# Entry and Exit of Manufacturing Plants over the Business Cycle*

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**Abstract**

This paper analyzes the plant-level entry and exit over the business cycle. We document basic patterns of entry and exit of U.S. manufacturing plants between 1972 and 1997. We find that the entry rate is more cyclical than the exit rate. We also find that the differences in productivity and employment between booms and recessions are particularly larger for entering plants than for exiting plants. Our new finding suggests that the selection at the entry margin may be more important than the selection at the exit margin in understanding the plant-level dynamics over the business cycle.

*Keywords*: plant-level dynamics, entry and exit, business cycles
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# 1 Introduction

A growing number of recent studies using plant-level data find a large degree of heterogeneity in the size, productivity, and growth patterns of manufacturing plants.[1] In this paper, we explore the implications of this plant-level heterogeneity for macroeconomic dynamics. In particular, we focus on plant-level dynamics over the business cycle, especially on entry and exit of plants.

We document the heterogeneity of U.S. manufacturing plants, using the Annual Survey of Manufactures (ASM) from the U.S. Census Bureau from 1972–1997. While previous studies on the entry and exit of producers document considerable fluctuations in entry and exit rates (e.g., Chaterjee and Cooper, 1993; Campbell, 1998), relatively little is known about how the characteristics of entering and exiting plants vary over the business cycle. We document the patterns of entry and exit over the business cycle in terms of rate, employment, and productivity. We find that entry rates are on average significantly higher in booms than in recessions. Furthermore, the differences in productivity and employment in booms and recessions are particularly larger for entering plants than exiting plants. For example, the average size of entering plants (relative to the incumbents) is about 25 percent smaller in booms than in recessions. Moreover, plants entering in booms are about 10–20 percent less productive (in terms of the relative productivity to the incumbents) than those entering in recessions. Such differences are relatively small for plants exiting in booms or recessions.

The characteristics of entrants are among the important determinants of the size distribution of firms and establishments in an industry. Recent studies utilizing establishment-level data find that entry is an important source of aggregate productivity growth (see, e.g., Foster, Haltiwanger, and Krizan, 2001 and 2002). The fact that the plants that enter in recessions are different from those that enter in booms indicates that there is a much larger barrier to entry during recessions.[2]

[1]See Bartelsman and Doms (2000) for a review of the literature.

[2]Our companion paper, Lee and Mukoyama (2014), shows that the standard Hopenhayn-style model (Hopenhayn (1992) and Hopenhayn and Rogerson (1993)) can match the properties of the data presented

It has long been argued that recessions have "cleansing" effects: low-productivity plants are scrapped during recessions, enhancing aggregate efficiency. Many recent papers have provided an alternative to this prevailing view. For example, analyzing a model of creation and destruction of production units, Caballero and Hammour (1994) argue that low-productivity firms can be "insulated" from recessions because fewer new plants are created during recessions. Barlevy (2002) considers a model of on-the-job search and shows that recessions may reduce aggregate efficiency by discouraging the reallocation of workers. In a more recent study, Caballero and Hammour (2005) provide evidence that recessions reduce the amount of cumulative reallocation in the economy.

Focusing on the permanent shutdown, we do not find strong effects of cleansing from exit during recessions. Overall, annual exit rates are similar across booms and recessions. Furthermore, exiting plants in recessions are not very different from those in booms in terms of employment or productivity. Our finding suggests that recessions do not necessarily cause productive plants—those that could have survived in good times—to shut down in large numbers. Rather, strongly procyclical entry rate suggests that the "insulation" effect at the entry margin predominates. In contrast to the finding on the exiting plants, the average size and productivity of entrants vary substantially over the business cycle. Only highly productive plants enter and begin production during recessions. While previous studies on the effects of recessions have focused on the selection at the exit margin,[3] our new finding suggests that the selection at the entry (or "creation") margin may be more important than the selection at the exit (or "destruction") margin in understanding the firm dynamics over the business cycle.

