and Business Dynamic Statistics.

Table 3. Productivity Growth, IQR Dispersion Growth, and Firm Entry Rates (1997–2017)

	Labor Productivity		Total Factor Productivity	
	Dispersion	**Productivity**	**Dispersion**	**Productivity**
	(1)	**(2)**	**(3)**	**(4)**
Lag 1 Entry	0.90^{***}	0.31^{*}	-0.36	-0.00
	(0.31)	(0.16)	(0.39)	(0.06)
Lag 2 Entry	-0.43^{*}	-0.18	-0.35	-0.11
	(0.25)	(0.20)	(0.41)	(0.08)
Lag 3 Entry	-0.24	-0.09	0.26	-0.02
	(0.30)	(0.16)	(0.31)	(0.07)
Lag 1 Entry x Tech	-1.86	-0.78	1.63	-0.13
	(1.29)	(0.52)	(1.85)	(0.27)
Lag 2 Entry x Tech	1.41	0.82	-4.60^{**}	0.34
	(1.40)	(0.75)	(1.83)	(0.37)
Lag 3 Entry x Tech	1.04	1.32^{**}	2.22	0.92^{*}
	(0.65)	(0.66)	(1.59)	(0.47)
Joint Hypothesis Tests:				
Lag 1 Entry + Lag 1 Entry x Tech	-0.96	-0.47	1.27	-0.13
	(1.27)	(0.50)	(1.80)	(0.27)
Lag 2 Entry + Lag 2 Entry x Tech	0.98	0.65	-4.95^{***}	0.23
	(1.38)	(0.72)	(1.82)	(0.36)
Lag 3 Entry + Lag 3 Entry x Tech	0.80	1.23^{*}	2.48	0.90^{*}
	(0.63)	(0.66)	(1.54)	(0.48)
Observations	860	860	860	860
R-squared	0.08	0.27	0.09	0.34

Notes: Robust standard errors in parentheses are clustered at the industry level. Controls include a constant, period effects, and industry effects. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Source: Authors' analysis based on BLS Industry Productivity Statistics, Dispersion Statistics on Productivity, and Business Dynamic Statistics.

Table 4. 75–50 and 50–25 TFP Dispersion Growth and Entry Rates (1997–2017)

	Establishment Entry		**Firm Entry**	
	75–50	**50–25**	**75–50**	**50–25**
	(1)	**(2)**	**(37)**	**(4)**
Lag 1 Entry	-0.39	0.50	-0.48	0.03
	(0.53)	(0.75)	(0.40)	(0.61)
Lag 2 Entry	0.11	-1.27	0.35	-1.34
	(0.56)	(0.79)	(0.42)	(0.91)
Lag 3 Entry	-0.94*	0.97*	-1.13**	1.23***
	(0.49)	(0.56)	(0.48)	(0.44)
Lag 1 Entry + Lag 1 Entry x Tech	3.34	3.04	1.45	1.85
	(2.22)	(1.86)	(1.56)	(2.00)
Lag 2 Entry + Lag 2 Entry x Tech	-7.20***	(1.54)	-9.75***	(0.30)
	(2.72)	(1.50)	(3.31)	(2.30)
Lag 3 Entry + Lag 3 Entry x Tech	4.51***	-1.02	7.67***	-0.83
	(1.69)	(1.66)	(1.90)	(1.38)
Joint hypothesis tests:				
Lag 1 Entry + Lag 1 Entry x Tech	2.95	3.54**	0.97	1.88
	(2.20)	(1.76)	(1.54)	(1.95)
Lag 2 Entry + Lag 2 Entry x Tech	-7.09***	-2.80**	-9.41***	-1.64
	(2.69)	(1.36)	(3.30)	(2.14)
Lag 3 Entry + Lag 3 Entry x Tech	3.57**	-0.05	6.54***	0.41
	(1.65)	(1.61)	(1.79)	(1.35)
Observations	859	859	859	859
R-squared	0.10	0.08	0.12	0.08

Notes: One observation is missing for the TFP regressions because the productivity levels at the different points in the distribution were the same in one period, and thus the percent change was undefined. Robust standard errors in parentheses are clustered at the industry level. Controls include a constant, period effects, and industry effects. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Source: Authors' analysis based on restricted-use dispersion measures and Business Dynamic Statistics.

