

**Dispersion in Dispersion: Measuring Establishment-Level Differences in Productivity**

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## Abstract

We describe new experimental productivity statistics, Dispersion Statistics on Productivity (DiSP), jointly developed and published by the Bureau of Labor Statistics (BLS) and the Census Bureau. Productivity measures are critical for understanding economic performance. Official BLS productivity statistics, which are available for major sectors and detailed industries, provide information on the sources of aggregate productivity growth. A large body of research shows that within-industry variation in productivity provides important insights into productivity dynamics. This research reveals large and persistent productivity differences across businesses even within narrowly-defined industries. These differences vary across industries and over time and are related to productivity-enhancing reallocation. Dispersion in productivity across businesses may provide information about the nature of competition and frictions within sectors, and about the sources of rising wage inequality across businesses. Because there were no official statistics providing this level of detail, BLS and the Census Bureau partnered to create measures of within-industry productivity dispersion. These measures complement official BLS aggregate and industry-level productivity growth statistics and thereby improve our understanding of the rich productivity dynamics in the U.S. economy. The underlying micro data for these measures are available for use by qualified researchers on approved projects in the Federal Statistical Research Data Center (FSRDC) network. These new statistics confirm the presence of large productivity differences and we hope that these new data products will further encourage research into understanding these differences.

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## 1. Introduction

Productivity measures are critical for understanding economic performance in the U.S. economy. The Bureau of Labor Statistics (BLS) produces the official labor and multifactor productivity growth statistics for major sectors and industries in the U.S. These statistics are constructed using aggregate industry-level data, and can be thought of as changes in the first moment of establishment-level productivity (appropriately weighted). That is, these statistics show how productivity changes *on average* within sectors and industries, but they cannot provide insight into the variation in productivity levels across establishments within sectors or industries.<sup>1</sup>

To fill this void, the BLS and the Census Bureau initiated the Collaborative Micro-productivity Project (CMP) to develop and publish experimental statistics on *within-industry* productivity dispersion (i.e., second-moment measures of establishment-level productivity) and to produce restricted-use research datasets. The public-use statistics developed via this project, Dispersion Statistics on Productivity (DiSP)<sup>2</sup>, released in fall 2019 cover all 4-digit NAICS industries in the manufacturing sector and are published jointly by the BLS and the Census Bureau. Restricted-use establishment-level data with micro-based estimates of productivity as well as its underlying components (e.g., output and input measures) are also available to qualified researchers on approved projects in secure Federal Statistical Research Data Centers (FSRDCs).<sup>3</sup>

Economic theory and recent empirical evidence suggest the second moments of productivity are informative on a number of important dimensions. One of the most important findings in the literature on micro-level productivity is the large productivity differences across establishments even within narrowly-defined industries.<sup>4</sup> For example, using data from the 1977

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<sup>1</sup> Although usually referred to as industry productivity growth or aggregate productivity growth, these statistics can be thought of as the weighted average of within-industry growth rates.

<sup>2</sup> These are available on both BLS and Census Bureau websites at: <https://www.bls.gov/lpc/productivity-dispersion.htm> and <https://www.census.gov/disp>.

<sup>3</sup> For more information on the FSRDCs: <http://www.census.gov/fsrdc>. An earlier version of this dataset was analyzed in Foster et al. (2016a).

<sup>4</sup> Syverson (2011) provides a survey of this literature.

Census of Manufactures (CM), Syverson (2004a) found that establishments at the 90<sup>th</sup> percentile of the within-4-digit-SIC productivity distribution are about four times as productive as those at the 10<sup>th</sup> percentile.

Syverson's findings generated considerable interest in the causes and consequences of this dispersion. Possible market explanations include curvature of the profit function that prevents the most-productive business from taking over an industry, frictions in factor adjustments (such as costs of adjusting input factors), barriers to entry and exit, and distortions that inhibit the equalization of marginal products across businesses (such as the regulatory environment). Drivers of establishment-level productivity variation include differences in management skills, the quality of production factors, innovation, and investments in R&D.

Research has shown that the dispersion of establishment-level productivity varies across sectors, by geographic area, and over time. For example, Syverson (2004a, 2004b) shows that variation in dispersion across industries and geographic areas is related to product substitutability, market structure, and competition. Hsieh and Klenow (2009) argue that both cross-country variation and within-country variation in the dispersion of productivity are related to distortions that inhibit productivity-enhancing reallocation. Asker, Collard-Wexler, and De Loecker (2014) present evidence that the patterns of dispersion reflect the dynamic factor adjustment frictions within sectors. The findings in Foster et al. (2016b) suggest that productivity differences across establishments may be generated by differences in efficiency levels, demand shocks, frictions/distortions or all of the above. Alternatively, Foster et al. (2017a) present evidence that industries experiencing a surge in innovation exhibit a burst of firm entry, followed by an increase in productivity dispersion during an experimentation and shakeout phase, followed ultimately by an increase in productivity.

Establishment-level productivity differences are also correlated with important economic outcomes at the micro level, such as the survival and growth of establishments. There is a large

literature on the connection between productivity, reallocation and growth (Baily, Hulten, and Campbell, 1992; Griliches and Regev, 1992; Baily, Bartelsman, and Haltiwanger, 2001; Petrin, White, and Reiter, 2011; Hsieh and Klenow, 2009, 2014). These studies show that more-productive businesses are more likely to survive and grow. This implies that reallocation—the process by which low-productivity businesses contract and exit while high-productivity businesses survive and expand—is an important contributor to aggregate productivity growth.

Productivity dispersion is also important for understanding rising wage inequality, which has been shown to be a between-firm phenomenon (Davis and Haltiwanger, 1991; Barth et al., 2016; Song et al., 2018; Haltiwanger and Spletzer, 2019). In addition, a number of studies have found that high-wage establishments are also highly-productive and that rising between-establishment dispersion in wages is closely associated with rising between-establishment dispersion in productivity (e.g., Dunne et al., 2004). Economic theories of search and matching provide theoretical justification for the connection between productivity dispersion and wage dispersion (e.g., Burdett and Mortensen, 1998). Search and matching frictions create quasi-rents for worker-firm matches that make it optimal for high-productivity firms to pay high wages.

Our results using the experimental data confirm earlier findings about the large differences in productivity. To preview our results, we find that on average, the manufacturing plant at the 75<sup>th</sup> percentile of the within-industry labor productivity distribution is more than twice as productive as the plant at the 25<sup>th</sup> percentile.<sup>5</sup> If we instead focus on multifactor productivity, we find that the 75<sup>th</sup> percentile plants are not quite twice as productive as plants at the 25<sup>th</sup> percentile. Underlying these averages, we find substantial differences in dispersion across industries. For example, labor productivity dispersion in the industry at the 75<sup>th</sup> percentile of the dispersion distribution is about 1.4 times as big as the dispersion in the industry at the 25<sup>th</sup> percentile. The

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<sup>5</sup> We use the terms “establishment” and “plant” interchangeably in this paper.

corresponding multiplier for multifactor productivity is 1.2.

The experimental statistics on productivity dispersion are intended to complement official BLS data, so it is crucial to understand the relationship between the dispersion of the productivity distribution derived from Census Bureau microdata and the statistics from BLS built from industry-level aggregates. Section 2 describes BLS productivity measures and productivity measures we construct from Census microdata. Section 3 compares the two approaches to measuring inputs, output, and productivity measures for the manufacturing sector, and for 4-digit NAICS manufacturing industries. We also compare these measures to data from the NBER-CES Manufacturing Industry Database, and examine a number of data and measurement issues such as imputation and weighting of the microdata. In section 4, we explore the variation in the industry-level productivity dispersion measures across industries and over time. Section 5 summarizes our conclusions and describes plans for future work.

## **2. Measuring Productivity**

Because a primary goal of this project is to create within-industry productivity dispersion statistics to complement BLS industry productivity data, it is useful to first describe how the BLS constructs its measures from published aggregates, and then compare it to our measures that are constructed by aggregating Census microdata.

### *2.1. BLS Industry-level Productivity*

The BLS publishes quarterly and annual measures of labor productivity for major sectors; annual measures of labor productivity for 199 3-digit and 4-digit NAICS industries; and annual measures of multifactor productivity for major sectors, 18 3-digit NAICS manufacturing industries, 86 4-digit NAICS manufacturing industries, the air transportation industry, and the line-haul railroad industry. Productivity growth is measured as the difference between percentage

changes in output and inputs (calculated as indexes). The BLS does not publish industry productivity levels, although they are available on request.

BLS industry output is based on a sectoral concept, which measures the value of goods produced for sale outside the industry.<sup>6</sup> For manufacturing industries, the BLS uses published Annual Survey of Manufactures (ASM) and Census of Manufactures (CM) data on the total value of shipments, which it adjusts to remove intrasectoral transactions and resales, and to account for changes in finished goods and work-in-process inventories.<sup>7</sup> This adjusted nominal output measure is then distributed to detailed categories of products and services using the mix of annual wherever-made product shipments from the ASM. Nominal output in each category is deflated using the appropriate detailed producer price index from the BLS prices program. These real output measures are then Tornqvist-aggregated into industry output indexes. Self-employment revenues for manufacturing firms, which come from Internal Revenue Service data, are also added to these output measures.

The BLS measures labor input as the total annual hours worked by all persons in an industry. This measure is constructed by combining data from three BLS surveys: the Current Employment Statistics (CES) survey, the Current Population Survey (CPS), and the National Compensation Survey (NCS). The CES provides detailed information on the employment and average weekly hours *paid* for production and non-supervisory employees (henceforth referred to as production workers).<sup>8</sup> The NCS data are used to adjust CES hours from an hours-paid to an hours-worked basis by removing paid vacation accrued and sick leave taken.<sup>9</sup> To estimate

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<sup>6</sup> Sectoral output is less than gross output, but greater than value-added output. In the most detailed industries, sectoral and gross output are the same or very close. However, going from very detailed industries to more aggregated industries, sectoral output moves closer to value-added output. In the limit, at the aggregate level, sectoral output is the same as value-added output, except for imported intermediate inputs.

<sup>7</sup> See <https://www.census.gov/programs-surveys/asm.html> and <https://www.census.gov/programs-surveys/economic-census.html>.

<sup>8</sup> Workers in goods-producing industries are referred to as being production or non-production workers and in the service-providing industries as nonsupervisory or supervisory workers.

<sup>9</sup> Note that this adjustment does not account for off-the-clock hours.

nonproduction worker hours, the BLS uses data from the CPS to calculate the ratio of nonproduction to production worker hours worked, which is then multiplied by the adjusted CES production worker hours (worked). Specifically, nonproduction worker hours are estimated as:

$$TH_{NP} = \text{Emp}_{NP}^{\text{CES}} \times \text{AWH}_P^{\text{CES}} \times \text{hwhp}_P^{\text{NCS}} \times \frac{\text{AWH}_{NP}^{\text{CPS}}}{\text{AWH}_P^{\text{CPS}}} \times 52 \quad (1)$$

where  $\text{Emp}_{NP}^{\text{CES}}$  is nonproduction worker employment from CES,  $\text{AWH}_P^{\text{CES}}$  is production worker average weekly hours from CES,  $\text{hwhp}_P^{\text{NCS}}$  is the hours-worked-to-hours-paid ratio from NCS, and  $\left(\frac{\text{AWH}_{NP}^{\text{CPS}}}{\text{AWH}_P^{\text{CPS}}}\right)$  is the CPS nonproduction/production hours ratio. CPS data are also used to directly obtain hours worked by self-employed and unpaid family workers (Eldridge et al., 2004).

## 2.2. Establishment-level Productivity using Census Data

To measure establishment-level labor productivity, we combine establishment-level information from three Census Bureau restricted-use microdata files with public-use industry-level data from BLS. Given that one of the goals of our research is to shed light on BLS industry productivity statistics, we try to match BLS concepts and measures as closely as possible.

