Chaos Before Order: Productivity Patterns in U.S. Manufacturing

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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 labour productivity dispersion from the Dispersion Statistics on Productivity dataset 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. An increase in entry rates in a two-year period t is associated with an increase in dispersion and decrease in aggregate productivity growth in two-year

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period t+1 and a decrease in dispersion and increase in aggregate productivity growth in two-year period t+2.

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 labour 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 article, 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

2 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 public-use data and STATA code to

from the Bureau of Labor Statistics (BLS) to examine the relationships between entry, dispersion, and productivity.[2]. 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 article 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 aggregate TFP growth, especially for high-tech industries, using entry rates as a proxy for innovation. A surge in entry in 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 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 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 growth, 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 article proceeds as follows. In the first main section, we describe the data and present descriptive statistics. The main results are in section two. Concluding remarks are in section three.

Data and Descriptive Statistics

This article uses detailed industry-level data on productivity growth, establishment and firm entry rates, and establishment level productivity dispersion from three public-use data sources: BLS Industry Productivity Statistics, Business Dynamics Statistics (BDS), and Dispersion Statistics on Productivity (DiSP). In addition, we construct additional dispersion measures from the restricted-use data underlying DiSP.[3] Throughout the article, we use industry-level measures for all 86 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.

BLS produces the official U.S. measures of LP and TFP growth for four-digit NAICS manufacturing industries (Bureau of Labor Statistics, 2020).The industry LP measures are defined as the ratio of the growth in real sectoral output—the total value of goods and services sold outside

replicate the analyses based on the public-use data are available at https://doi.org/10.5281/zenodo.5770628

3 The experimental data product DiSP was first released in September 2019. Industry-level BDS data were first released in September 2020.

the four-digit NAICS industry — to the growth in hours worked by all persons in the industry.[4] For most industries, real output is derived by deflating 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] The industry TFP measures are defined as the ratio of the growth in real sectoral output to the growth in the cost-weighted combined inputs utilized in producing that output. Inputs include capital, labour hours, energy, materials, and purchased business services.

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 Online Appendix Table A1 for four-digit NAICS industry productivity means and coefficients of variation).[7]

http://www.csls.ca/ipm/41/IPM_41_Data_Appendix.xlsx

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).[8]

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, where output is based on the value of shipments adjusted for resales and changes in inventories and the deflator is the BLS implicit price deflator for that industry.[9] TFP is the log of real output per unit of all factor input costs, where the factors are capital, labour hours, energy, and materials. These measures are available with and without activity weighting, where the activity weights for LP are an establishment's hours share (the share of

4 For very detailed industries, sectoral output is very close to gross output. For more-aggregated industries, sectoral output is closer to value added. 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 The online appendix tables are posted at http://www.csls.ca/ipm/41/IPM_41_Productivity_Dispersion.pdf.

8 We use standard growth rate measures calculating the ratio of indexes in the current (2-year) period to the prior (2-year) period and then annualizing. For example, $LP_{1997-1999} = (\text{index}_{1999}/\text{index}_{1997})^{0.5} - 1) * 100$.

9 To make the dispersion measures comparable across industries and over time, we normalize each establishment's productivity level each year by subtracting the mean productivity of that establishment's four-digit industry.

a plant's hours of the total hours in its industry) and for TFP are an establishment's share of combined inputs.[10] 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 LP and MFP dispersion 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.[11]

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

Our entry rates come from the BDS, which the Census Bureau (2020) significantly redesigned and expanded with the release of the 2018 data 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.[13] 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

10 See Cunningham *et al.* (2021) for a detailed description of these new dispersion measures.

11 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.

12 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 Annual Survey of Manufactures. Activity weighting is the product of the inverse propensity weight and an activity weight.

13 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.

t-1.[14] 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 per cent for the 1997–2017 period. Over the same period, TFP grew on average 0.4 per cent per year. Dispersion growth is the growth rate in the IQR for LP and TFP dispersion. The LP dispersion growth rate was 0.6 per cent on average, while the TFP dispersion growth rate was 1.5 per cent on average; however, there was considerable variation in aggregate productivity and productivity dispersion growth across industries and time (see the minimum and maximum values). Entry rates were 6.1 per cent 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 have 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 based on the share of jobs held by STEM workers (including engineers, IT workers, scientists, and managers of these workers). The industry is considered high-tech if the share of these workers in the industry exceeds 2.5 times the national average, as determined by Wolf and Terrell (2016).[15] 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 (1) establishment entry rates and TFP dispersion growth and (2) establishment entry rates 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,

14 See https://www.census.gov/programs-surveys/bds/documentation/faq.html for more details on the construction of the entry rates.