Appendix

Table A1. Mean and Coefficient of Variation of Productivity Growth, by 4-digit NAICS Manufacturing Industry (1997─2017)

2012 NAICS code	4-digit NAICS industry	Labor Productivity		Total Factor Productivity	
		mean	CV	mean	CV
3111	Animal Food Manufacturing	2.0	35.0	-0.2	5.2
3112	Grain and Oilseed Milling	1.4	35.0	0.1	7.1
3113	Sugar and Confectionery Product Manufacturing	1.1	23.7	-0.3	9.7
3114	Fruit and Vegetable Preserving and Specialty Food	0.9	20.5	0.1	4.7
3115	Dairy Product Manufacturing	1.0	29.9	0.2	11.7
3116	Animal Slaughtering and Processing	0.6	26.2	0.6	30.6
3117	Seafood Product Preparation and Packaging	3.6	49.6	0.6	14.9
3118	Bakeries and Tortilla Manufacturing	0.2	7.3	-0.7	30.6
3119	Other Food Manufacturing	0.1	3.9	0.2	11.2
3121	Beverage Manufacturing	-0.6	11.0	0.2	8.2
3122	Tobacco Manufacturing	1.9	27.0	-1.2	23.4
3131	Fiber, Yarn, and Thread Mills	2.8	41.2	1.3	24.5
3132	Fabric Mills	2.9	44.1	1.1	35.2
3133	Textile and Fabric Finishing and Fabric Coating Mills	2.4	33.8	-0.1	3.1
3141	Textile Furnishings Mills	0.3	6.8	-1.0	27.4
3149	Other Textile Product Mills	0.3	4.0	0.0	0.2
3151	Apparel Knitting Mills	-0.9	9.4	-1.1	23.3
3152	Cut and Sew Apparel Manufacturing	-1.6	20.6	-1.5	35.9
3159	Apparel Accessories and Other Apparel Manufacturing	-2.9	35.1	-1.4	49.0
3161	Leather and Hide Tanning and Finishing	0.9	6.7	0.5	11.3
3162	Footwear Manufacturing	0.5	9.0	-0.6	27.0
3169	Other Leather and Allied Product Manufacturing	0.6	5.6	-0.2	8.3
3211	Sawmills and Wood Preservation	2.1	52.4	1.4	55.3
3212	Veneer, Plywood, and Engineered Wood Product Manufacturing	1.6	51.9	0.8	39.3
3219	Other Wood Product Manufacturing	1.2	36.8	-0.3	11.2
3221	Pulp, Paper, and Paperboard Mills	3.2	111.0	1.1	55.2
3222	Converted Paper Product Manufacturing	1.6	71.0	-0.3	19.2
3231	Printing and Related Support Activities	1.6	72.8	0.2	11.1
3241	Petroleum and Coal Products Manufacturing	1.8	92.0	-0.8	25.1
3251	Basic Chemical Manufacturing	3.2	39.9	0.6	12.9
3252	Resin, Synthetic Rubber, and Artificial Synthetic Fibers and Filaments	2.1	40.8	0.2	8.5
3253	Pesticide, Fertilizer, and Other Agricultural Chemical	1.8	25.1	0.8	14.4
3254	Pharmaceutical and Medicine Manufacturing	-0.8	23.2	-1.7	62.1
3255	Paint, Coating, and Adhesive Manufacturing	0.4	10.6	0.1	1.9
3256	Soap, Cleaning Compound, and Toilet Preparation Manufacturing	1.4	23.1	0.5	9.7
3259	Other Chemical Product and Preparation Manufacturing	1.6	55.7	0.6	25.4
3261	Plastics Product Manufacturing	1.2	39.9	0.2	8.9
3262	Rubber Product Manufacturing	0.9	29.8	0.1	5.1
3271	Clay Product and Refractory Manufacturing	1.3	25.0	-0.1	2.3
3272	Glass and Glass Product Manufacturing	2.2	67.3	0.5	19.9
3273	Cement and Concrete Product Manufacturing	-0.2	5.6	-0.7	22.4
3274	Lime and Gypsum Product Manufacturing	1.7	39.7	-0.2	5.0
3279	Other Nonmetallic Mineral Product Manufacturing	0.8	18.7	0.2	4.6
3311	Iron and Steel Mills and Ferroalloy Manufacturing	3.4	60.8	1.2	51.9
3312	Steel Product Manufacturing from Purchased Steel	-0.3	5.9	-0.4	7.6
3313	Alumina and Aluminum Production and Processing	2.8	47.9	1.5	38.2
3314	Nonferrous Metal (except Aluminum) Production and Processing	1.6	32.7	0.4	8.5
3315	Foundries	1.5	56.2	0.1	2.4
3321	Forging and Stamping	2.4	65.2	0.9	15.2
3322	Cutlery and Hand Tool Manufacturing	1.5	32.1	0.3	9.1