Our establishment-level microdata come from the CM, the ASM, and the Longitudinal Business Database (LBD). The CM is collected every 5 years in years ending in ‘2’ and ‘7’. It collects data from all manufacturing establishments except those that are very small. The Census Bureau imputes data for these very small establishments using information from administrative records. The ASM sample is a 5-year panel of manufacturing establishments, updated every year for births, and data are collected annually. ASM panels begin in years ending in ‘4’ and ‘9’, and the probability of selection into the ASM sample is a function of both industry and size (generally employment or shipments). Like the CM, the ASM does not collect data from very small establishments but accounts for them using administrative information. In CM years, ASM data are collected as part of the CM data collection, but we use only the ASM establishments to create our

within-industry dispersion measures.<sup>10</sup> Data are imputed for establishments that do not respond or that fail to report some data elements (item non-response); we discuss this further in section 2.3. The LBD is a longitudinally-linked version of the Census Bureau’s Business Register and covers the non-agricultural employer universe of business establishments (see Jarmin and Miranda, 2002). The LBD provides us with both high-quality longitudinal links and information on the universe of manufacturing establishments, which we use to generate our propensity-score weights.

We cannot exactly replicate the BLS sectoral output concept because the ASM does not collect information on who the output was sold to or which industries intermediate inputs were purchased from, making it impossible to account for intra-sectoral transactions. However, we can add intra-sectoral transactions back into BLS output measures for comparisons. Using Census microdata, we replicate the value of shipments as closely as possible. Specifically, we calculate plant-level real output as deflated revenues, adjusted for resales and changes in inventories.<sup>11</sup> Thus, we measure plant-level output as:

$$Q_{et} = (TVS_{et} + DF_{et} + DW_{et} - CR_{et})/PISHIP_{it} \quad (3)$$

where  $TVS$  = total value of shipments,  $DF_{et} = FIE_{et} - FIB_{et}$  and  $DW_{et} = WIE_{et} - WIB_{et}$  are the changes in finished-goods and work-in-process inventories respectively ( $FIB$ ,  $FIE$  = beginning-of-year and end-of-year finished goods inventories and  $WIB$ ,  $WIE$  = beginning-of-year and end-of-year work-in-process inventories),  $CR$  = cost of resales,  $PISHIP$  = deflator for the value of shipments<sup>12</sup>, and the  $i$ ,  $e$ , and  $t$  subscripts index industries, establishments and years. Note if either  $FIE_{et}$  or  $FIB_{et}$  is missing, then we set  $DF_{et} = 0$  ( $DW_{et}$  is imputed similarly when either of its components are missing). Also, if  $Q_{et} \leq 0$ , we set:

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<sup>10</sup> The microdata made available in the FSRDCs contains productivity measures for all CM establishments when productivity calculation is possible.

<sup>11</sup> In practice, subtracting resales does not make much difference because they are only a small fraction of revenue.

<sup>12</sup> The shipments deflator is constructed as part of NBER-CES data, using price indexes in BEA’s GDP-by-Industry data.

$$Q_{et} = TVS_{et}/PISHIP_{it} \quad (3')$$

We measure labor input as total hours worked. For each establishment, the ASM collects the total number of employees and, for production workers, it collects both hours worked and the number of employees. We calculate total annual hours by summing ASM production worker hours and an estimate of nonproduction worker hours, which is calculated as the product of: the number of non-production workers from the ASM, the average weekly hours worked by production workers from the ASM, and the CPS nonproduction/production ratio (similar to equation 1):<sup>13</sup>

$$TH_{et} = PH_{et} + \left( (TE_{et} - PW_{et}) \times \frac{PH_{et}}{PW_{et}} \times \left( \frac{AWH_{NP}^{CPS}}{AWH_P^{CPS}} \right) \right) \quad (4)$$

where  $PH$  = production worker hours,  $PW$  = average number of production workers,  $TE$  = total employment, and  $\frac{AWH_{NP}^{CPS}}{AWH_P^{CPS}}$  = CPS non-production/production average weekly hours ratio. We calculate establishment-level log labor productivity as:<sup>14</sup>

$$\ln LP_{et} = \ln Q_{et} - \ln TH_{et}. \quad (5)$$

Establishment-level multifactor productivity (MFP) in logs is measured as:

$$\ln MFP_{et} = \ln Q_{et} - \alpha_K \ln K_{et} - \alpha_L \ln TH_{et} - \alpha_M \ln M_{et} - \alpha_E \ln E_{et}, \quad (6)$$

where  $Q$  and  $TH$  are real output and total hours as defined above in (3) and (4),  $K$  denotes real productive capital stock,  $M$  and  $E$  denote deflated values of expenditures on intermediate inputs and energy. The productive capital stock is created using the perpetual inventory method for equipment and structures separately.<sup>15</sup> The value of  $M$  is calculated as the deflated sum of cost of

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<sup>13</sup> Note that it is not necessary to apply the hours-worked-to-hours-paid ratio because establishments are requested to report hours worked.

<sup>14</sup> Future versions of the DiSP will include dispersion in productivity as measured by value-added per worker.

<sup>15</sup> We do not include rented capital due to its irregular collection in the ASM. Pre-1986 and post-2006 this information is collected annually on the ASM. In the intervening years, this information was only collected in the Economic Census. Exploratory analysis for the years when this is available shows rented capital is small does not make much difference to plant-level capital measures. We plan on exploring this further in future research.

materials, the cost of resales and the cost of contract work done for the establishment by others.<sup>16</sup> The nominal value of E is obtained as the sum of the cost of electricity and fuels. The two expenditures are deflated using the appropriate deflators from the NBER-CES database. We measure factor elasticities  $\alpha_K$ ,  $\alpha_L$ ,  $\alpha_E$ ,  $\alpha_M$  using the share of expenditures of the corresponding input in total cost in each 6-digit NAICS industry.<sup>17</sup>

### 2.3. *Missing Data and Imputation*

As noted above, the ASM microdata are subject to item non-response, and these missing values are imputed by the Census Bureau. The Census Bureau's imputation methods are designed to yield accurate published aggregates but do not necessarily preserve the distribution or adequately reflect the variability of the underlying microdata. There is evidence that certain imputation methods may affect microdata analyses. However, there are techniques available to mitigate the effects of imputation on dispersion measures. For example, White, Petrin, and Reiter (2018) analyze dispersion statistics using classification and regression-tree methods. Foster et al. (2017b) follow a different approach and address imputation by dropping observations with imputed data and reweighting the remaining observations. The results from these studies suggest that both of these approaches reduce within-industry dispersion. For the purposes of this paper, we consider the entire set of observations in the sample and leave further analysis of these issues for future work.

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<sup>16</sup> Published ASM measures of value-added are based on the difference between the value of output and a composite operating expenses measure inclusive of materials and energy expenditures. We break out the cost of materials and energy separately in our MFP measure. The inclusion of contract work implies some aspects of purchased services are included in the materials expenditures. However, since 2006 the ASM survey has included questions on other operating expenses including leased employees and additional purchased services not included in the cost of contract work. We are actively working on exploring the inclusion of those operating expenses for a supplemental multifactor productivity dispersion measure commencing in 2006. Challenges for inclusion of these variables are the short time series, item non-response rates and the treatment of establishments of single-unit versus multi-unit establishment firms. Establishments of the latter are less likely to have such additional operating expenses since the headquarters establishment of the parent firm may be providing and/or purchasing those services.

<sup>17</sup> See web appendix B in Foster et al. (2016a) for more details. Procedures for extending the output and input price deflators are described in this appendix.

### 3. Comparing Micro-Aggregated Data to Published Industry Data

The next step is to compare our micro-aggregated estimates to the official data published by BLS. Based on earlier work comparing similar business data across the two government agencies, we expect that there will be some systematic differences between these measures (Elvery et al., 2006). Even though differences in the levels of the micro and published first moments do not directly affect our conclusions about dispersion (we sweep out industry-year effects), we want to confirm those first moments are not too far from each other. If the first moments are close, then it is more reasonable to think of micro-based second moments as measuring variation around the published first moments.

Below, we compare micro estimates to published estimates from the ASM, data from the BLS productivity program, and data from the NBER-CES database, covering the 1997-2011 period. The NBER-CES database is used for comparisons in this section and should be thought of as equivalent to the official published ASM and CM statistics upon which it is based.<sup>18</sup> We start by comparing input and output measures, and then we compare productivity measures.

#### 3.1. *Input and Output Measures*

Figure 1 shows the total number of employees in the manufacturing sector from the different series. The first thing to note is that employment levels based on ASM microdata (using ASM sample weights) are significantly lower than the published ASM and BLS estimates because they exclude the “non-mail” stratum—small establishments that are not sampled by the ASM. The published ASM series includes adjustments for the non-mail stratum and is much closer to the BLS estimates.

In order to account for the issue described above, we construct an alternative set of weights.

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<sup>18</sup> For more information on the NBER-CES Manufacturing Industry Database, see <http://www.nber.org/nberces/>. The NBER-CES series we use ends in 2011.

As noted, the weighted sample totals calculated from the ASM (using ASM sample weights) is by design not equal to the published total since there are additional adjustments in the latter for the non-mail cases. Fortunately, there are some very small establishments in the ASM sample each year that are below the thresholds for non-mail cases. This occurs because, among the smaller establishments that were selected for the ASM (that is, establishments with employment above threshold), some had fallen below the size threshold by the time they provided data. This implies that there is coverage for all business sizes in the ASM sample (e.g., there are ASM establishments in any given year and industry with 1-4 employees even though this is typically below the ASM sample threshold). To create an alternative set of weights, we use the LBD. Specifically, we define the manufacturing universe using the LBD, and use LBD data to estimate the probability that an establishment is included in the ASM sample, and then use these probabilities to construct inverse propensity score weights (see the Appendix for a full discussion of the weighting procedures). These weights (PSW hereafter) yield weighted sample totals that are consistent with the LBD.<sup>19</sup> Moreover, as can be seen in Figure 1, the micro-aggregated employment series using PSW yields totals that align with the published BLS and ASM more closely than that using ASM weights.<sup>20</sup> Our goal is to replicate the LBD totals rather than the published ASM.<sup>21</sup>

We next compare total manufacturing hours growth between the BLS series, the CMP–PSW series, and the NBER series (Figure 2). To increase comparability of the NBER series to the

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<sup>19</sup> In addition, unreported results suggest that PSW do a good job matching the industry/year-specific size and age distributions of the LBD.

<sup>20</sup> We explored the possibility of benchmarking CMP employment (based on the manufacturing universe in the Census Business Register) to BLS employment (based on the manufacturing universe in the BLS Quarterly Census of Employment and Wages). While this benchmarking, by definition, improves the correlation between labor (employment and hours) measures between BLS and CMP, it actually decreases the correlation between BLS and CMP output and measures of other inputs, which are both based on the manufacturing universe in the Census Business Register.

<sup>21</sup> An alternative approach would be to target the published ASM. For this approach, we could use imputed data for the non-mail cases in the ASM. This is done for post-2003 data although White, Petrin, and Reiter (2018) raise a variety of questions about Census imputation procedures. Given these concerns, we think a better procedure would be to use an imputation model like that developed for White, Petrin, and Reiter (2018) for the non-mail cases. We plan to explore this possibility in future work. This will require imputing data for non-mail cases pre- and post-2003.

other two series, we estimate nonproduction worker hours using the CPS nonproduction/production worker hours ratio. In Figure 2, we see that the growth rates of hours exhibit similar dynamics, except for 2005–2007, when the NBER series diverges.

Figure 3 compares the three real output growth rates. As noted earlier, the ASM collects data on sales but not who products are sold to, which makes it impossible to account for intrasectoral transactions at the establishment-level. Therefore, we add intrasectoral transactions back into the BLS output series for these comparisons.<sup>22</sup> In all three series, we use the BLS implicit price deflator. The BLS and NBER series track each other closely. The CMP series is generally similar to the previous two but exhibits some volatility not present in the other two series.