15 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.

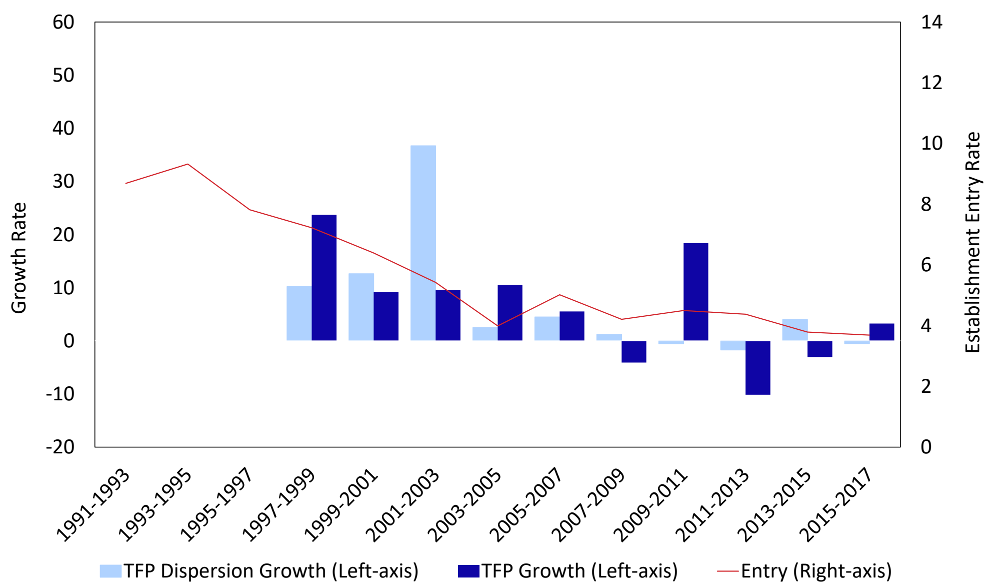
Table 1: Summary Statistics, All Four-digit NAICS Industries in the Manufacturing Sector

Variable	Years	N	Mean	Std. dev.	Min	Max
Productivity growth						
BLS labour productivity (LP)	1997–2017	860	1.6	6.0	-24.4	38.4
BLS total factor productivity (TFP)	1997–2017	860	0.4	4.0	-11.1	28
Dispersion growth						
LP dispersion	1997–2016	860	0.6	8.6	-33.9	79.4
TFP 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 (per cent 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., $LP_{1997-1999} = (index_{1999}/index_{1997})^{0.5} - 1) * 100$. Entry rates are two-year-average rates, i.e., $entry_{1999-1998} = (entry_{1999} + entry_{1998})/2$. LP (TFP) dispersion is the interquartile range of within-industry log real output per hour (log real output per unit of combined inputs), activity weighted. Min and max statistics are for industry by period (two-year) variation.

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

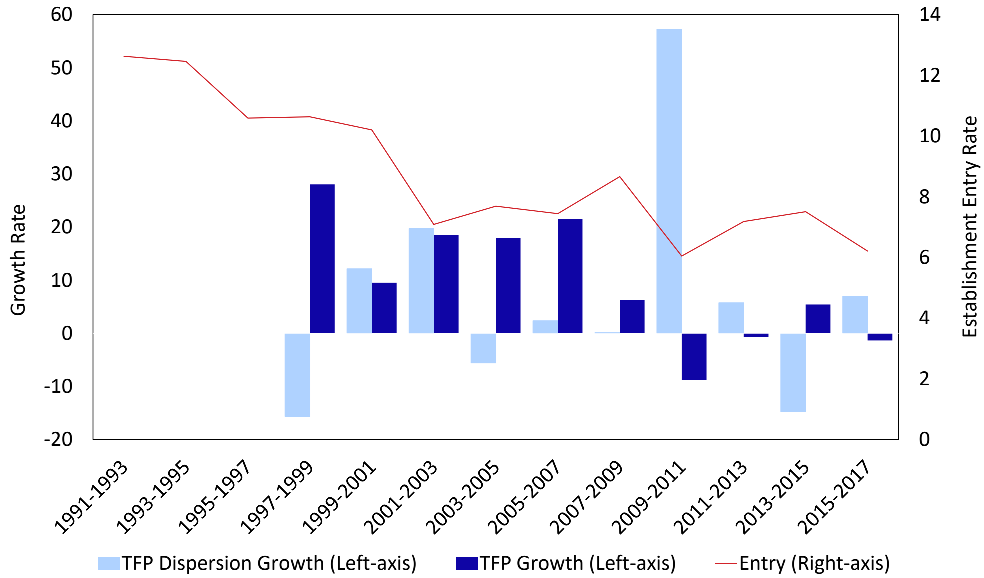
Chart 1: Semiconductor and Other Electronic Component Manufacturing, 1991–2017