The paper is organized as follows. In the next section, we document the empirical facts on entry, exit, and employment in U.S. manufacturing. Section 3 concludes.

in this paper when entry costs are cyclical.

[3] See, e.g., Mortensen and Pissarides (1994), Hall (2000), and Caballero, Hoshi, and Kashyap (2008).

# 2 Empirical evidence on employment and productivity dynamics

## 2.1 Measurement and data

We use the ASM portion (from 1972 through 1997) of the Longitudinal Research Database (LRD), which is constructed by the U.S. Census Bureau, to analyze the behavior of plants during the business cycle. Many recent theoretical studies on plant-level dynamics are based on the evidence provided by Dunne, Roberts, and Samuelson (1988, 1989a, 1989b). They utilize the Census of Manufacturers (CM) dataset, which is a part of the LRD. The CM is conducted for the universe of U.S. manufacturing plants, and the evidence from the CM has been used to calibrate stationary equilibrium models describing the entry, exit, and employment dynamics of U.S. plants (e.g., Hopenhayn and Rogerson, 1993). However, because the CM is conducted every five years, it is not suitable for describing plant-level behavior over the business cycle. The ASM, conducted annually for non-census years, overcomes this issue. The ASM utilizes a probability-based sample of plants drawn from the universe of plants identified by the CM. We use ASM sample weights so that the sample is representative of the entire U.S. manufacturing sector.[4]

In this study, entering plants are new plants, which appear in the ASM or CM for the first time with at least one employee (birth). Similarly, exiting plants include only permanent shutdowns (death). We do not include temporary exit and re-entry of plants, in order to exclude possible spurious entries and exits in the ASM panels. As discussed in detail in Davis, Haltiwanger, and Schuh (1996), samples in the ASM panels are rotated every five years. Only large "certainty" plants are continuously observed across different ASM panels. In order to avoid measurement errors in entry and exit that are caused by the panel rotations, the results reported in this paper exclude entries and exits measured between two different ASM panels, namely for the years 1973-74, 1978-79, 1983-84, 1988-89, and 1993-94.

[4]See the Online Appendix and Davis, Haltiwanger, and Schuh (1996) for details about the data. The Online Appendix is available at `https://sites.google.com/site/toshimukoyama/Online_Appendix_LM.pdf`.

In addition to employment dynamics, we also examine the extent to which the productivity of entering and exiting plants varies over the business cycle. The ASM contains data on material inputs, output, and capital stock in addition to employment at each plant. We construct various measures of productivity.

First we look at total factor productivity (TFP), as in the standard macroeconomic growth-accounting analysis. Our plant-level TFP measurement closely follows Baily, Hulten, and Campbell (1992).[5] Assuming that the production function is $y_t = s_t k_t^{\alpha_k} n_t^{\alpha_n} m_t^{\alpha_m}$, where $y_t$ is real gross output, $s_t$ is TFP, $k_t$ is real capital stock, $n_t$ is labor input, and $m_t$ is real material inputs, TFP ($s_t$) can be measured from the growth accounting equation

$$\ln(s_t) = \ln(y_t) - \alpha_k \ln(k_t) - \alpha_n \ln(n_t) - \alpha_m \ln(m_t). \tag{1}$$

We measure factor elasticities ($\alpha_k$, $\alpha_n$, and $\alpha_m$) using 4-digit industry-level revenue shares. Real capital stocks are obtained from the perpetual inventory method. Output and material inputs are measured in 1987 constant dollars using deflators from the NBER manufacturing productivity dataset. Labor input is measured as total hours for production and non-production workers following Baily, Hulten, and Campbell (1992).

