Online Appendix

A Data and measurement

A.1 Access and use of the unpublished Census data

A.1.1 Access of the data:

We use the Annual Survey of Manufactures and the Census of Manufactures, confidential plant-level data from the U.S. Census Bureau. Qualified researchers with approved research projects may gain restricted access to the unpublished Census data at secure Census Bureau Research Data Center (RDC) locations under the provisions of Title 13, sec. 9 United States Code (U.S.C). The Center for Economic Studies (CES) is a research unit of the Office of the Chief Economist, U.S. Bureau of the Census and currently operates 15 Research Data Centers across the country. Title 13 permits the Census Bureau to provide Special Sworn Status (SSS) to outside researchers (i.e., non-employees) who help the Census Bureau carry out its work, by making them liable for penalties for unauthorized disclosure or use of protected information, just as Census employees are.

Researchers should submit a research proposal that demonstrates the need to use non-public data, no risk of disclosure of confidential information, and benefit to the Census Bureau data collection programs. The CES staffs review each proposal to check the feasibility of the project given the data, disclosure risk, scientific merit, etc. The CES researchers should be sworn for life to protect the confidentiality of the data they access. More information about CES, RDCs, requirements for access to data, and examples of research produced at the RDCs is at https://www.census.gov/ces/index.html.

A.1.2 Summary of processing the data:

We will provide SAS and STATA codes that will help researchers with access to the Census micro data replicate statistics reported in the paper.

Preparing the data (extract1.sas): We extract all manufacturing plants in the ASM panels for years 1972-1997. For Census years we use plants that are part of the ASM panels only. There is a flag variable to indicate these ASM plants in the file. We append all the ASM panels in a panel format. We label the data set produced in this step Sample A.

Linking the panels and identifying birth and death (bdlink2.sas): We merge ASM panels for all sample years, using the plant identification code. We first flag potential birth and death candidates from the merged data set. Using information in the Census year, we identify birth and death plants. Continuing plants should have a positive employment. Detailed description of identifying entry and exit is explained in the next subsection. This step will produce Sample B. By merging Sample A and B, we have Sample C which contains birth and death information.

Measuring size and productivity of plants: The number of employment is given in the data (total employment). We will provide STATA codes that will generate plant-level labor productivity, TFP, and the relative size and productivity of entering and exiting plants compared to continuing plants in the industry. For detailed description of measuring productivity, see the subsection, "Variables for productivity measures." For this step, we use Sample C. We drop plants with zero employment and administrative records (imputed values). This process produces the final sample, Sample D.

Measuring entry and exit statistics: We will provide programs that generate statistics reported in the paper: entry and exit rates, size of entering and exiting plants, size distribution of plants, productivity of entering and exiting plants, and AR(1) process of employment. We use Sample C in counting the number and the rates of entering and exiting plants. For the size and productivity statistics we use Sample D, which exclude plants with imputed variables (i.e., administrative records).

A.2 Measuring entry and exit over the business cycle

Identifying entry and exit: In this paper, we focus on first-time plant openings (i.e., birth) and permanent shutdowns (i.e., death). The Census Bureau adds new plants from the Company Organization Survey and the Business Register into the ASM panel. The Business Register is updated based on the information available from the Census Bureau and other Federal statistical and administrative records programs, including the IRS (Internal Revenue Service) Federal Tax Returns and Return Information (FTI). The business register, which is frequently updated from every quarter to every 5 years depending on the data items, is used to identify entry of new establishment. The Company Organization Survey (or Report of Organization) covers all companies with payroll, and their establishments, with the exception of companies in agricultural production, in which companies report establishments that have been sold, closed, continued, started, and acquired. This annual survey is used to identify new establishments of multi-unit firms and maintain the Business Register.