Table A1 Continued. Mean and Coefficient of Variation of Productivity Growth, by 4-digit Manufacturing Industry (1997—2017)

2012 NAICS code	4-digit NAICS industry	Labor Productivity mean	Labor Productivity CV	Total Factor Productivity mean	Total Factor Productivity CV
3323	Architectural and Structural Metals Manufacturing	0.5	18.2	-0.3	9.0
3324	Boiler, Tank, and Shipping Container Manufacturing	0.3	9.0	-0.2	3.4
3325	Hardware Manufacturing	0.4	9.5	-0.8	30.8
3326	Spring and Wire Product Manufacturing	1.9	51.8	0.4	11.4
3327	Machine Shops; Turned Product; and Screw, Nut, and Bolt	1.0	40.2	0.0	1.5
3328	Coating, Engraving, Heat Treating, and Allied Activities	1.2	28.4	0.9	20.0
3329	Other Fabricated Metal Product Manufacturing	0.0	1.3	-0.5	16.4
3331	Agriculture, Construction, and Mining Machinery Manufacturing	0.6	9.8	-0.7	16.9
3332	Industrial Machinery Manufacturing	0.9	14.0	1.0	17.4
3333	Commercial and Service Industry Machinery Manufacturing	1.4	26.4	0.0	1.2
3334	Ventilation, Heating, Air-Conditioning, and Commercial Refrigeration Equipment Manufacturing	1.4	34.5	0.5	23.2
3335	Metalworking Machinery Manufacturing	1.9	56.9	1.1	26.7
3336	Engine, Turbine, and Power Transmission Equipment Manufacturing	0.9	16.2	-0.1	2.4
3339	Other General Purpose Machinery Manufacturing	1.7	41.0	0.2	5.2
3341	Computer and Peripheral Equipment Manufacturing	10.9	65.5	9.6	82.6
3342	Communications Equipment Manufacturing	3.6	35.4	0.9	16.3
3343	Audio and Video Equipment Manufacturing	2.0	16.2	2.4	59.6
3344	Semiconductor and Other Electronic Component Manufacturing	10.0	78.4	6.3	61.0
3345	Navigational, Measuring, Electromedical, and Control Instruments	2.8	77.7	0.5	23.4
3346	Manufacturing and Reproducing Magnetic and Optical Media	0.2	1.8	0.5	8.5
3351	Electric Lighting Equipment Manufacturing	1.4	34.0	0.6	20.1
3352	Household Appliance Manufacturing	2.8	67.7	1.7	65.2
3353	Electrical Equipment Manufacturing	0.4	9.2	-0.3	12.3
3359	Other Electrical Equipment and Component Manufacturing	0.4	8.4	0.3	8.1
3361	Motor Vehicle Manufacturing	3.3	40.8	0.3	7.9
3362	Motor Vehicle Body and Trailer Manufacturing	1.7	30.6	0.2	6.6
3363	Motor Vehicle Parts Manufacturing	3.0	82.3	1.4	75.8
3364	Aerospace Product and Parts Manufacturing	2.3	52.7	0.9	34.7
3365	Railroad Rolling Stock Manufacturing	2.8	55.3	0.7	18.2
3366	Ship and Boat Building	2.3	64.3	0.9	39.7
3369	Other Transportation Equipment Manufacturing	4.6	40.0	1.5	24.5
3371	Household and Institutional Furniture and Kitchen Cabinet	0.8	30.8	0.1	4.9
3372	Office Furniture (including Fixtures) Manufacturing	1.4	28.5	0.2	4.5
3379	Other Furniture Related Product Manufacturing	2.4	72.8	0.0	1.0
3391	Medical Equipment and Supplies Manufacturing	2.0	48.7	0.3	14.3
3399	Other Miscellaneous Manufacturing	1.1	30.2	0.5	19.2