While this measure of TFP follows the practice used in the literature for measuring plant-level TFP, it may be subject to measurement errors of the capital stock. To avoid this issue, we also consider the following specification, $y_t = s_t {n_t}^{\theta}$. Now we measure $y_t$ by value added, rather than output. Then $s_t$ can be measured from[6]

$$\ln(s_t) = \ln(y_t) - \theta \ln(n_t). \tag{2}$$

[5]Without a proper measure of prices for individual plants, it is not possible to measure total factor productivity at the plant level. While we call this measure TFP, it is actually real revenue per unit input and reflects within-industry price variation. See Foster, Haltiwanger, and Syverson (2008) for possible issues involved in using revenue-based productivity measures.

[6]One interpretation of the production function $y_t = s_t {n_t}^{\theta}$ is that the other inputs such as capital stock are fixed (and included in $s_t$). Alternatively, it can be considered to be the relationship between $y_t$ and $n_t$ after all of the other variable inputs are taken into account. Suppose, for example, that the "true" production function is $y_t = \tilde{s}_t ({x_t}^{\alpha} {n_t}^{1-\alpha})^{\phi}$, where $\alpha \in (0,1)$, $\phi \in (0,1)$ and $x_t$ is a variable input. Suppose that the price of $x_t$ is $r$. Then, optimally choosing $x_t$ and plugging the optimal solution into the "true" production function yields the relationship $y_t = s_t {n_t}^{\theta}$, where $\theta \equiv \phi(1-\alpha)/(1-\alpha\phi)$ and $s_t$ is a function of $\tilde{s}_t$, $\alpha$, $\phi$, and $r$.

Table 1: Average size and productivity of plants

| | Continuing | Entering | Exiting |
|---|---|---|---|
| Average size | 87.5 | 50.3 | 35.0 |
| Relative size | – | 0.60 | 0.49 |
| TFP based on (1) | – | 0.96 | 0.86 |
| TFP based on (2) | – | 0.75 | 0.64 |
| Labor productivity (using employment) | – | 1.00 | 0.92 |
| Labor productivity (using hours) | – | 0.98 | 0.91 |

Note: The table reports the simple averages of yearly means for the variables listed, between 1972 and 1997. The first row reports average employment (number of workers) for continuing, entering, and exiting plants. From the second through the sixth row, size (employment) and various measures of productivity relative to the industry average of continuing plants are reported.

## 2.2 Employment and productivity of entering and exiting plants

### 2.2.1 Average employment and productivity statistics

First, we document the employment and productivity characteristics of entering and exiting plants. Those statistics are useful in calibrating the steady state of a firm dynamics model. The first row of Table 1 documents the average size of the plants, in terms of the number of workers. Entering plants (using the time-$t$ size of the plants which entered between time $t-1$ and time $t$) and exiting plants (using the time-$(t-1)$ size of the plants which exited between time $t-1$ and time $t$) are much smaller than continuing plants (using the time-$t$ size of the plants which survived from time $t-1$ to time $t$). The second row of Table 1 reports the relative size of entering and exiting plants. The relative size of an entering (exiting) plant is obtained by dividing the size of the entrant by the average size of continuing plants in the same four-digit SIC industry.[7] Entering plants are 40 percent smaller than continuing plants in the same four-digit SIC industry, while exiting plants are about half of the size of continuing plants in the same industry.

[7] By dividing by the average size of continuing plants in the same four-digit industry, we control for the effects of changes in the industrial composition of entrants over the cycle, as well as differences in plant size across industries.

These differences in size are partly explained by differences in productivity. The third through sixth rows of Table 1 show various measures of relative productivity. This finding is one of the main contributions of our paper, because direct measures of productivity were not available at an annual frequency in the previous literature. Each cell in these rows represents the relative productivity (as compared to the four-digit SIC industry average of continuing plants) of entering and exiting plants. Two properties are consistently found across different productivity measures. First, entering and exiting plants are less productive than continuing plants (except for one case).[8] Second, exiting plants are less productive than entering plants. These findings are consistent with the pattern of employment size in the first two rows of Table 1, provided that a productive plant employs more workers.