We identify startup and shutdown candidates following Davis, Haltiwanger, and Schuh (1996). All startup plants should have at least one employee, while plants with zero employees are considered to be shutdowns (either temporary or permanent). We exclude reopened plants and temporary or indefinite shutdowns using the Census of Manufactures. In order to exclude spurious startup and shutdowns, we mainly use information from the Census of Manufactures. For example, when a new plant appears for the first time in the ASM panel, we check all Census of Manufactures files prior to the ASM panel in order to distinguish an entry due to panel rotation from a true startup. While Davis, Haltiwanger, and Schuh (1996) use the coverage code (CC), we find the coverage code less useful for more recent cohorts. We find the number of startup and shutdown candidates with "CC= 0 (no change in operations)" increases over time. Furthermore, even valid coverage codes are reported with some leads and lags in the timing of startup or shutdown.[20]

It is possible that the timing of birth in the ASM panel may be earlier or later than actual

[20] Foster, Haltiwanger, and Kim (2006) also uses information from the Longitudinal Business Database (LBD) to identify births and deaths.

birth, due to the time lag in adding start-ups into the survey. While this may cause a problem with statistics for an individual year (e.g., annual averages for entrants or job creation from startups), it is less likely be a problem in our statistics on booms and recessions because our classification of booms and recessions has an average duration of 3 years. Because plants that enter during this multi-year window of recessions (e.g., recessions between 1979-1983) are all counted as entrants during recessions, a lag of a year or two would not alter our statistics substantially.[21]

Recently the Census Bureau has developed the Longitudinal Business Database (LBD), which is a longitudinal version of the Census business register. While the LBD contains more accurate information about the timing of births and deaths, we were not authorized to access the LBD during the course of this project.

ASM sample weights: We use the ASM sample weights to measure representative entry and exit rates as well as average size and productivity statistics. The sample weights in the ASM are related to the probability of selection and are intended to create a representative sample of establishments in terms of size (i.e., shipments). We apply sample weights to birth and death in the manner that has been used in gross job flow statistic (Davis, Haltiwanger, and Schuh, 1996). While it is a more reliable way of using the ASM than simply counting the number of births and deaths, appropriate caution is needed because sample weights applied to birth and death rates are activity-weights and may result in birth and death rates that are less *strictly* representative of the manufacturing sector than average statistics of employment or productivity are.

Manufacturing output: We use the growth rate of manufacturing output to divide sample years into good and bad years. To measure the changes in the deflated output, we aggregate the 4-digit SIC level real value of shipments, deflated by the 4-digist SIC level price defla-

[21] We also constructed job creation and destruction rates based on our measure of birth and death and compared those to Foster, Haltiwanger, and Kim (2006). Our job creation and destruction rates are highly correlated with Foster, Haltiwanger, and Kim (2006) and show a cyclical pattern that is similar to theirs.

tor. We use industry-level price because aggregate price deflator may reflect changes in the composition of industries with different prices.

A.3 Variables for productivity measures

This appendix documents how variables in the productivity measures used in this paper are constructed.

Capital: We follow Dunne, Haltiwanger, and Troske (1997) closely in constructing the capital stock. For the initial benchmark, we use the book value of structures or equipment, deflated by the two-digit industry capital deflator from the BEA (2-digit). We use the average of beginning-of-year assets and end-of-year assets. While we separately examine structures and equipment, for recent years for which the ASM reports only total assets (structures and equipment together) the deflated book value of total assets is used as the initial benchmark. Investment deflators are from the NBER manufacturing productivity database (Bartelsman and Gray, 1996). The depreciation rate for each two-digit industry was also obtained from the BEA. Real capital stocks are obtained by summing up the real value of structures and the real value of equipment constructed from the perpetual inventory method.

Labor input: Labor input for TFP (based on (1)) is measured as total hours for production and nonproduction workers. Because hours for nonproduction workers are not collected, we estimate the value for total hours by following the method in Baily, Hulten, and Campbell (1992), which is to multiply the total hours of production workers by the ratio of the total payroll for all workers by the payroll for production workers. Following the model, we use the total number of workers as labor input for the TFP based on (2).

Materials: Costs of materials are deflated by material deflators from the NBER manufacturing productivity database.

Output: For TFP, we use the total value of shipments (TVS) deflated by the shipments deflator from the NBER manufacturing productivity database. Although it is possible to adjust output for the change in inventories, inventories for some plants (in particular, for small plants) are imputed (Baily, Bartelsman, and Haltiwanger, 2001). To avoid a possible measurement issue, we have chosen to use gross shipments as a simple measure. For the measure of productivity based on (2), we use value added deflated by shipment deflators. We also used deflated shipments ($TVS/PISHIP$) minus the real value of materials, but the results did not change much.