Source: Authors' calculations based on the BLS Industry Productivity Statistics.

Table A2. 90–10 Dispersion Growth and Entry Rates (1997–2016)

	Establishment Entry		Firm Entry	
	LP Dispersion (1)	TFP Dispersion (2)	LP Dispersion (3)	TFP Dispersion (4)
Lag 1 Entry	-0.12	0.02	-0.08	-0.27
	(0.32)	(0.45)	(0.29)	(0.38)
Lag 2 Entry	0.33	-0.27	0.10	-0.12
	(0.27)	(0.38)	(0.19)	(0.36)
Lag 3 Entry	-0.43*	-0.36	-0.26	-0.32
	(0.26)	(0.24)	(0.17)	(0.20)
Lag 1 Entry x Tech	-0.12	1.83*	-0.10	1.39
	(0.50)	(0.98)	(0.44)	(1.09)
Lag 2 Entry x Tech	-0.28	-1.14	0.09	-1.04
	(0.47)	(0.92)	(0.65)	(1.01)
Lag 3 Entry x Tech	0.70	0.16	0.35	0.40
	(0.56)	(0.73)	(0.59)	(0.62)
Joint Hypothesis Tests:				
Lag 1 Entry + Lag 1 Entry x Tech	-0.24	1.85**	-0.18	1.12
	(0.43)	(0.87)	(0.37)	(1.02)
Lag 2 Entry + Lag 2 Entry x Tech	0.05	-1.41	0.19	-1.16
	(0.40)	(0.85)	(0.63)	(0.96)
Lag 3 Entry + Lag 3 Entry x Tech	0.27	-0.20	0.10	0.08
	(0.52)	(0.70)	(0.58)	(0.60)
Observations	860	860	860	860
R-squared	0.07	0.07	0.06	0.06

Notes: Standard errors in parentheses are clustered at the industry level. Controls include a constant, period effects, and industry effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Source: Authors' analysis based on Dispersion Statistics on Productivity and Business Dynamic Statistics.

Table A3. IQR Dispersion Growth and Entry Rates (1997–2016)

	Establishment Entry		Firm Entry	
	LP Dispersion (1)	**TFP Dispersion (2)**	**LP Dispersion (3)**	**TFP Dispersion (4)**
Lag 1 Entry	0.12	0.84	0.09	0.59
	(0.66)	(0.61)	(0.58)	(0.43)
Lag 2 Entry	-0.63	-1.10*	-0.62*	-0.93*
	(0.45)	(0.62)	(0.32)	(0.53)
Lag 3 Entry	0.18	-0.75	0.18	-0.68
	(0.32)	(0.56)	(0.33)	(0.46)
Lag 1 Entry x Tech	0.25	-0.07	-0.10	0.32
	(0.85)	(1.52)	(0.84)	(1.85)
Lag 2 Entry x Tech	-0.36	-1.76	-0.28	-2.22
	(0.99)	(1.68)	(0.96)	(2.07)
Lag 3 Entry x Tech	0.53	0.97	0.94	1.15
	(0.67)	(1.19)	(0.78)	(1.09)
Joint Hypothesis Tests:				
Lag 1 Entry + Lag 1 Entry x Tech	0.37	0.77	-0.01	0.91
	(0.67)	(1.41)	(0.67)	(1.79)
Lag 2 Entry + Lag 2 Entry x Tech	-1.00	-2.87*	-0.89	-3.15
	(0.90)	(1.59)	(0.91)	(2.01)
Lag 3 Entry + Lag 3 Entry x Tech	0.71	0.22	1.12	0.47
	(0.65)	(1.09)	(0.78)	(1.02)
Observations	860	860	860	860
R-squared	0.06	0.05	0.07	0.05

Notes: This table corresponds to columns 1 and 3 in Tables 2 and 3; however, here we use dispersion statistics that are not activity weighted. Standard errors in parentheses are clustered at the industry level. Controls include a constant, period effects, and industry effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Source: Authors' analysis based on Dispersion Statistics on Productivity and Business Dynamic Statistics.