The third row in Table 1 is the TFP, based on (1). The fourth row is the productivity measure based on equation (2). Here, instead of using (2) directly, we control for industry heterogeneity in labor shares by postulating the production function $y_t = s_t n_t^{\theta_I}$. We obtain $s_t$ by calculating $\ln(s_t) = \ln(y_t) - \theta_I \ln(n_t)$. $\theta_I$ is obtained from the four-digit SIC industry-level labor share.[9] The advantage of the measure based on (2) is that the measurements of output and employment are relatively more reliable than those for capital and material inputs. The fifth and sixth rows are measures of labor productivity (output divided by labor input). The fifth row measures labor input by employment, and the sixth row measures labor input by hours.

[8] Differences in plant-level productivity must be interpreted with caution. Because plant-level prices are not observed, our revenue-based productivity measures reflect price or demand variation within an industry in addition to differences in technical efficiency. In a study focusing on a small number of industries where producer-level prices and quantities are observed separately, Foster, Haltiwanger, and Syverson (2008) argue that the true technological productivity of entrants may be understated when traditional revenue-based measures are used because new plants have lower prices than incumbents.

[9] In using labor share for $\theta_I$, we are assuming that all inputs other than labor are fixed. As we argued in footnote 6, if there is another variable input $x_t$ and the production function is $y_t = \tilde{s}_t ({x_t}^{\alpha} {n_t}^{1-\alpha})^{\phi}$, where $\alpha \in (0,1)$, $\phi \in (0,1)$, and the price of $x_t$ is $r$, then we can represent the relationship between $y_t$ and $n_t$ by $y_t = s_t {n_t}^{\theta}$, where $\theta \equiv \phi(1-\alpha)/(1-\alpha\phi)$ and $s_t$ is a function of $\tilde{s}_t$, $\alpha$, $\phi$, and $r$. In that case, $\theta = \phi(1-\alpha)/(1-\alpha\phi)$ is larger than the labor share $\phi(1-\alpha)$, and thus we should use a larger value than the labor share as the estimated value of $\theta_I$.

### 2.2.2 Business cycle patterns

Here we characterize how entry and exit, employment, and productivity differ during booms and recessions. When considering business cycles, we divide the sample years into two categories, good and bad, based on the growth rate of manufacturing output. If the growth rate of manufacturing output from year $t-1$ to $t$ is above average, we call year $t$ a good year; if it is below average, we call year $t$ a bad year.[10] The reason why we base our distinction on the growth rate rather than the level is twofold. First, the division based on the (HP-filtered) level does not match the conventional boom-recession division. For example, based on the level criterion, 1990 (the only year in the 1990s for which more than half of one year was recorded as a "contraction," according to NBER business cycle dates) is considered a good year, while most years of the mid-1990s are considered bad. Second, we consider the growth rate to be an important indicator because our analysis stresses the cyclical movement of entry and exit rates, which are more related to the "change" than the "level."

Figure 1 displays the entry and exit rates of plants over the sample period, along with the annual growth rates of manufacturing output. The entry (exit) rate is measured by the number of entering (exiting) establishments as a percentage of the total number of establishments each period. Overall, the entry rates move together with the growth rates of manufacturing output. The entry rate rises during the expansion period in the mid-1970s and the mid-1990s and sharply declines in the late 1970s. While the entry rate started rising in the late 1980s, it experienced a decline during the 1990 recession. On average, the entry rate is much higher during booms than recessions as summarized in Table 2. In contrast, exit rates are similar between good and bad years. The p-value associated with the t-test of the mean difference in entry rates between good and bad years is 0.023, while that of exit rates is 0.371.[11] The simple correlation between entry rates and the annual growth rates of

[10] Good years are '72, '73, '76, '77, '78, '83, '87, '88, '92, '93, ('94,) '95, '96, '97 and bad years are ('74,) '75, ('79,) '80, '81, '82, ('84,) '85, '86, ('89,) '90, '91. The years in parenthesis are not used because of the ASM panel rotation.