Revenue shares: We use the four-digit industry-level revenue shares as factor elasticities. This procedure implicitly assumes that all plants in the industry operate with the same production technology, a common assumption in studies measuring plant-level productivity. In calculating labor's share of total costs, we follow Bils and Chang (2000), magnifying each four-digit industry's wage and salary payments to reflect other labor payments, such as fringe payments and employer FICA payments. We use information from the National Income and Product Accounts to calculate the ratio of these other labor payments to wages and salaries at the two-digit industry level.

A.4 Additional statistics

Job creation from startups and job destruction from shutdowns: Campbell (1998) used Davis, Haltiwanger, and Schuh (1996) measures of job creation at entering plants and destruction at exiting plants to study cyclical patterns of employment-weighted entry and exit rates. Using the updated job creation and destruction data, we examine the cyclicality of employment-weighted entry and exit rates across different sample periods. Figure 2 displays job creation and destruction rates from entering, exiting, and continuing plants over the sample period. The figure confirms Davis, Haltiwanger, and Schuh's (1996) finding that job creation and destruction from continuing plants drive the cyclical properties of job flows. To focus on entry and exit, Figure 3 displays job creation from startup (birth) and job destruction from shutdown (death) over the sample period.

Figure 2: Job creation and job destruction rates of entering, exiting, and continuing plants

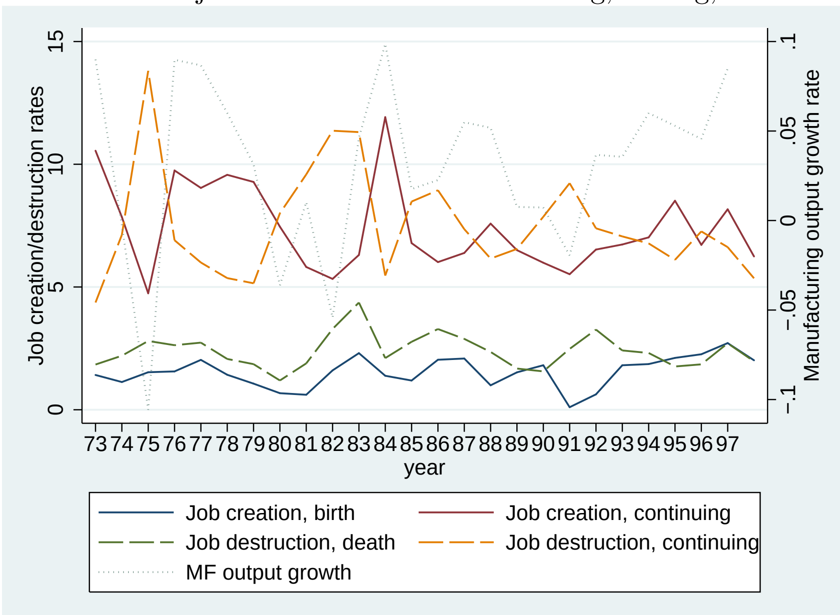


Figure 3: Job creation rate from startups and job destruction rate from shutdowns

Table 9: Cyclicality of job creation from startups and job destruction from shutdowns—correlations with output growth

	Job creation from startups	Job destruction from shutdowns
1972–1998	0.368 (0.071)	−0.006 (0.977)
1972–1988	0.247 (0.356)	−0.048 (0.861)
1989–1998	0.752 (0.020)	0.248 (0.520)

Note: The correlation between annual manufacturing output growth rate and annual job creation (destruction) rates from startups (shutdowns) for three different sample periods. The p-values of the estimated correlations are reported in parentheses. Campbell's (1998) results are based on the sample period between 1972 and 1988 (second row).

Table 9 reports simple correlations between manufacturing output and annual job creation (destruction) rate from startup (shutdown). The correlation between the job destruction rate due to shutdowns and the percentage change in manufacturing output is −0.048 in Campbell's (1998) sample period (i.e., 1972–1988) while that has a positive value of 0.184 between 1989 and 1998. The correlation between the job creation rate due to startups and the percentage change in manufacturing output is higher for the sample period between 1989 and 1998 than the one for the sample period used in Campbell (1998). While annual job destruction rates due to shutdowns are positively correlated with output in the later time period, we find that quarterly job destruction rates due to shutdowns are negatively correlated with output. It is worth noting that these entry and exit rates, based on job creation and destruction data, are employment-weighted measures. Simple entry and exit rates (that are not employment-weighted) are not available in quarterly frequency.