Table 1 shows correlations between the three data sources for inputs and output for the total manufacturing sector. The correlations in top panel are based on pooled industry-year observations, while the bottom panel shows the average of the within-industry correlations for 4-digit NAICS industries, calculated over the 19 years of the sample and weighted using the share of BLS employees in each industry. The top panel of the table indicates that hours, intermediate inputs, energy and output, both in levels and growth rates, are highly correlated across data series, ranging from 0.91 to 0.99. Average industry-level correlations, shown in the bottom panel, are lower than for total manufacturing, but they are still reasonably high for these variables, both in levels and growth rates.

The correlation between capital variables is significantly lower. There are several possible explanations. First, there is a fundamental difference in the underlying data. In particular, BLS investment data for 4-digit industries combine expenditures on structures and equipment from the ASM with data on investment in different types of assets by industry from BEA and the Annual

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<sup>22</sup> Another difference that we do not account for is the inclusion of unincorporated self-employed output in the BLS series.

Capital Expenditure Survey (ACES). In contrast, the approach in CMP takes investment flows directly from the establishment, and uses these flows with the perpetual inventory method at the plant level to generate capital stocks. Second, given the difference in source data, the BLS investment series covers a longer period of time than the micro-aggregated series. The BLS capital stock is built up from investment flows that stretch back to 1958 (and longer for some assets). For CMP, we initialize new plants using book value, and the earliest book value and investment data we use dates back to 1972. With the previous reservations, we can conclude that, despite differences in data sources and methodologies, micro-aggregated data are largely consistent with published aggregate data.

### *3.2. Productivity Growth*

We calculate productivity growth as the change in the log-productivity for output per hour and multifactor productivity.<sup>23</sup> Figure 4(a) shows that output per hour growth rates for the manufacturing sector are broadly similar with some greater discrepancies in various subperiods (e.g., 2003–2009). These differences can be attributed to the differences in data sources and methodologies, some of which were illustrated in Figures 2–3. Despite underlying differences, multifactor productivity growth shows remarkable similarity across these data sources, see Figure 4(b). Table 2 echoes these findings: the correlations between the series of different data sources are highest for multifactor productivity growth.

This comparison of inputs, output, and productivity serves as an important backdrop to our new experimental statistics on within-industry dispersion. Although there are some differences between the BLS and the micro-aggregated series, they are close enough to each other to allow us to make meaningful inferences about the relationship between within-industry dispersion and

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<sup>23</sup> The official BLS productivity series are calculated using percentage changes in the index, and thus the BLS series we refer to here differs from the published series. Additionally, the official total manufacturing productivity series is published by the BLS Division of Major Sector Productivity, whereas the data here are aggregated from industry data provided by the BLS Division of Industry Productivity Statistics.

BLS's published estimates of industry productivity growth.

#### 4. Productivity Dispersion

For our analysis of productivity dispersion, we focus on levels rather than growth rates. Because we are interested in comparing within-industry dispersion of productivity across industries and over time, it is necessary to account for industry differences in average productivity. To do this, we calculate establishment-level productivity as a deviation from average productivity in that establishment's 4-digit industry in each year.<sup>24</sup> The interpretation of normalized productivity levels is intuitive: they tell us how far above or below the mean the establishment sits in the productivity distribution.

We use the interquartile range (IQR) as our primary measure of dispersion, because it is intuitive and easy to interpret. The IQR shows how much more productive an establishment at the 75<sup>th</sup> percentile of the productivity distribution is than an establishment at the 25<sup>th</sup> percentile of the productivity distribution. The standard deviation may seem like an obvious alternative to the IQR, but, in addition to being harder to interpret, it is known to be more sensitive to outliers than quantile-based dispersion measures. We also report the 90-10 differential as well as the 10-1 and 99-90 differentials.

Table 3 shows the descriptive statistics of the distribution of dispersion measures.<sup>25</sup> The first entry in the table (0.876) says that in the average industry and year, establishments at the 75<sup>th</sup> percentile are about ( $e^{0.876} \approx$ ) 2.4 times as productive as those at the 25<sup>th</sup> percentile. Establishments in the 90<sup>th</sup> percentile are about 5.6 times as productive as those at the 10<sup>th</sup> percentile. Average dispersion in multifactor productivity is lower.<sup>26</sup> Still, establishments at the 75<sup>th</sup> percentile are

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<sup>24</sup> These are weighted averages (using our propensity score weights, see appendix) where establishment-level productivity is expressed as a deviation from average productivity in that establishment's 4-digit industry. This normalizes productivity across industries and thereby accounts for industry differences in average productivity.

<sup>25</sup> We present standard deviations in Table 3 but do not discuss these results.

<sup>26</sup> The range for output per hour is somewhat larger than that found by Syverson (2004a)—he found a multiplier of about 1.9—but our findings are generally in line with his results.

about 1.6 times as productive as those at the 25<sup>th</sup> percentile using multifactor productivity measures. This implies substantial differences in a core measure of business performance at the establishment-level within narrowly-defined industries.

Many factors may underlie the observed dispersion in measured productivity across establishments in the same industry.<sup>27</sup> We define a “wedge” as any mechanism that prevents equalization of marginal revenue products across producers. Because the measures of productivity dispersion reported here are revenue-based, the presence of widespread dispersion is consistent with the presence of some form of wedges. One form of wedges is adjustment frictions that inhibit businesses from adjusting their scale of operations and specific inputs to changing economic conditions. These adjustment frictions may be related to the costs of adopting new technologies or business practices; thus dispersion in an industry may reflect the gap between the frontier establishments and other producers. In a similar fashion, dispersion may reflect experimentation in new methods of production or new products. Alternatively, additional sources of wedges are market distortions such as differences in markups across producers, or financial constraints in the same industry. Complicating matters is that in the presence of wedges that are correlated with fundamentals, the variation in the dispersion will also reflect differences in business fundamentals such as technical efficiency and product appeal across businesses. Adjustment frictions are one source of wedges that yields such a correlation. For example, an increase in the dispersion in product appeal across producers in the presence of adjustment frictions will yield an increase in dispersion of revenue productivity across producers (even if the adjustment frictions remain constant).

It is well beyond the scope of the current paper to determine the relative importance of these alternative factors. Instead, the objective here is to describe this new data product that will

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<sup>27</sup> See Syverson (2011) for more detailed discussion of these issues and Foster et al. (2017b) with discussion more closely related to the new data product.

permit greater investigation into these alternative determinants of dispersion. One of the strengths of the new data product is that dispersion measures are provided at a detailed level of aggregation by year. Figure 5a summarizes how within-industry dispersion in output per hour—measured as the IQR— varies across industries and over time. The mean and median IQR are fairly close to each other, but the large differences between the 25<sup>th</sup> and 75<sup>th</sup> percentiles indicate that there is a lot of variation in the IQR across industries. For example, in 2002, the productivity difference between establishments at the 75<sup>th</sup> and 25<sup>th</sup> percentiles is about 100 log points in the industry at the 75<sup>th</sup> percentile of the IQR distribution, while this difference is approximately 70 log points in the industry at the 25<sup>th</sup> percentile of the IQR distribution. These findings are confirmed by multifactor productivity dispersion, with IQRs of 70 and 50 log points at the 75<sup>th</sup> and 25<sup>th</sup> percentiles, respectively (see Figure 5b).

The differences in IQRs suggest that there are factors such as those discussed above that generate “dispersion in dispersion”, including differences in shocks, adjustment costs, distortions, technology, and distributions of capital intensities. In addition, dispersion is rising during the period under investigation, more so for multifactor productivity than for labor productivity. The rising trend suggests that wedges, and the dispersion in business fundamentals underlying the observed dispersion, are changing in systematic ways over time.<sup>28</sup> We can also see from Figure 5 that although the volatility of (the mean) dispersion is non-trivial, it is dwarfed by the variation across industries.<sup>29</sup> For the remainder of this section, we consider two extensions to our analysis to illustrate further the nature of the dispersion. We first examine how our results change when we

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<sup>28</sup> There is an ongoing debate about the source of the rising dispersion in revenue productivity measures. See, e.g., Bils et al. (2017), Foster et al. (2017b) and Decker et al. (2018). We do not seek to directly address that debate here but note that Decker et al. (2018) find that rising (revenue-based) labor productivity dispersion in manufacturing is present in both the ASM survey data used here and in administrative data from the Business Register. This finding suggests that rising measurement error is not driving the rising dispersion.

<sup>29</sup> It is important to emphasize that following the movements of percentiles in Figure 5a is informative about industry dynamics only if it is based on a distribution where we can assume that industry-year observations are i.i.d., i.e. compositional changes are not important. In order to make inference about the business cycle behavior of dispersion, one should focus on genuine changes in dispersion, which is calculated as the average of the growth rates of dispersion measures. We found significant churning in the IQR distribution, as shown by nonzero transition probabilities across quintiles, see Table 4. Therefore, caution is necessary when interpreting Figure 5a.

weight establishments using activity weights. Activity weights are generated by multiplying our PSWs by an activity measure such as employment or hours. Activity weighting paints a potentially different picture of dispersion because there may be differences between the dispersion of different size groups. Our second extension is to examine the tails of the productivity distribution. There has been great interest in the finding that a substantial portion of wage inequality is driven by the upper tail of the distribution and by increasing between-establishment wage differentials. Investigating the upper tail of the productivity distribution is analogously interesting, as theory and evidence show that the productivity and earnings distributions are related.

#### *4.1. Activity-Weighted Dispersion Measures*

Figure 6 replicates the dispersion measures in Figure 5 using a combination of propensity score weights and activity weights. For output per hour, the activity weights are defined by hours shares while for multifactor productivity they are defined by composite input shares. The main difference relative to previous results is that activity-weighted dispersion is smaller and exhibits less year-to-year variation. These findings suggest that although dispersion seems smaller among large establishments, it has been rising over the period under investigation, which is likely to be the main driver behind the increase in the mean IQR.

#### *4.2. Dispersion in the Tails*

Turning to the tails of the productivity distributions, a distinctive feature of the within-industry productivity distribution is that mean and median dispersion in the right tail (the 99-to-90 ratio) are about the same order of magnitude as the mean and median dispersion in the center of the support as measured by the IQR (see Figure 7). This is remarkable given that each tail covers only one-fifth as many establishments as the IQR. Comparing Figure 7a to Figure 5a, output per hour differences among the most productive establishments are slightly lower than differences among those around the average. In contrast, multifactor productivity differences among the most

productive establishments are larger relative to those in the center of the support. In addition, these differences in the right tail of multifactor productivity are rising faster: the mean indicates that dispersion in the right tail approximately doubled between 1997 and 2015 (compare Figures 7b and 5b). The weighted dispersion measures (Figure 8) show generally similar patterns. Also, notable is that dispersion in dispersion is substantial in the right tail across industries.

In contrast to the right tail, the left tail (the 10-to-1 ratio) exhibits lower dispersion relative to the center. In particular, mean output per hour differences among the least productive establishments are 20-30 log-points smaller relative to the set of establishments in the middle, though with similar volatility, see Figure 9a. Mean multifactor productivity differences in the left tail are similarly smaller initially than in the center, and exhibit no positive trend, see Figure 9b. The weighted dispersion measures (Figure 10) tell a similar story.

These findings highlight the importance of looking at the entire distribution. The IQR is a convenient measure that covers half of the distribution. However, there is just as much dispersion in the upper and lower tails as there is in the middle. We also see that weighting matters: accounting for size tends to reduce both productivity dispersion and its volatility.

#### 4.3. *Description of the New Data Product*

The new data product, Dispersion Statistics on Productivity (DiSP), which will be updated by the two agencies on an annual basis,<sup>30</sup> contains a balanced panel of productivity statistics summarizing the within-industry distributions of output per hour and multifactor productivity.<sup>31</sup> Dispersion statistics include standard deviations, interquartile and interdecile ranges of the within-industry distributions of plant-level productivity. All data moments are frequency weighted; see

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<sup>30</sup> The timeliness of the data depends on the release of establishment- and firm-level information. In non-Census years, the ASM is available in the fall of the subsequent year, while the LBD becomes available in spring of the year after. In Census years, microdata become available later. The productivity dataset can be created approximately a month after the underlying micro data becomes available.