[11] While we find that exit rate is acyclical in the ASM data, appropriate caution should be used in interpreting the result. First, our data set is limited to the manufacturing sector. Second, our sample excludes

Figure 1: Entry and exit rates

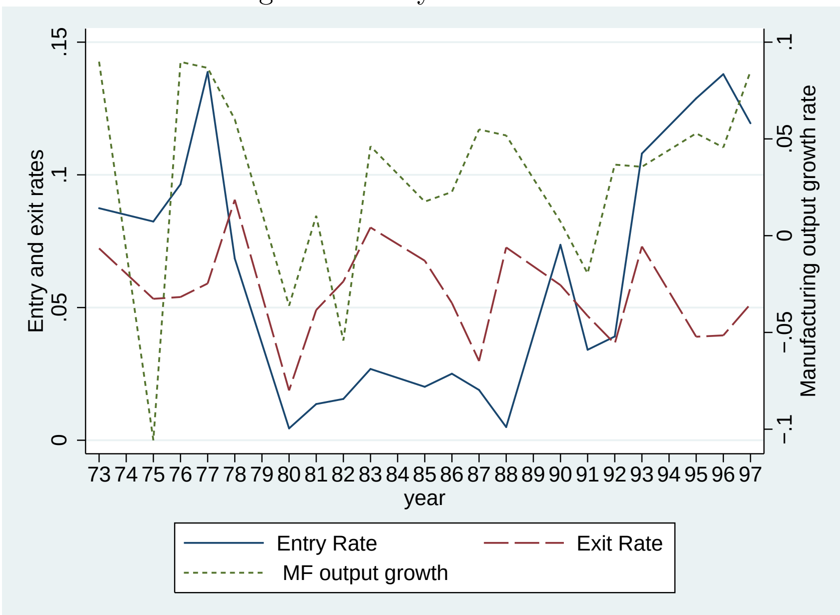


Table 2: Entry and exit rates

| | Good | Bad | Total average | p-value |
|---|---|---|---|---|
| Entry (birth) | 8.1% | 3.4% | 6.2% | 0.023 |
| Exit (death) | 5.8% | 5.1% | 5.5% | 0.371 |

Note: Entry (exit) rate is measured by the number of entering (exiting) establishments as percentage of the total number of establishments each period. The p-values associated with the t-tests of the mean difference in entry and exit rates between good and bad years are reported in the last column.

manufacturing output is 0.413 (p-value=0.070), while the same statistic for the exit rates is 0.240 (p-value=0.308).[12]

We also analyze cyclical patterns in annual job creation due to startups and job destruc-

all first years of ASM panels to avoid the panel rotation issue. In other data sets such as Business Dynamics Statistics (BDS) or Business Employment Dynamics (BED), the exit rate is counter-cyclical. While these data sets may provide better measures of entry and exit rates, the ASM is more suitable to study the size and productivity of entering and exiting establishments.

[12] Using firm-level data from the Statistics of Canada, Hyunh, Petrunia, and Voia (2008) find a similar pattern of entry and exit rates. During a recession period for the Canadian economy between 1990 and 1993, the entry rate went down to its lowest level. However, the exit rate did not move as much during this time period.

Table 3: Job creation and job destruction rates

| | Good | Bad | Total average | p-value |
|---|---|---|---|---|
| Job creation from startups | 1.79 | 1.22 | 1.52 | 0.020 |
| Job creation from continuers | 7.91 | 6.93 | 7.44 | 0.173 |
| Total job creation | 9.70 | 8.16 | 8.96 | 0.041 |
| Job destruction from shutdowns | 2.55 | 2.26 | 2.41 | 0.298 |
| Job destruction from continuers | 6.82 | 8.46 | 7.61 | 0.056 |
| Total job destruction | 9.38 | 10.72 | 10.02 | 0.200 |