Size distribution: Figures 4 and 5 describes the distribution of plant size and that of employment shares, respectively. The figure shows that employment is skewed towards large plants. Figure 6 reports hiring shares, firing shares, and exit rates for each size class. Hiring and firing are also concentrated in large plants. Although exit rates are higher in smaller plants, some large plants also exit. Standard models of plant-level dynamics such as Hopenhayn and Rogerson (1993) cannot explain this particular phenomenon. Because productivity

Figure 4: Size distribution—fractions of the total number of plants

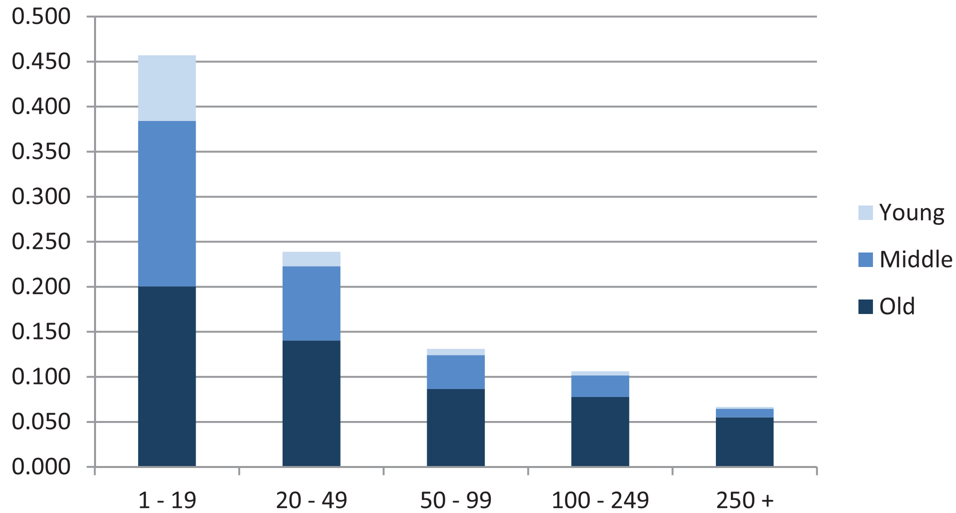
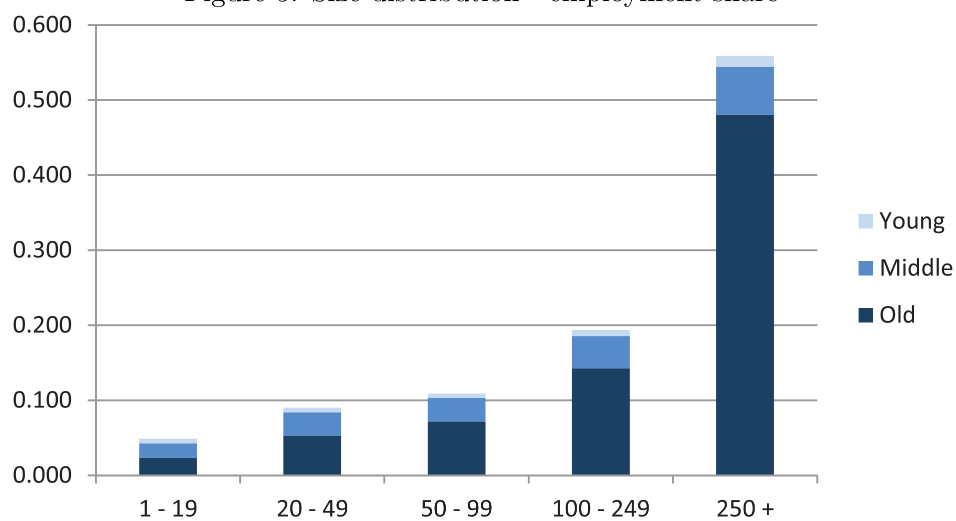