<sup>31</sup> See both BLS and Census Bureau websites: <https://www.bls.gov/lpc/productivity-dispersion.htm> and <https://www.census.gov/disp>.

sections 2.2 and A.2. In addition, the dataset includes activity-weighted versions of dispersion measures. The 99-to-90 and 10-to-1 ranges are currently under consideration for future releases given the interesting patterns in the right and left tails highlighted above.

The data product will be useful in analyzing the relationship between productivity dynamics at the plant, industry and entire manufacturing sector. As discussed above, many factors may underlie the cross-industry and time series variation in dispersion. We anticipate that this new data product will facilitate our understanding of the connection between micro- and macro-level productivity. A key benefit of making these data available will be to allow researchers without access to the confidential microdata to explore the various possible causes – and effects – of the differences in within-industry dispersion across industries and over time.

## **5. Concluding Remarks**

A growing literature uses micro-level data to examine establishment-level productivity dynamics and finds substantial within-industry productivity dispersion. This paper provides an overview of a new data product, Dispersion Statistics on Productivity (DiSP), released jointly by BLS and the Census Bureau. This new data product provides measures of productivity dispersion within narrowly-defined industries by year.

Much of the paper discusses the measurement methodology used to produce this data product. We compare inputs and output aggregated from micro-level data, to BLS aggregates at the industry and manufacturing-wide level that are part of the official industry and manufacturing-level productivity statistics produced and released by BLS. Not surprisingly, we find some differences between BLS industry-level data and micro-aggregated ASM data; however, in general, we find high correlations between BLS and micro-aggregated outputs and inputs (for example, at the total manufacturing level the correlation between the BLS published series and the micro-aggregated data for output and hours growth are both about 0.93).

Using measures of inputs and output, we develop measures of labor productivity (output per hour) and multifactor productivity and examine some of their properties. Correlations between BLS and micro-aggregated labor productivity growth are also reasonably high and especially high for multifactor productivity growth (e.g., at the total manufacturing level the MFP growth correlation is 0.94).

Illustrating the properties of the new data product, we find large within-industry dispersion in labor productivity: establishments at the 75th percentile are about 2.4 times as productive as those at the 25<sup>th</sup> percentile on average. Using multifactor productivity, we find that the analogous ratio is 1.6. These patterns indicate enormous differences in measures of business performance across plants in the same narrowly-defined industry and year. Differences might stem from many factors but they highlight both great potential for growth (e.g., if the gaps between high- and low-productivity businesses could be reduced) and also possible sources of frictions or distortions that are impeding a more efficient allocation of resources.

A core feature of the new data product is the release of measures of within-industry productivity dispersion by detailed industry. We find significant dispersion in within-industry dispersion across industries. For the top quartile of industries, the ratio of multifactor productivity across plants implied by the IQR exceeds 1.7 while for the bottom quartile of industries the ratio is lower than 1.4. Dispersion in dispersion over time is small by comparison, but it is likely still important. There is rising dispersion in both labor productivity and multifactor productivity, which is the source of ongoing debate in the academic literature.

Our results also indicate that average dispersion depends on where we measure it: average dispersion is greater as we move further away from the center of the support of the within-industry productivity distribution. Specifically, average productivity differences across establishments are largest in the right tail. Similar to what we find for average dispersion, the dynamics of these measures depend on where we measure productivity differences. We find evidence that dispersion

among the most productive establishments has been increasing during our sample period, while differences in the left tail do not show these patterns. This suggests that positively trending dispersion found in earlier studies may be a consequence of the dynamics of the most productive establishments. Our analysis suggests these patterns are sensitive to how dispersion is measured. We find that activity weights generally imply smaller, less volatile productivity differences among establishments in the entire distribution. We also find that, on average, weighted dispersion among more productive establishments shows a more pronounced positive trend.

In future work, we plan to explore extending the data product in a number of directions. As noted, one active area of exploration is releasing statistics on the tails of the productivity distribution. Another area of exploration is to release statistics by additional characteristics such as firm age and firm size. Research has shown that young businesses exhibit especially high productivity dispersion. This may reflect greater experimentation by young businesses as well as greater challenges that young businesses face in changing their scale of operations.

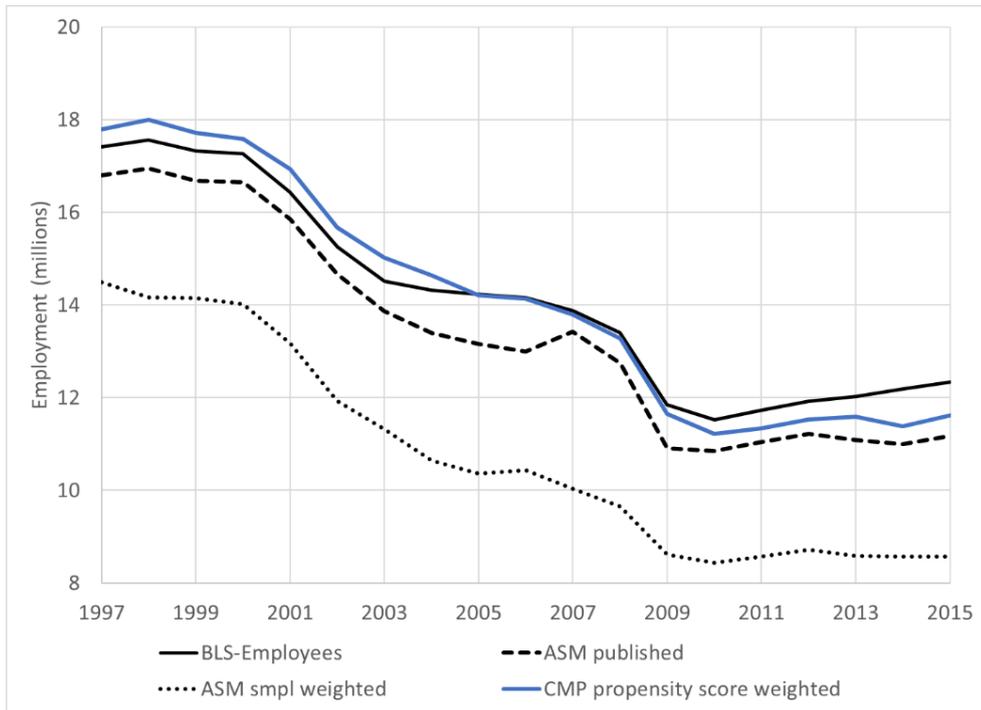
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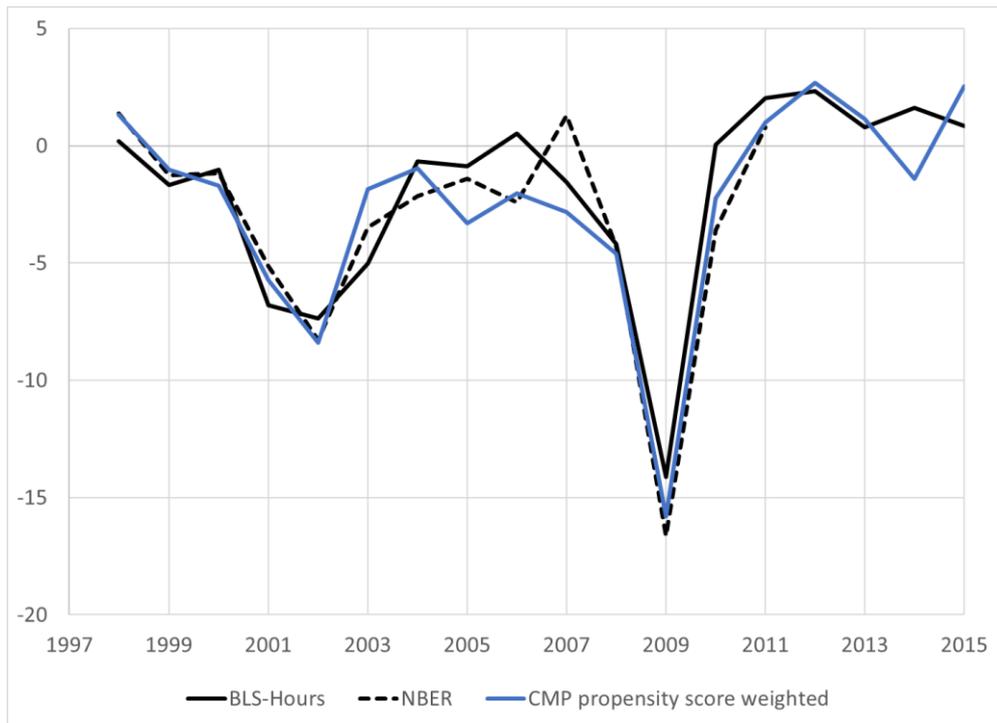
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**Figure 1. Manufacturing Employment Levels, 1997–2015**



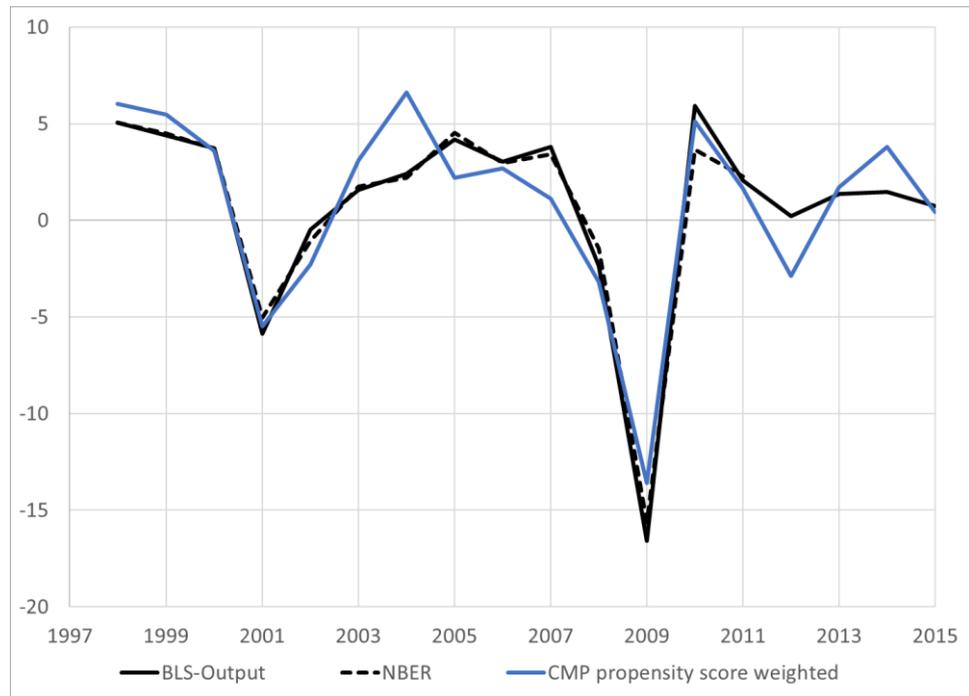
Source: “BLS-Employees” is the annual average of the not seasonally adjusted employment in manufacturing [CEU300000001, Current Employment Statistics program]. “ASM Published” is the published aggregate employment series from the ASM. CMP denotes micro-aggregated series using the ASM: CMP-ASM Sample Weighted total employment is calculated using ASM sample weights. CMP-Propensity Score Weighted total employment is calculated using our estimated inverse propensity score weights.