Note: Job creation (destruction) rate is measured by the number of jobs created (destroyed) in each category of establishments (i.e., startups, continuers, shutdowns, and all establishments (total)) as percentage of total employment. The p-values associated with the t-tests of the mean difference in job creation(destruction) rates between good and bad years are reported in the last column.

tion due to shutdowns, which can be interpreted as employment-weighted entry and exit rates. Table 3 presents job creation and job destruction rates calculated from the published job flows data for our sample period (1972–1997).[13] The job creation rate from startups is measured by the number of jobs created in entering establishments as percentage of the total employment in manufacturing in each period. Job creation rate from continuers is measured by the number of jobs created in continuing (expanding) establishments as percentage of the total employment. Total job creation rate is simply the sum of job creation rate from startups and job creation rate from continuers. Job destruction rates from shutdowns and continuers are measured in a similar way. We find that job creation rate from startups is much higher during booms and the difference is statistically significant. However, job destruction rate from shutdowns is only slightly higher and the difference is not statistically significant. The simple correlation between the job creation rate due to startups and the percentage change in manufacturing output (annual) is 0.368 (p-value=0.071), while the simple correlation between the job destruction rate due to shutdowns and the percentage change in manufacturing output is $-0.006$ (p-value=0.977).[14] Focusing on employment flows, Davis, Haltiwanger, and

[13] The job flows data are available from the webpage of John Haltiwanger, `http://www.econ.umd.edu/~haltiwan/download.htm`.

[14] Using the aggregate job flows data from the earlier period (Davis, Haltiwanger, and Schuh, 1996), Camp-

Table 4: Average and relative size (employment) of entering and exiting plants

| | Good | Bad | Average | p-value |
|---|---|---|---|---|
| Average size, entering | 45.1 | 59.2 | 50.3 | 0.000 |
| Average size, exiting | 34.9 | 35.9 | 35.3 | 0.102 |
| Relative size, entering | 0.53 | 0.70 | 0.60 | 0.000 |
| Relative size, exiting | 0.50 | 0.46 | 0.49 | 0.000 |

Note: Each column reports the simple averages of yearly means for the size variables during good times, bad times, and the entire period. The relative size is obtained by dividing the average size of entering (exiting) establishments by the average size of continuing establishments in the same four-digit SIC industry. The p-values from the t-test of comparing the means are reported in the last column.

Schuh (1996) find that the job destruction rate is more cyclical than the job creation rate. Although we also find that the job destruction rate for continuing plants is higher during recessions, we do not see the "cleansing" effect in the exit margin during recessions. This finding suggests that, if we consider a plant as a production unit, the adjustment over the business cycle at the entry margin may be more important. Quantitatively, the size of job creation by entrants are smaller than the size of job creation by continuing plants. However, in a recent paper, Haltiwanger, Jarmin, and Miranda (2013) emphasize the importance of job creation by young firms through the expansion of continuing establishments. Given that these expansions come after establishment entry (but counted as job creation by continuing plants in the data), Table 3 may in fact understate the importance of entry on job creation over time.

The first two rows of Table 4 describe the average plant size (employment) of entering

bell (1998) finds that *labor-weighted* entry rates (i.e., job creation rates from startups) are procyclical, whereas *labor-weighted* exit rates (i.e., job destruction rates from shutdowns) are countercyclical. Overall, *quarterly* job destruction rates from shutdown are negatively correlated with the percentage change in output (i.e., manufacturing output or real GDP), as discussed in Campbell (1998). However, in the latest panel (1994–1998) used in Foster, Haltiwanger, and Kim (2006), quarterly job destruction rates are positively correlated with the percentage change in output. Because we use annual data and also drop years between the ASM panels, we cannot directly compare our results to the previous studies using the quarterly data. When we examined the annual job creation and destruction data, we find that cyclical property of employment-weighted birth and death rates (measured as correlation with industry output) may change depending on the sample periods. See Table 9 in the Online Appendix.