Table A4. Productivity Growth and Entry Rates (1987–2017)

	Establishment Entry		Firm Entry	
	LP	**TFP**	**LP**	**TFP**
	(1)	**(2)**	**(3)**	**(4)**
Lag 1 Entry	0.27^{**}	0.05	0.17	0.01
	(0.12)	(0.05)	(0.11)	(0.04)
Lag 2 Entry	-0.25	-0.17^{***}	-0.22	-0.10^{*}
	(0.17)	(0.06)	(0.16)	(0.05)
Lag 3 Entry	-0.07	0.04	-0.02	0.04
	(0.12)	(0.06)	(0.12)	(0.05)
Lag 1 Entry x Tech	-0.68^{**}	-0.36	-0.21	-0.08
	(0.33)	(0.23)	(0.36)	(0.21)
Lag 2 Entry x Tech	0.55	0.40	0.24	0.15
	(0.41)	(0.25)	(0.42)	(0.23)
Lag 3 Entry x Tech	1.12^{***}	0.57^{**}	1.12^{***}	0.67^{***}
	(0.34)	(0.28)	(0.32)	(0.25)
Joint Hypothesis Tests:				
Lag 1 Entry + Lag 1 Entry x Tech	-0.42	-0.31	-0.04	-0.07
	(0.32)	(0.24)	(0.35)	(0.21)
Lag 2 Entry + Lag 2 Entry x Tech	0.30	0.23	0.02	0.05
	(0.38)	(0.25)	(0.39)	(0.23)
Lag 3 Entry + Lag 3 Entry x Tech	1.06^{***}	0.61^{**}	1.10^{***}	0.71^{***}
	(0.32)	(0.28)	(0.30)	(0.25)
Observations	1,290	1,290	1,290	1,290
R-squared	0.30	0.36	0.31	0.37

Notes: This table corresponds to columns 2 and 4 in Tables 2 and 3; however, here we use a longer time series. Robust standard errors in parentheses are clustered at the industry level. Controls include a constant, period effects, and industry effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Source: Authors' analysis based on the BLS Industry Productivity Statistics and Business Dynamic Statistics.

Table A5. 75–50 and 50–25 LP Dispersion Growth and Entry Rates

	Establishment Entry		**Firm Entry**	
	75–50	**50–25**	**75–50**	**50–25**
	(1)	**(2)**	**(3)**	**(4)**
Lag 1 Entry	0.80**	0.16	0.75**	0.24
	(0.34)	(0.34)	(0.29)	(0.29)
Lag 2 Entry	-0.39	-0.15	-0.68	-0.15
	(0.35)	(0.38)	(0.48)	(0.33)
Lag 3 Entry	-0.27	-0.24	0.09	-0.26
	(0.85)	(0.47)	(0.85)	(0.39)
Lag 1 Entry + Lag 1 Entry x Tech	-0.50	-2.61	-1.35	-2.00
	(2.11)	(1.89)	(1.92)	(1.68)
Lag 2 Entry + Lag 2 Entry x Tech	0.57	0.12	1.64	(0.09)
	(1.55)	(1.30)	(1.61)	(1.44)
Lag 3 Entry + Lag 3 Entry x Tech	0.9	2.22*	0.64	1.61
	(0.96)	(1.25)	(0.90)	(1.12)
Joint hypothesis tests:				
Lag 1 Entry + Lag 1 Entry x Tech	0.30	-2.45	-0.60	-1.76
	(2.13)	(1.88)	(1.92)	(1.67)
Lag 2 Entry + Lag 2 Entry x Tech	0.18	-0.03	0.96	-0.24
	(1.54)	(1.27)	(1.55)	(1.41)
Lag 3 Entry + Lag 3 Entry x Tech	0.63	1.97*	0.72	1.35
	(0.70)	(1.16)	(0.75)	(1.06)
Observations	860	860	860	860
R-squared	0.06	0.06	0.06	0.06

Notes: Robust standard errors in parentheses are clustered at the industry level. Controls include a constant, period effects, and industry effects. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.
Source: Authors' analysis based on restricted-use dispersion measures and Business Dynamic Statistics.