Note: Productivity and dispersion growth are calculated as non-overlapping two-year-average annual growth rates. Entry rates are two-year-average rates. TFP dispersion is the interquartile range of within-industry log real output per unit of combined inputs, activity weighted.

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

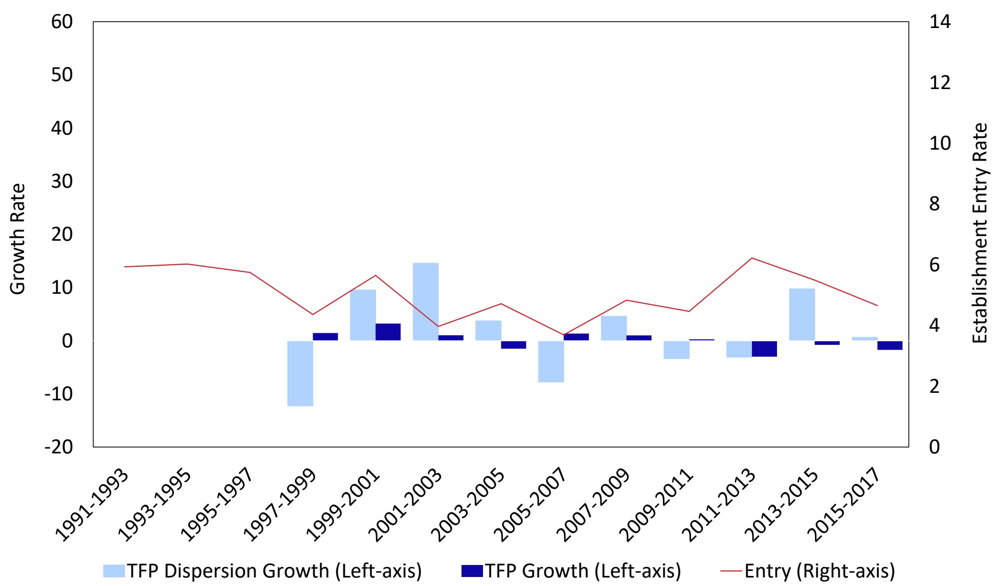
Chart 2: Computer and Peripheral Equipment Manufacturing, 1991–2017



Note: Productivity and dispersion growth are calculated as non-overlapping two-year-average annual growth rates. Entry rates are two-year-average rates. TFP dispersion is the interquartile range of within-industry log real output per unit of combined inputs, activity weighted.

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

Chart 3: Grain and Oilseed Manufacturing, 1991–2017



Note: Productivity and dispersion growth are calculated as non-overlapping two-year-average annual growth rates. Entry rates are two-year-average rates. TFP dispersion is the interquartile range of within-industry log real output per unit of combined inputs, activity weighted.

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

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.

In Chart 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 per cent. Around 2003, entry rates became relatively stable at around 4 to 5 per cent, 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 two out of the four periods following the Great Recession, TFP growth was negative.

Chart 2 shows the relationships for computer and peripheral equipment manufacturing. Again, we see that entry rates are initially very high through 2001, exceeding 10 per cent. Thereafter, entry rates are consistently below 8 per cent, except during the Great Recession when the entry rate rose to about 8.7 per cent. 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.

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

Empirical Model and Results

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

$$\begin{aligned} Y_{i,t} = {} & \alpha + \lambda_t + \lambda_i + \sum_{k=1}^{3} [\beta_k Entry_{i,t-k} \\ & + \delta_k Entry_{i,t-k} * Tech_i] + \epsilon_{i,t} \end{aligned} \tag{1}$$

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). The parameter 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.