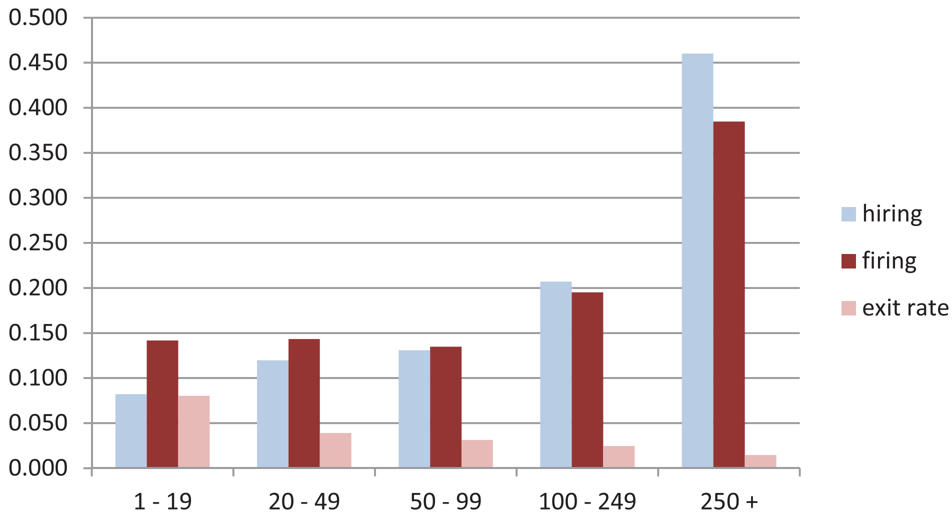
Figure 5: Size distribution—employment share



and size have a one-to-one relationship (when adjustment costs and frictions are absent), very large plants have high productivity levels and do not exit in their model. The distribution of plant size and employment shares are also presented for each age category.[22] This

[22]The age categories follow Davis, Haltiwanger, and Schuh (1996, p.225). In the ASM, panel rotation makes it impossible to determine the exact age of plants. Roughly speaking, "Young" corresponds to 0–1 years in operation,"Middle" corresponds to 2–10 years, and "Old" corresponds to 11 years or more.

Figure 6: Hiring share, firing share, and exit rate for each size class



presentation shows that young plants tend to be small.

Relative productivity with various assumed values of returns to scale: In Table 10, we examine the extent to which fluctuations in relative productivity changes as the assumed returns to scale vary. In particular, in addition to the specifications (1) and (2) reported in the first two rows of Table 5, we consider the case where the production function exhibits decreasing returns to scale.

$$\ln(s_t) = \ln(y_t) - \gamma(\alpha_k \ln(k_t) + \alpha_n \ln(n_t) + \alpha_m \ln(m_t)). \tag{3}$$

Here, $\gamma \in [0, 1]$ is the returns to scale parameter. The specification (1) in the first row of Table 5 corresponds to the case in which $\gamma = 1$. Although the magnitude of the relative productivity becomes smaller as we reduce the value of the returns to scale parameter, the pattern of cyclical fluctuations in the relative productivity of entering and exiting plants remains the same: the relative productivity of exiting plants is similar across booms and recessions, whereas the relative productivity of entering plants is substantially different in the two phases of the cycle.

Table 10: Relative productivity of entering and exiting plants

	Relative TFP, entering			Relative TFP, exiting		
TFP based on:	Good	Bad	Average	Good	Bad	Average
(3), $\gamma = 0.99$	0.92	1.01	0.96	0.87	0.83	0.86
(3), $\gamma = 0.95$	0.89	0.99	0.93	0.85	0.81	0.84
(3), $\gamma = 0.90$	0.86	0.96	0.90	0.82	0.79	0.80
(3), $\gamma = 0.85$	0.83	0.94	0.87	0.80	0.76	0.78

Note: Each row reports the relative TFP based on (3), with various assumed values of returns to scale (γ). Relative productivity of entrering (exiting) plant is obtained by dividing the productivity of the entering (exiting) plant by the average productivity of continuing plants in the same four-digit industry.

Additional References for Appendix

[1] Bartelsman, E. J. and W. B. Gray (1996). "The NBER Manufacturing Productivity Database," NBER Working Paper T0205.

[2] Bils, M. and Chang, Y. (2000). "Understanding How Price Responds to Costs and Production," *Carnegie-Rochester Conference Series on Public Policy* 52, 33–78.

[3] Dunne, T.; J. C. Haltiwanger; and K. Troske (1997). "Technology and Jobs: Secular Changes and Cyclical Dynamics," *Carnegie-Rochester Conference Series on Public Policy* 46, 107–178.