Table A6. 90–50 and 50–10 Dispersion Growth and Entry Rates

	Establishment entry				Firm entry			
	LP		TFP		LP		TFP	
	90–50	50–10	90–50	50–10	90–50	50–10	90–50	50–10
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lag 1 Entry	-0.12	-0.23	-0.09	-0.17	-0.14	-0.11	-0.31	-0.39
	(0.25)	(0.46)	(0.62)	(0.57)	(0.24)	(0.42)	(0.53)	(0.52)
Lag 2 Entry	0.50	0.78	0.07	-0.61	0.24	0.52	-0.08	-0.33
	(0.40)	(0.57)	(0.53)	(0.58)	(0.30)	(0.43)	(0.40)	(0.49)
Lag 3 Entry	-0.30	-0.52	-0.91**	0.46	-0.11	-0.31	-0.72**	0.42
	(0.41)	(0.43)	(0.36)	(0.35)	(0.30)	(0.30)	(0.28)	(0.31)
Lag 1 Entry + Lag 1 Entry x Tech	0.25	-0.74	2.07*	3.01**	-0.24	-0.03	2.65*	2.51*
	(0.81)	(1.24)	(1.20)	(1.19)	(0.72)	(1.10)	(1.34)	(1.48)
Lag 2 Entry + Lag 2 Entry x Tech	0.34	-0.66	-5.17*	0.13	1.16	-0.81	-5.98	1.07
	(0.57)	(0.78)	(2.91)	(0.93)	(0.88)	(0.86)	(4.04)	(1.29)
Lag 3 Entry + Lag 3 Entry x Tech	-0.06	1.81**	2.54	-1.77*	-0.26	1.17*	2.83	-2.12**
	(0.65)	(0.79)	(1.86)	(1.06)	(0.66)	(0.60)	(1.70)	(0.96)
Joint hypothesis tests:								
Lag 1 Entry + Lag 1 Entry x Tech	0.13	-0.97	1.98*	2.84***	-0.38	-0.15	2.34*	2.12
	(0.77)	(1.18)	(1.15)	(1.04)	(0.70)	(1.05)	(1.26)	(1.40)
Lag 2 Entry + Lag 2 Entry x Tech	0.84*	0.11	-5.10*	-0.48	1.40*	-0.29	-6.07	0.74
	(0.43)	(0.57)	(2.96)	(0.77)	(0.84)	(0.76)	(4.06)	(1.19)
Lag 3 Entry + Lag 3 Entry x Tech	-0.36	1.29*	1.63	-1.31	-0.36	0.86	2.11	-1.70*
	(0.55)	(0.69)	(1.79)	(1.02)	(0.60)	(0.54)	(1.67)	(0.93)
Observations	860	860	860	860	860	860	860	860
R-squared	0.07	0.09	0.07	0.07	0.07	0.08	0.08	0.06

Notes: Robust standard errors in parentheses are clustered at the industry level. Controls include a constant, period effects, and industry effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Source: Authors' analysis based on restricted-use dispersion measures and Business Dynamic Statistics.