We estimate both the productivity and dispersion models in growth rate specifications. Differences in levels of productivity are difficult to interpret. For productivity dispersion, levels are more readily interpretable. However, there are industry-

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

	Labour 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

Note: 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' tabulations based on BLS Industry Productivity Statistics, Dispersion Statistics on Productivity, and Business Dynamics Statistics.

specific differences in trends in productivity dispersion. The growth rate specifications control for these differences, which are outside the scope of our analysis, in a parsimonious manner.

Our main results are presented in Table 2. The first three rows in Table 2 present the associations for non-tech industries. The second three rows are the differential associations for high-tech industries. The last three rows, which are calculated by summing the associations for non-tech industries and the differential associations for high-tech industries, are the associations for high-tech industries.

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-percentage-point decrease in TFP growth in the next period (column 4).[16] In the second period after entry, dispersion growth falls dramatically (a 4.6-percentage-point decrease) while TFP growth rises (a 0.6-

16 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 (Online Appendix Table A2). We also looked at the relationships using dispersion statistics that were not activity weighted (Online Appendix Table A3). Results are not as strong without activity weighting.

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 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 Online 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 two subsequent periods later. 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.[17]

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 in Table 2, 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 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 the dispersion growth for the 75–50 and 50–25 ranges of the productivity distribution. We focus on the TFP results for this exercise.[18] For high-tech industries, entry

17 The weaker results for LP are not inconsistent with the findings by Foster *et al.* (2021) who focused on LP dispersion, growth, and firm entry. Foster *et al.* (2021) used four-digit NAICS data for the entire private sector, while the current article 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.

18 Results for LP are presented in Online Appendix Table A5. Results using the 90–50 and 50–10 ranges for both TFP and LP are presented in Online Appendix Table A6.

Table 3: Productivity Growth, IQR Dispersion Growth, and Firm Entry Rates, 1997–2017

	Labour Productivity		Total Factor Productivity	
	Dispersion (1)	Productivity (2)	Dispersion (3)	Productivity (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

Note: 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' tabulations based on BLS Industry Productivity Statistics, Dispersion Statistics on Productivity, and Business Dynamics Statistics.

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 IQR (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), dispersion (LP and TFP), and entry levels all exhibit substantial persistence within industries.[19] Our findings highlight that these persistent processes relate to each other in complex and interesting ways.

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

Table 4: **75–50 and 50–25 TFP Dispersion Growth and Entry Rates, 1997–2017**

	Establishment Entry		Firm Entry	
	75–50 **(1)**	**50–25** **(2)**	**75–50** **(3)**	**50–25** **(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

Note: 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' tabulations based on BLS Industry Productivity Statistics, Dispersion Statistics on Productivity, and Business Dynamics Statistics.

We regard our findings as suggestive rather than definitive. Gort and Klepper (1982) examine lags over many years using business registry data that tracked entering, exiting, and continuing firms after 46 specific product innovations (e.g. electric shavers or windshield wipers). They found long and varying lags in the responses to innovations, but they did not relate these dynamics to either productivity dispersion or growth, which we explore in this article. We have imposed a relatively simple lag structure to investigate the timing of the relationships between entry, productivity dispersion growth (a proxy for experimentation), and productivity growth. Exploring the long and variable lags from the suggestive evidence in Gort and Klepper (1982) from business registry data will require longer time series and likely a more disaggregated analysis.[20]

Conclusion

This article uses novel detailed industry-level data on TFP and LP dispersion in establishment level productivity levels 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 growth, and entry for U.S. manufacturing industries. We test the hypothesis that pe-

20 Given these issues, generating cumulative effects from Tables 2 and 3 would be incomplete. We also note that because we used standard growth rates, the cumulative effect is not the simple sum of the lagged effects.

riods 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 reasons we observe a stronger relationship between entry and productivity dispersion for the upper half of the productivity distribution. Future research using the restricted-use micro-productivity data could also explore whether high entry increases dispersion because the new establishments are more disperse than the existing ones or they change the productivity levels of the incumbent firms. A more disaggregated analysis, such as at the 6-digit NAICS level or detailed product class, would also permit greater flexibility in exploring the variable lags in the entry, experimentation, and productivity growth dynamics suggested by Gort and Klepper (1982). Finally, it would be interesting to explore how measures of innovation such as patenting relate to dispersion and productivity growth.[21]

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 and the first three quarters of 2021 suggests the possibility of a new round of productivity growth (Dinlersoz, Dunne, Haltiwanger, and Penciakova, 2021; Haltiwanger, 2021).

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