**Figure 2. Manufacturing Hours Growth, 1998–2015**



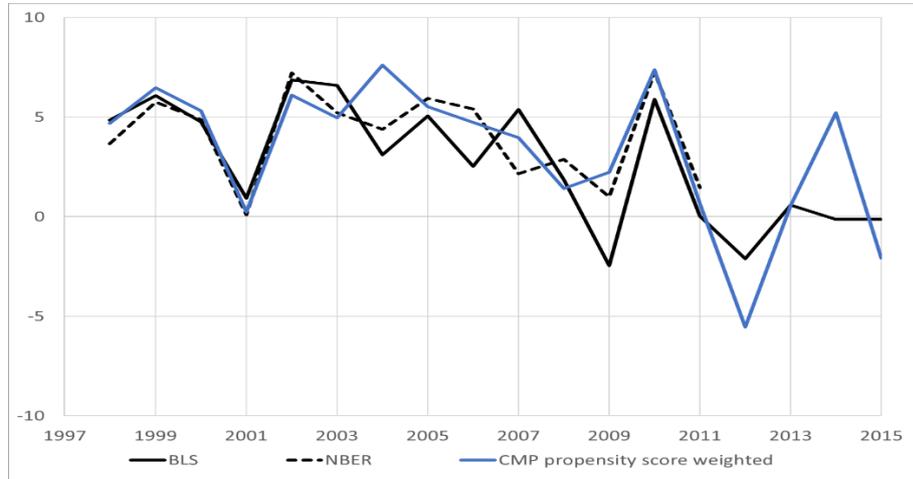
Source: “BLS” denotes total hours, based on authors’ calculations from Industry Productivity Program data. “CMP – Propensity Score Weight” is the authors’ calculations on the ASM. “NBER” is the authors’ calculations on the NBER database, see Table 5 for details.

**Figure 3.** Manufacturing Output Growth, 1998–2015

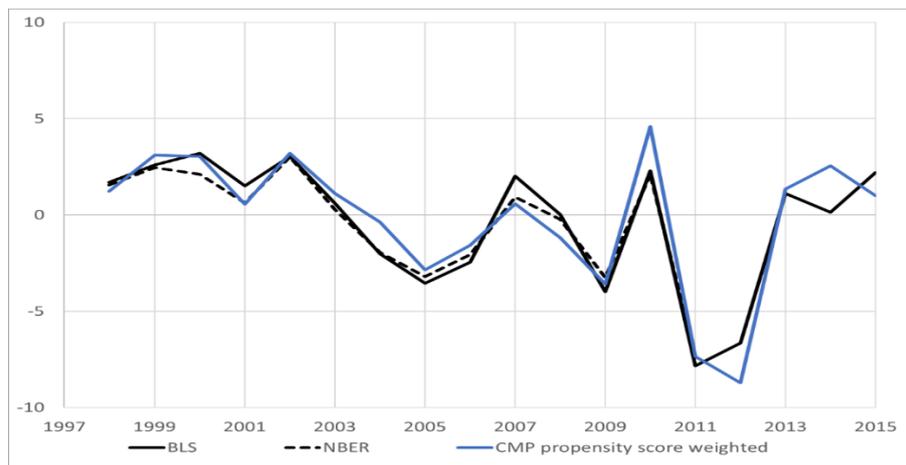


Source: “BLS” is from the Industry Productivity Program, intrasectoral transactions included. “CMP – Propensity Score Weight” is the authors’ calculations on the ASM, cost of resales removed. “NBER” is the NBER Productivity Database, see Table 5 for details.

**Figure 4.** Productivity Growth over Sources and Measures, 1998–2015



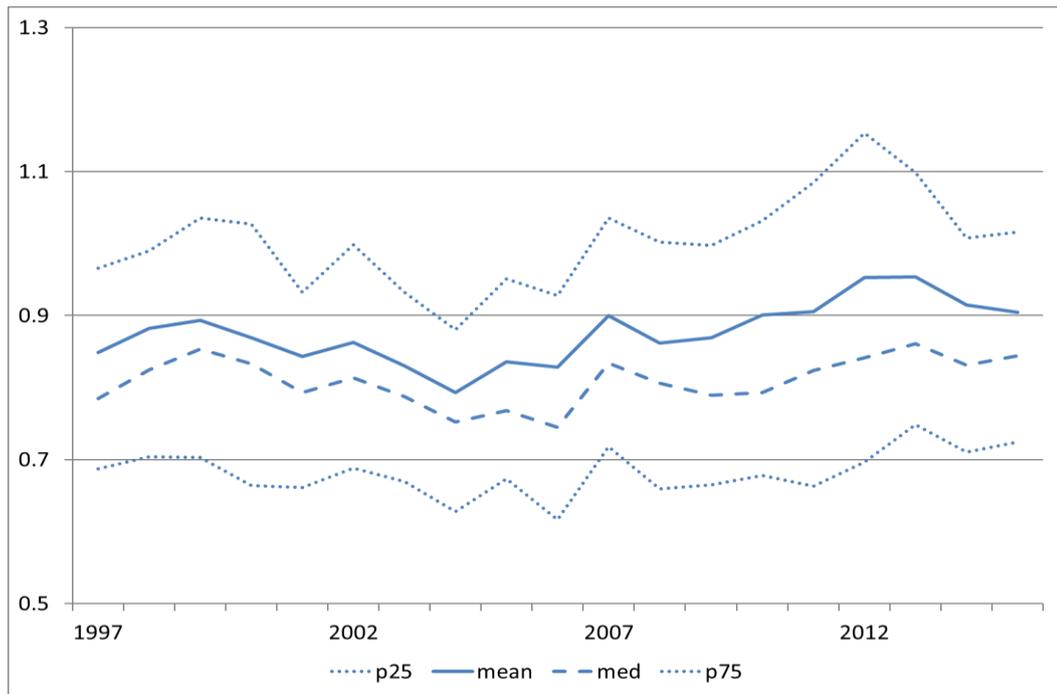
a) Output per hour



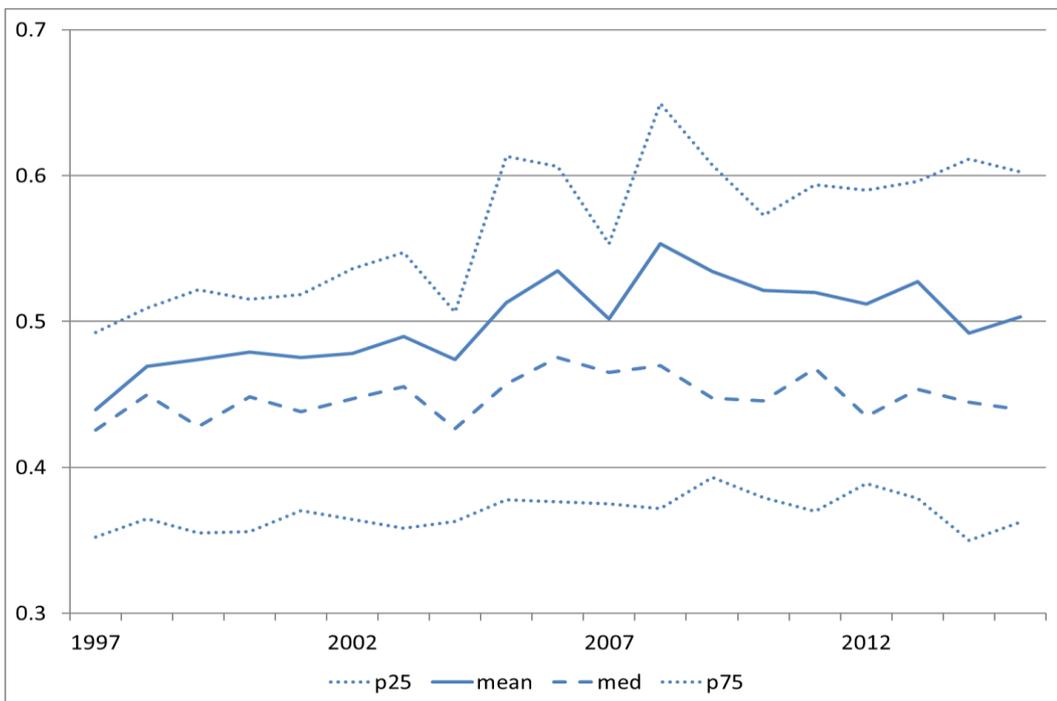
b) Multifactor productivity

Source: See the notes to Figures 2-3 and Table 5 for details.

**Figure 5.** Distribution of IQR of Productivity, 1997–2015



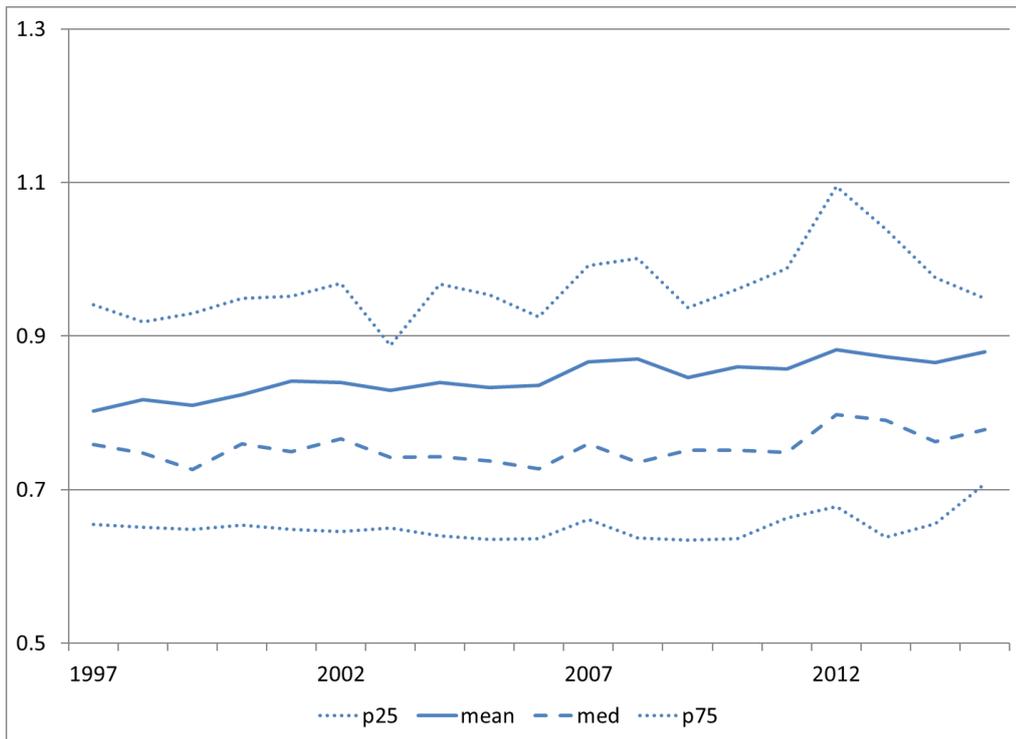
(a) Output per hour



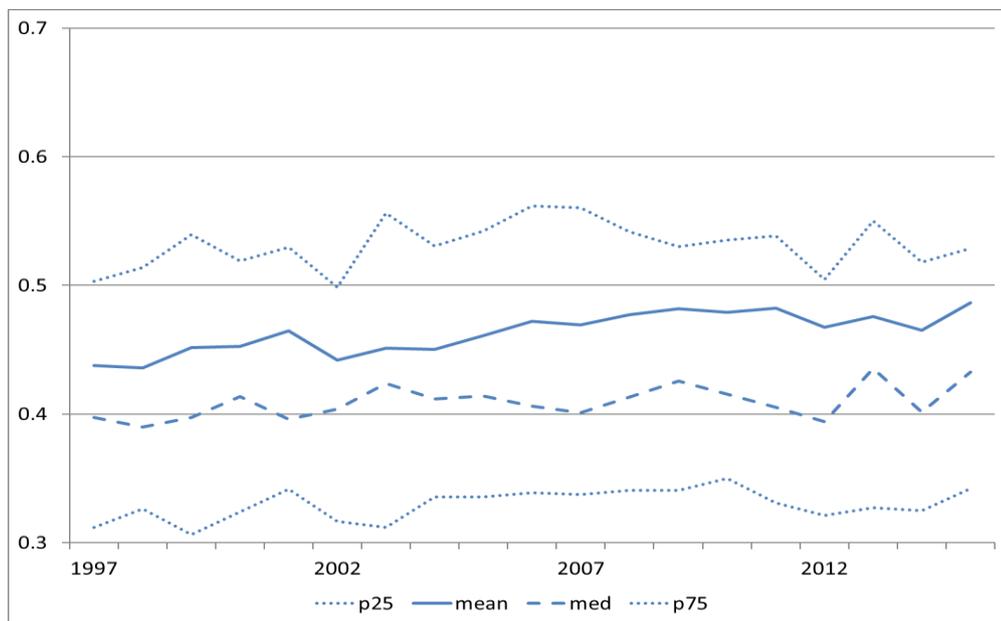
(b) Multifactor productivity

Source: Authors' calculations on the ASM. Notes: Within-industry productivity moments are created at the 4-digit NAICS level, weighted by our propensity score weight. Annual descriptive statistics of industry dispersion are unweighted.