Table A7. AR1 Model of Establishment Entry by 4-digit NAICS Industry (1991–2015)

2012 NAICS code	High-Tech	4-digit NAICS industry	Coef	S.E.	R-squared
3111		Animal Food Manufacturing	0.33	(0.21)	0.14
3112		Grain and Oilseed Milling	-0.01	(0.24)	0.00
3113		Sugar and Confectionery Product Manufacturing	0.59***	(0.17)	0.52
3114		Fruit and Vegetable Preserving and Specialty Food Manufacturing	0.32	(0.33)	0.04
3115		Dairy Product Manufacturing	0.66	(0.42)	0.29
3116		Animal Slaughtering and Processing	0.65***	(0.17)	0.63
3117		Seafood Product Preparation and Packaging	0.75***	(0.16)	0.62
3118		Bakeries and Tortilla Manufacturing	0.79***	(0.14)	0.67
3119		Other Food Manufacturing	-0.19	(0.28)	0.03
3121		Beverage Manufacturing	1.15***	(0.23)	0.73
3122		Tobacco Manufacturing	0.06	(0.30)	0.00
3131		Fiber, Yarn, and Thread Mills	0.51*	(0.25)	0.26
3132		Fabric Mills	0.92***	(0.12)	0.88
3133		Textile and Fabric Finishing and Fabric Coating Mills	0.57**	(0.18)	0.34
3141		Textile Furnishings Mills	0.79***	(0.13)	0.66
3149		Other Textile Product Mills	0.77***	(0.15)	0.68
3151		Apparel Knitting Mills	0.70***	(0.21)	0.53
3152		Cut and Sew Apparel Manufacturing	0.50**	(0.20)	0.25
3159		Apparel Accessories and Other Apparel Manufacturing	0.68***	(0.15)	0.51
3161		Leather and Hide Tanning and Finishing	-0.05	(0.35)	0.00
3162		Footwear Manufacturing	0.49	(0.30)	0.05
3169		Other Leather and Allied Product Manufacturing	0.25	(0.32)	0.04
3211		Sawmills and Wood Preservation	0.67**	(0.22)	0.54
3212		Veneer, Plywood, and Engineered Wood Product Manufacturing	0.66***	(0.20)	0.48
3219		Other Wood Product Manufacturing	0.76***	(0.18)	0.63
3221		Pulp, Paper, and Paperboard Mills	0.34	(0.25)	0.11
3222		Converted Paper Product Manufacturing	0.93***	(0.10)	0.87
3231		Printing and Related Support Activities	0.68***	(0.05)	0.87
3241	Y	Petroleum and Coal Products Manufacturing	0.46**	(0.16)	0.18
3251	Y	Basic Chemical Manufacturing	0.49	(0.29)	0.20
3252	Y	Resin, Synthetic Rubber, and Artificial Synthetic Fibers and Filaments Manufacturing	0.82***	(0.20)	0.48

Table A7 Continued. AR1 Model of Establishment Entry by 4-digit NAICS Industry (1991–2015)

2012 NAICS code	High-Tech	4-digit NAICS industry	Coef	S.E.	R-squared
3253		Pesticide, Fertilizer, and Other Agricultural Chemical Manufacturing	-0.44	(0.30)	0.21
3254	Y	Pharmaceutical and Medicine Manufacturing	0.42	(0.31)	0.16
3255		Paint, Coating, and Adhesive Manufacturing	0.48	(0.26)	0.23
3256		Soap, Cleaning Compound, and Toilet Preparation Manufacturing	0.70***	(0.17)	0.58
3259		Other Chemical Product and Preparation Manufacturing	0.41	(0.25)	0.23
3261		Plastics Product Manufacturing	0.84***	(0.10)	0.83
3262		Rubber Product Manufacturing	0.83***	(0.10)	0.89
3271		Clay Product and Refractory Manufacturing	0.66***	(0.17)	0.56
3272		Glass and Glass Product Manufacturing	0.76***	(0.12)	0.80
3273		Cement and Concrete Product Manufacturing	0.40	(0.23)	0.18
3274		Lime and Gypsum Product Manufacturing	0.63***	(0.20)	0.57
3279		Other Nonmetallic Mineral Product Manufacturing	0.77**	(0.25)	0.46
3311		Iron and Steel Mills and Ferroalloy Manufacturing	0.16	(0.23)	0.03
3312		Steel Product Manufacturing from Purchased Steel	0.43**	(0.17)	0.17
3313		Alumina and Aluminum Production and Processing	0.89***	(0.25)	0.54
3314		Nonferrous Metal (except Aluminum) Production and Processing	0.43	(0.24)	0.16
3315		Foundries	0.67***	(0.13)	0.56
3321		Forging and Stamping	0.68***	(0.13)	0.64
3322		Cutlery and Handtool Manufacturing	0.68***	(0.17)	0.59
3323		Architectural and Structural Metals Manufacturing	0.66***	(0.16)	0.51
3324		Boiler, Tank, and Shipping Container Manufacturing	0.41*	(0.22)	0.21
3325		Hardware Manufacturing	0.61***	(0.17)	0.45
3326		Spring and Wire Product Manufacturing	0.70***	(0.15)	0.66
3327		Machine Shops; Turned Product; and Screw, Nut, and Bolt Manufacturing	0.90***	(0.14)	0.76
3328		Coating, Engraving, Heat Treating, and Allied Activities	0.75***	(0.14)	0.59
3329		Other Fabricated Metal Product Manufacturing	0.31*	(0.17)	0.12
3331		Agriculture, Construction, and Mining Machinery Manufacturing	0.47**	(0.20)	0.21
3332	Y	Industrial Machinery Manufacturing	0.73***	(0.17)	0.59
3333	Y	Commercial and Service Industry Machinery Manufacturing	0.72***	(0.16)	0.67
3334		Ventilation, Heating, Air-Conditioning, and Commercial Refrigeration Equipment Manufacturing	0.93***	(0.16)	0.70
3335		Metalworking Machinery Manufacturing	0.83***	(0.12)	0.77