**Figure 6.** Distribution of *Weighted* IQR of Productivity, 1997–2015



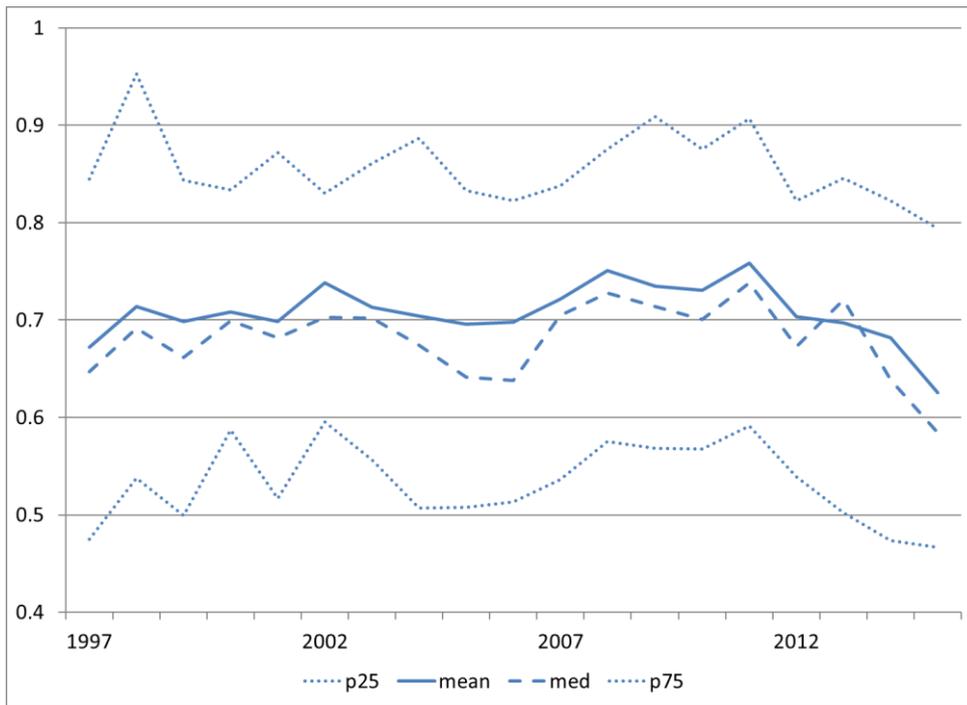
(a) Output per hour (hours-weighted)



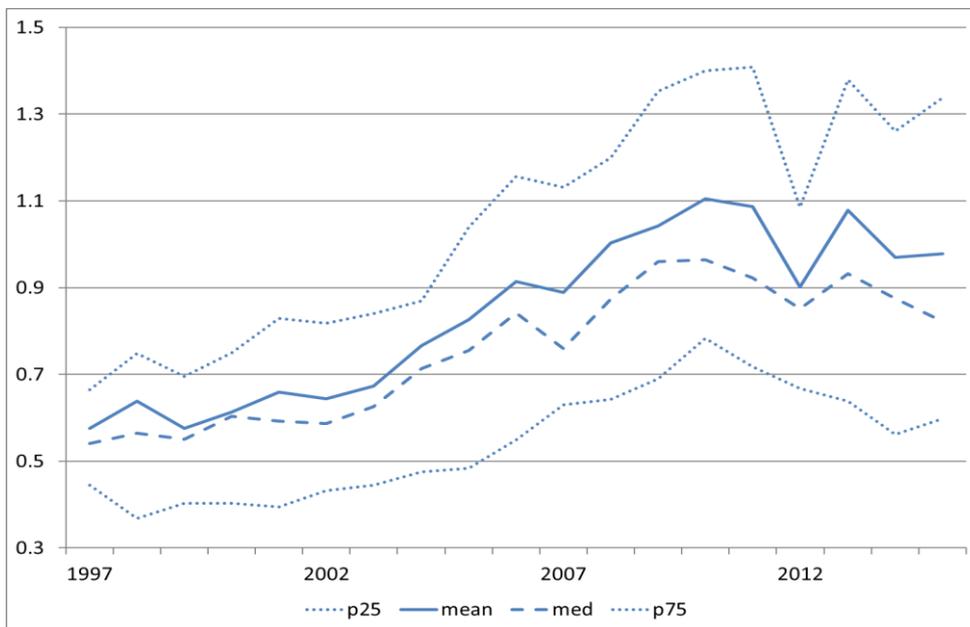
(b) Multifactor productivity (composite-input-weighted)

Source: See notes to Figure 5.

**Figure 7.** Distribution of 99-90 Difference of Productivity, 1997–2015



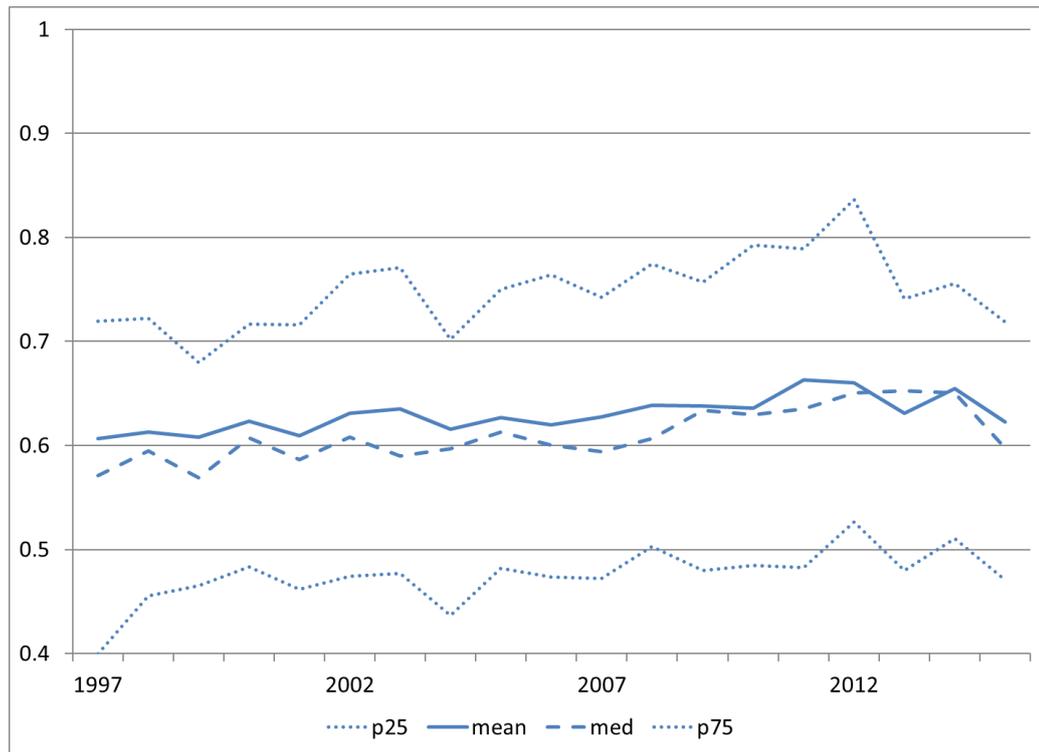
(a) Output per hour



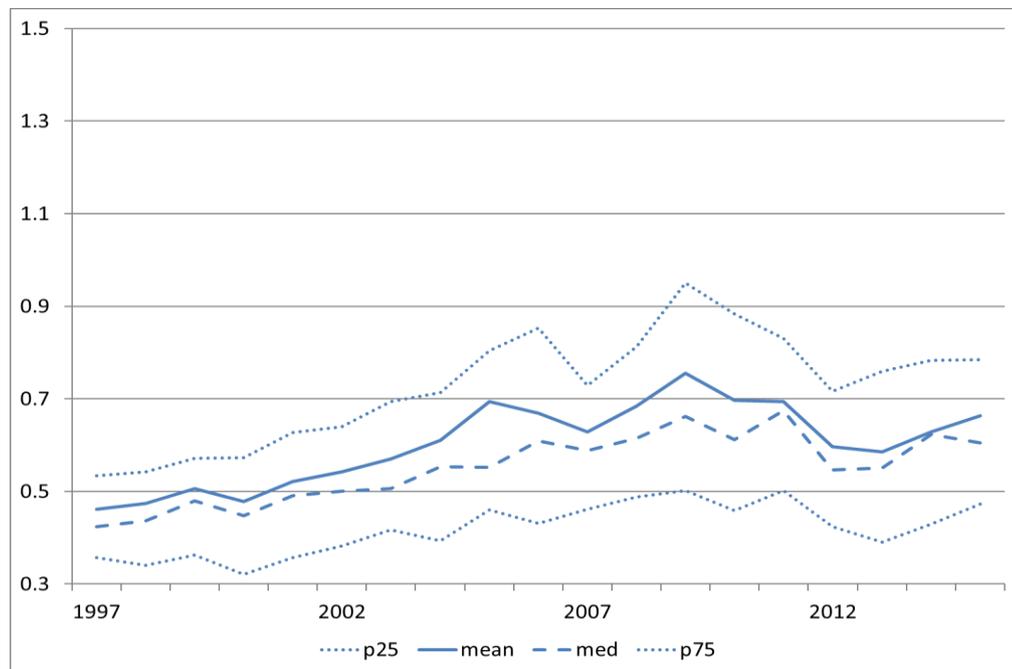
(b) Multifactor productivity

Source: See notes to Figure 5.

**Figure 8.** Distribution of *Weighted* 99-90 Difference of Productivity, 1997–2015



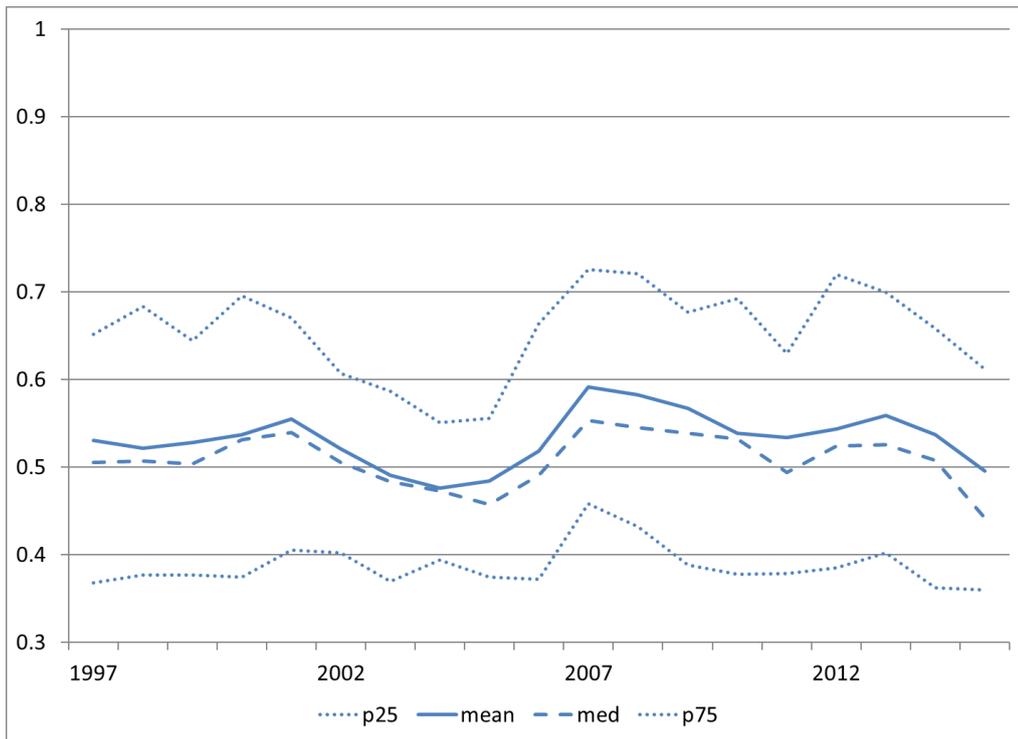
(a) Output per hour (hours-weighted)



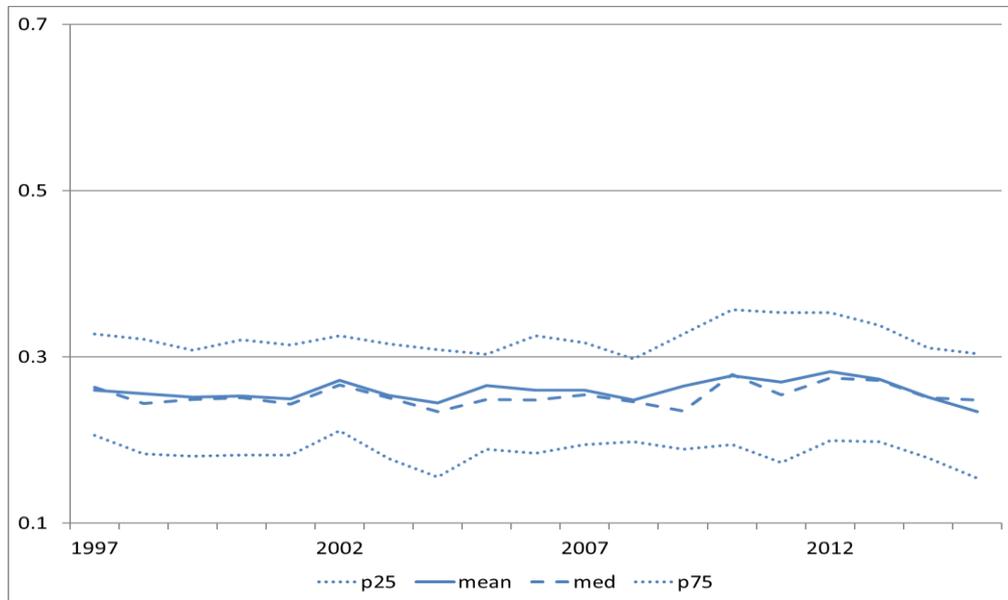
(b) Multifactor productivity (composite-input-weighted)

Source: See notes to Figure 5.

**Figure 9.** Distribution of 10-1 Difference of Productivity, 1997–2015



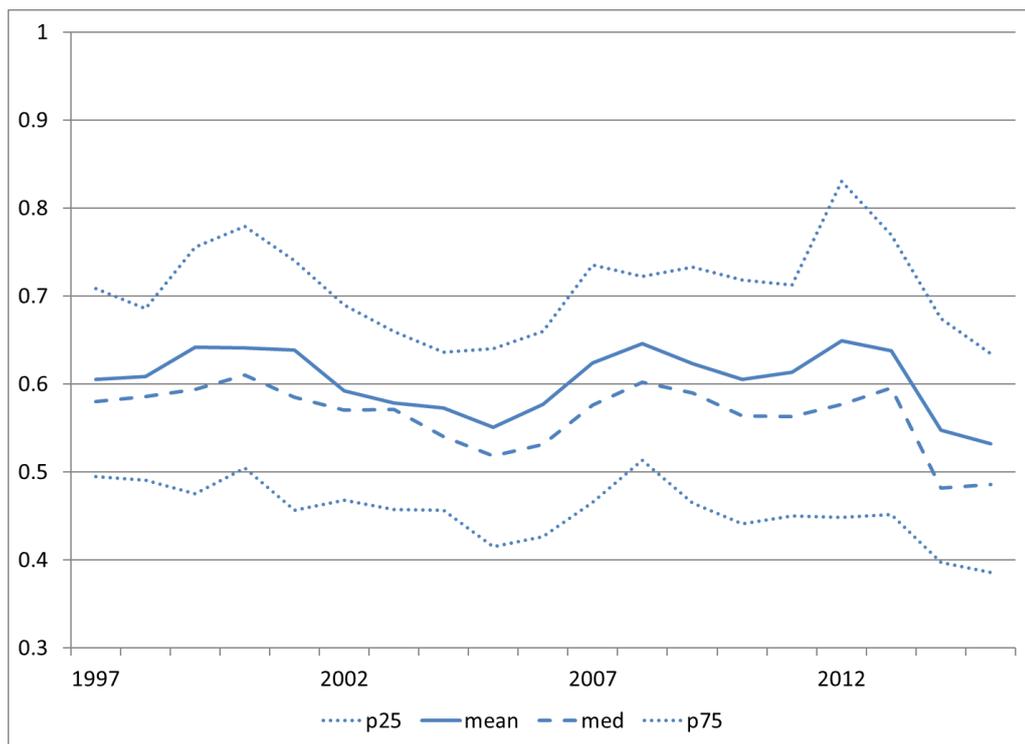
(a) Output per hour



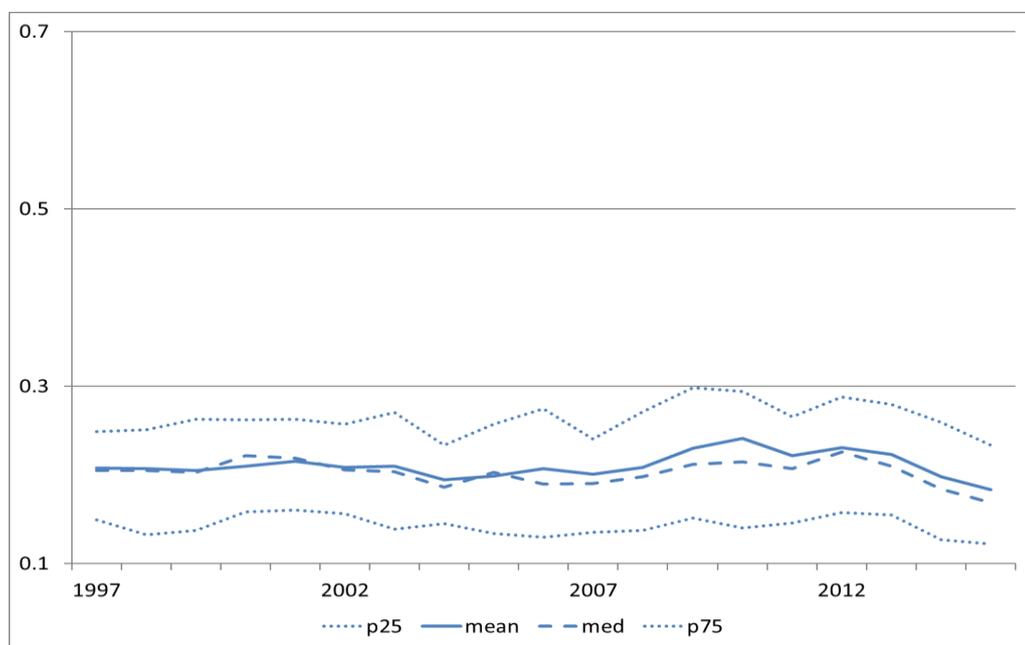
(b) Multifactor productivity

Source: See notes to Figure 5.

**Figure 10.** Distribution of *Weighted* 10-1 Difference of Productivity, 1997–2015



(a) Output per hour (hours-weighted)



(b) Multifactor productivity (composite-input-weighted)

Source: See notes to Figure 5.

**Table 1.** Input and Output Correlations between BLS, CMP, and NBER (1997–2015)

	<b>BLS/CMP</b>	<b>BLS/NBER</b>	<b>CMP/NBER</b>
<b>Total Manufacturing</b>			
Hours worked, levels	0.989	0.993	0.997
Hours worked, growth	0.927	0.915	0.949
Capital, levels	-0.141	0.916	0.369
Capital, growth	0.577	0.845	0.674
Energy, levels	0.967	0.997	0.977
Energy, growth	0.962	0.985	0.948
Materials, levels	0.943	0.996	0.967
Materials, growth	0.908	0.992	0.908
Output, levels	0.955	0.996	0.967
Output, growth	0.930	0.993	0.943
<b>Average of 4-Digit NAICS</b>			
Hours worked, levels	0.835	0.905	0.91
Hours worked, growth	0.566	0.715	0.693
Capital, levels	0.486	0.496	0.754
Capital, growth	0.327	0.356	0.809
Energy, levels	0.874	0.863	0.987
Energy, growth	0.77	0.766	0.77
Materials, levels	0.882	0.885	0.965
Materials, growth	0.734	0.755	0.948
Output, levels	0.894	0.985	0.903
Output, growth	0.773	0.959	0.781

Source: Authors' calculations on the ASM.

Notes: Resales are removed from output. The BLS output deflator is used, see Table 5 for details.

**Table 2.** Productivity Growth Correlations between BLS, CMP, and NBER (1997–2015)

	<b>BLS/ CMP</b>	<b>BLS/ NBER</b>	<b>CMP/ NBER</b>
Labor productivity (Total Manufacturing)	0.747	0.778	0.855
Labor productivity (Average of 4-Digit NAICS)	0.498	0.618	0.664
Multifactor productivity (Total Manufacturing)	0.939	0.991	0.963
Multifactor productivity (Average of 4-Digit NAICS)	0.823	0.908	0.855

Source: Authors' calculations on the ASM, see Table 5 for details.

**Table 3.** Summary of Within-Industry Productivity Distributions (1997–2015)

<b>Within-Industry productivity moment</b>	<b>Mean</b>	<b>Standard deviation</b>	<b>IQR</b>
<b>Labor Productivity</b>			
IQR	0.876	0.285	0.322
90-10 differential	1.72	0.465	0.593
Standard deviation	0.664	0.164	0.208
99-90 differential	0.708	0.272	0.324
10-1 differential	0.532	0.225	0.268
<b>Multifactor productivity</b>			
IQR	0.5	0.217	0.197
90-10 differential	1.031	0.38	0.377
Standard deviation	0.44	0.141	0.148
99-90 differential	0.839	0.462	0.507
10-1 differential	0.259	0.111	0.137

Source: Authors' calculations on the ASM.

Notes: Log labor productivity is calculated as  $\log(\text{output}/\text{hours})$  where hours are BLS-adjusted total hours. The 4-digit NAICS industry mean log LP is subtracted off establishment-level log LP. Within-industry productivity moments are created at the 4-digit NAICS level using propensity score weights. Annual summary statistics of these industry statistics are then created weighting each industry equally. The numbers shown are means of the annual summary statistic values from 1997–2015 weighting each year equally. Resales have been removed from output, see Table 5 for details.

**Table 4.** Probability of Transition across Quintiles of the Cross-Industry Distribution of Dispersion (annual averages between 1997 and 2015)

	<b>IPS Weighted</b>					<b>IPS and Activity-Weighted</b>					
	<b>Output per hour</b>										
	1	2	3	4	5	1	2	3	4	5	
1	0.61	0.24	0.1	0.02	0.02	1	0.74	0.17	0.08	0.01	0
2	0.22	0.42	0.23	0.11	0.03	2	0.18	0.52	0.27	0.02	0
3	0.13	0.23	0.37	0.25	0.03	3	0.08	0.25	0.47	0.17	0.02
4	0.05	0.08	0.24	0.43	0.2	4	0.02	0.04	0.15	0.62	0.17
5	0.02	0.03	0.05	0.19	0.72	5	0	0	0.02	0.17	0.81

	<b>Multifactor productivity</b>										
	1	2	3	4	5	1	2	3	4	5	
1	0.64	0.24	0.05	0.05	0.02	1	0.74	0.19	0.05	0.01	0.01
2	0.22	0.37	0.31	0.08	0.03	2	0.21	0.53	0.21	0.05	0
3	0.1	0.25	0.37	0.22	0.06	3	0.05	0.22	0.49	0.21	0.04
4	0.04	0.1	0.23	0.49	0.14	4	0.01	0.03	0.22	0.58	0.15
5	0.02	0.03	0.04	0.16	0.75	5	0.01	0.02	0.03	0.15	0.8

Source: Authors' calculations on the ASM.