Table A7 Continued. AR1 Model of Establishment Entry by 4-digit NAICS Industry (1991–2015)

2012 NAICS code	High-Tech	4-digit NAICS industry	Coef	S.E.	R-squared
3336	Y	Engine, Turbine, and Power Transmission Equipment Manufacturing	0.27	(0.17)	0.07
3339	Y	Other General Purpose Machinery Manufacturing	0.99***	(0.13)	0.86
3341	Y	Computer and Peripheral Equipment Manufacturing	0.77***	(0.14)	0.65
3342	Y	Communications Equipment Manufacturing	0.41*	(0.20)	0.19
3343	Y	Audio and Video Equipment Manufacturing	0.15	(0.32)	0.02
3344	Y	Semiconductor and Other Electronic Component Manufacturing	0.83***	(0.11)	0.85
3345	Y	Navigational, Measuring, Electromedical, and Control Instruments Manufacturing	0.99***	(0.12)	0.83
3346	Y	Manufacturing and Reproducing Magnetic and Optical Media	0.83***	(0.16)	0.66
3351		Electric Lighting Equipment Manufacturing	0.08	(0.13)	0.01
3352		Household Appliance Manufacturing	0.03	(0.29)	0.00
3353	Y	Electrical Equipment Manufacturing	0.76***	(0.19)	0.55
3359		Other Electrical Equipment and Component Manufacturing	0.64**	(0.24)	0.39
3361		Motor Vehicle Manufacturing	0.35	(0.32)	0.10
3362		Motor Vehicle Body and Trailer Manufacturing	0.71***	(0.17)	0.49
3363		Motor Vehicle Parts Manufacturing	0.83***	(0.12)	0.71
3364	Y	Aerospace Product and Parts Manufacturing	0.08	(0.12)	0.01
3365		Railroad Rolling Stock Manufacturing	-0.27	(0.16)	0.14
3366		Ship and Boat Building	0.81***	(0.13)	0.70
3369		Other Transportation Equipment Manufacturing	0.44	(0.27)	0.18
3371		Household and Institutional Furniture and Kitchen Cabinet Manufacturing	0.90***	(0.09)	0.82
3372		Office Furniture (including Fixtures) Manufacturing	0.81***	(0.13)	0.81
3379		Other Furniture Related Product Manufacturing	0.72***	(0.10)	0.69
3391		Medical Equipment and Supplies Manufacturing	0.83***	(0.09)	0.89
3399		Other Miscellaneous Manufacturing	0.33	(0.27)	0.12

Notes: *** p<0.01, ** p<0.05, * p<0.1
Source: Authors' analysis based on the Business Dynamic Statistics.