**Table 5.** Summary of Variables used in Selected Tables and Figures

	Table 1 Correlation	Table 2 Correlation	Table 3 Dispersion	Figure 1 Employment	Figure 2 Hours	Figure 3 Output	Figure 4 Productivity
				Comparisons			
BLS implicit price deflator used for all estimates	yes	yes				yes	yes
Shipments deflator used to deflate output			yes				
Cost of resales (CR) removed from CMP	yes	yes	Yes			yes	yes
Employees only			Yes	yes		N/A	
Include BLS employees and self-employed (SE) and unpaid family workers (UFW) in BLS data only	yes	yes			yes	N/A	yes
CPS nonproduction/production hours ratio (even for NBER hours)	yes	yes	Yes		yes		yes
BLS intrasectorals included	yes	yes				yes	yes

## Appendix

### *A.1. Properties of ASM samples*

The ASM is a 5-year panel of roughly 50,000-70,000 manufacturing establishments and is a sample of establishments drawn from the manufacturing portion of the Census Bureau's Business Register using a probability proportional to size sampling scheme.<sup>32</sup> The largest establishments are sampled with certainty and are included in every panel.<sup>33</sup> Smaller establishments are sampled with a probability less than 1, where the probability increases with establishment size (measured by shipments). The smallest single-unit establishments, which are part of the "non-mail" stratum, are not mailed a form but they are included in the estimates. Due to the desire to reduce reporting burden, the Census Bureau uses administrative records to impute payroll, employment, industry and location from the administrative data for the smallest single-unit establishments, while total value of shipments are imputed using industry averages.<sup>34</sup>

The ASM sample is refreshed every 5 years. New ASM panels are drawn from the Economic Census and begin 2 years after the Census from which it was drawn (years ending in 4 and 9). The sample is also updated annually to include new establishments which are identified on the Census Bureau's Business Register. The Business Register is updated with information from the Economic Census as well as administrative records from the IRS and the Census Bureau's annual Company Organization Survey.

Data for the ASM are collected in all years except for years ending in 2 and 7, when the

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<sup>32</sup> More information about the ASM: <http://www.census.gov/manufacturing/asm/>.

<sup>33</sup> Prior to 1999, certainty units were establishments with 250 or more employees. In 1999, the cutoff was increased to 500 employees, and in 2004, it was increased again to 1,000 employees. Currently, the 10 largest establishments in an industry are also sampled with certainty. In addition to establishment size, certainty criteria include other characteristics such as industry, cell size, or energy use. For example, Computers, Flat-glass, Sugar, and Small industries (with less than 20 establishments), or establishments with large inventories, assets, fuel/electric expenditures are also sampled with certainty.

<sup>34</sup> Non-mail cases are included in the official estimates and have a weight of one. The survey is designed to tabulate cases from the mail and the non-mail component. The mail component was not designed to estimate the total population.

ASM data are collected as part of the Economic Census. Data on payroll, employment, industry, and geography for establishments in the non-mail stratum are obtained from administrative records.<sup>35</sup>

The ASM sample is designed to estimate unbiased national level estimates of a skewed population. The large establishments account for over 78% of the total value of shipments and the smallest establishments (5 or fewer employees) account for about 44% of the total number of establishments and only 1% of the total value of shipments. This sample design implies that the establishment counts in various size bins may not reflect those calculated from the LBD.

The ASM sample weights, which are inversely proportional to a shipments-based establishment size measure could, in principle, be used to correct for the effects of the ASM sample design. However, the sample design implies that the weighted sum of shipments from the mail stratum only will not match published totals.<sup>36</sup>

Another important aspect of the sample design is that the composition of establishments changes over time and between sample selections. Any weighting procedure aiming at creating unbiased estimates of productivity dispersion should account for the fact that the sampling probabilities, and therefore the composition of the ASM, change every 5 years. In addition, sampling and non-mail stratum thresholds vary across years.

#### *A.2. Establishment Characteristics and the Probability of Selection into the ASM*

The ASM's sample design has important implications for our analysis. For example, the sum of the ASM sample weighted employment or sales might equal total employment or total sales. However, it is not clear that the ASM sample weights are appropriate for our analysis. This section is devoted to describing our weighting procedure.

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<sup>35</sup> Federal regulations require the Census Bureau to limit small establishments' survey response burden.

<sup>36</sup> As mentioned above, only the mail component together with the adjustment for the non-mail stratum yields unbiased estimates of the total population. See Davis, Haltiwanger and Schuh (1996) for more details.

To address the effects of the ASM's sample design, we construct propensity score weights using the Longitudinal Business Database (LBD). See Jarmin and Miranda (2002) for more details about the LBD. The propensity score weights are constructed from a logistic regression in which we model the relationship between plant characteristics and the probability that an establishment is selected into the ASM. We start by matching establishments in the ASM to LBD establishments by year and "LBD Number."<sup>37</sup> Our dependent variable is a dummy variable that equals one if the establishment is in both the ASM and the LBD for that year and zero if the establishment is only in the LBD. For establishments in the non-mail stratum, the dummy variable is set to 0.

The set of regressors consists of dummy variables that classify each establishment based on its employment and payroll size class, whether the establishment is part of a multi-unit entity, the establishment's industry code, and the interaction between industry and employment size effects. Including industry-size interactions allows us to estimate industry-specific size distributions. These variables are obvious candidates for our logistic regressions because the probability of selection into the ASM sample and the cutoff for the non-mail stratum in the ASM vary by industry and size.

When determining weights, we define industries at the 3-digit NAICS level because the interaction of size indicators and more narrowly-defined industry codes leads to empty cells in smaller industries. Empty-size bins imply that the size distribution cannot be estimated in these industries.<sup>38</sup> When the size distribution cannot be estimated for an industry, propensity scores cannot be calculated because maximum-likelihood estimates of the size effects do not exist. Empty cells can, in principle, be avoided by collapsing size bins, combining similar narrowly-defined industries, or allowing bin definitions to vary across industries. We experimented with the number and definition of the size bins and the level of industry aggregation and found that using 3-digit

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<sup>37</sup> The LBD Number is an establishment identifier that is consistently defined across both datasets. Although linking the datasets by LBD Number is straightforward, a small percentage of establishment-year observations do not match due to timing issues between the ASM and the LBD.

<sup>38</sup> The size distribution cannot be estimated if all establishments are in the same size bin.

industry codes together with 4 size bins allows us to estimate the size distribution in every industry and year. Allowing for more heterogeneity by using either industry-specific size bins or more narrowly-defined industries leads to feasibility problems with the logistic regression.

We defined the size bins so that the resulting distribution allows the lowest size bins to vary over time. That is, in every year and every industry, the 50<sup>th</sup> percentile of establishments with fewer than 50 employees is used to define bins 1 and 2. For larger establishments, the following bins are defined: 50–99, 100–199, 200+.<sup>39</sup> There are 21 3-digit NAICS industries in the 2002 classification system, which results in 105 industry specific size distributions. We include a continuous size measure in order to allow the weights to vary within these cells. This is necessary to account for possible within-cell compositional changes. Adding 5 payroll classes and 2 groups related to multi-unit status increases the number of cells to 113.<sup>40</sup>

The 2002 change in the industry classification system resulted in missing NAICS-2002 codes for a nontrivial number of establishments in the LBD between 1997 and 2001. For example, the NAICS code is missing if an establishment exited prior to 2002. For these observations, we used imputed NAICS codes.<sup>41</sup> From 2002 on, NAICS codes are available for all establishments in the LBD.

Our inverse propensity score weights generate employment counts that do a good job of matching the trends and cyclical variation in BLS manufacturing employment, but they do not match BLS levels.

### *A.3 Comparison of Hours Measures*

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<sup>39</sup> The payroll size classes are 0–200, 201–500, 501–1000, 1001–5000, 5001+.

<sup>40</sup> If we were to use 4-digit industry, the number of cells would increase significantly. There are 86 4-digit NAICS industries implying 86 different size distributions and 430 industry-size cells. Such an increase in the number of cells yields empty size bins in several industries.

<sup>41</sup> NAICS codes are imputed using a method described in Fort (2013).

In this study, we use hours data from ASM, augmented with data from the CPS. However, for official estimates of productivity growth, BLS uses the CES as its main source of hours data. Although the CES and ASM are establishment surveys, the two surveys differ in what hours data they collect and how they collect it. The best information on these differences comes from studies completed in the early 2000s (Goldenberg and Willimack, 2003; and Fisher et al., 2001). These studies do a nice job of summarizing the differences between the two surveys and how those differences affect estimates of hours worked. In this appendix, we summarize that research and discuss the implications for comparing our estimates to published BLS estimates.

There are some general differences between the two surveys that are worth noting. First, the ASM is an annual survey, whereas the CES is conducted monthly. As a result, the reference periods of the two surveys differ. The reference period for the CES is the pay period that includes the 12<sup>th</sup> of the month. The CES collects data on the total number of employees, hours for all employees since 2006, the number of production workers, production worker payroll and production worker hours.

In contrast, the ASM has different reference periods for different data elements. For production worker employment, the ASM reference period is the pay period that includes the 12<sup>th</sup> of the month in the months of March, May, August, and November. These quarterly reports are then averaged into an annual number. The ASM collects employment data for Other Employees only for the pay period that includes March 12<sup>th</sup>. The implicit assumption is that non-production worker employment does not vary much over the year. Total employment is not collected directly, but rather is equal to the sum of non-production worker employment in March and the annual average of quarterly production worker employment.

Annual total employment in the two surveys can differ if there are seasonal patterns in production worker employment that are missed in the ASM's quarterly reports or if there is a seasonal pattern to non-production worker employment. We examined this issue using monthly

CES data. Specifically, we calculated the average employment for each quarter using CES data, and then calculated the ratio of average quarterly employment to CES employment in the ASM reference months (March, May, August, and November). The ratios were very close to 1, indicating that estimates of average annual employment are the same whether we use four quarterly reports or 12 monthly reports.

There are greater differences in the hours data collected in the two surveys. First, the two surveys use different concepts. The ASM asks employers to report hours *worked*, whereas the CES collects hours *paid*. The main difference is that the CES hours data include holidays, annual leave, and sick leave that were paid but not worked. Thus, we would expect total annual hours reported in the ASM to exceed total annual hours in the CES. For productivity measurement, hours worked is the correct concept, which is why BLS adjusts the CES data using hours-worked-to-hours-paid ratios from the NCS.

The two surveys also differ in how they ask respondents to report hours. The ASM asks respondents to report total annual production worker hours. The CES asks respondents to report total production workers for the pay period that includes the 12<sup>th</sup> of the month. The hours reports are converted to a weekly number using conversion factors that vary with the number of workdays in the month. Apart from the difference in concept, these two approaches to collecting hours data could result in different estimates of total annual hours. Research by Frazis and Stewart (2004) has shown that people work longer hours during the week that includes the 12<sup>th</sup> of the month.<sup>42</sup> This would lead to annual hours in the CES being higher than in the ASM and would offset some of the difference due to the difference in concept. Neither survey collects hours data for non-production workers. As noted in the text, nonproduction worker hours are estimated using data from the CPS.

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<sup>42</sup> Their research examined the accuracy of CPS hours reports by comparing the CPS hours data to hours data from the American Time Use Survey (ATUS). Subsequent research by Eldridge et al. (2019) found differences in some years, but not in others.