Table 5: Relative productivity of entering and exiting plants

| | Relative TFP, entering | | | | Relative TFP, exiting | | | |
|---|---|---|---|---|---|---|---|---|
| | Good | Bad | Average | p-value | Good | Bad | Average | p-value |
| TFP based on (1) | 0.93 | 1.02 | 0.96 | 0.000 | 0.88 | 0.84 | 0.86 | 0.000 |
| TFP based on (2) | 0.69 | 0.85 | 0.75 | 0.000 | 0.65 | 0.65 | 0.65 | 0.875 |

Note: The first row reports the relative TFP based on (1). The second row reports relative TFP based on (2). 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. The p-values from the t-test of comparing the means between good and bad times are reported.

and exiting plants during booms and recessions. Exiting plants are of similar size across booms and recessions, but the average size of entering plants dramatically changes during recessions. The difference in the average size of entering plants between boom and recession is statistically significant.[15] Compared to entering plants in booms, entering plants in recessions start with about 30 percent more workers. In the third and fourth row, we report the size of entering and exiting plants, relative to continuing plants in the same four-digit SIC industry. In relative terms, entering plants are about 25 percent larger in recessions than in booms. While the difference in the relative size is statistically significant both for entering and exiting plants, the magnitude is much smaller for exiting plants. The simple correlation between the relative size of exiting plants and the percentage change in manufacturing output is 0.066 (p-value=0.782), while the simple correlation between the relative size of entering plants and the percentage change in manufacturing output is $-0.241$ (p-value=0.320).

Relative productivity of entering and exiting plants, presented in Table 5, exhibits a similar pattern.[16] The relative productivity of entering plants in recessions is about 10–

[15]There were some outliers among entering plants in 1980. Because dropping a few outliers would cause disclosure issues, we chose to drop the whole year when calculating the average size and productivity of entering plants in Table 4. Because those outliers have substantially higher productivity levels, including them results in a much greater difference in entrants' productivity between booms and recessions, adding support to our finding. Although the results for average employment did not vary much with or without the outliers, we also dropped this year in Table 4 for consistency. Because the statistics for exiting plants are not affected by the outliers, we include the 1980 observations in the calculation.

[16]We also examined cyclical changes in the relative TFP based on (1) with various assumed values of returns to scale in the Online Appendix. The observed pattern is similar to Table 5.

Table 6: Entry and exit rates

| Cyclical indicator | | Good | Bad | p-value |
|---|---|---|---|---|
| [1] NBER | Entry (birth) | 6.7% | 5.0% | 0.459 |
| | Exit (death) | 5.6% | 5.0% | 0.632 |
| [2] Unemp. rate change | Entry (birth) | 7.5% | 3.8% | 0.087 |
| | Exit (death) | 6.0% | 4.6% | 0.093 |
| [3] GDP growth rate | Entry (birth) | 6.5% | 5.8% | 0.731 |
| | Exit (death) | 5.9% | 5.0% | 0.279 |
| [4] GDP HP filter | Entry (birth) | 5.5% | 6.7% | 0.575 |
| | Exit (death) | 6.3% | 5.0% | 0.119 |

Note: This table reports the average entry and exit rates for good and bad years based on alternative measures of business cycles. First, we divide good and bad years based on the NBER business cycle reference dates ([1] NBER). Second, the division is based on the unemployment rate change, i.e., whether the unemployment rate has increased or not ([2] Unemp rate change). Third, the division is based on the growth rate of real GDP, i.e., whether the growth rate is above or below the average of growth rates ([3] GDP growth rate). Fourth, the division is based on the HP-filtered level ([4] GDP HP filter). The p-values from the t-test of comparing the means are reported in the last column.

20 percent higher than that of entering plants in booms and the difference is statistically significant. We find that the relative productivity of exiting plants is similar across booms and recessions under specification (2), while the relative productivity of exiting plants is slightly higher in booms with specification (1).[17] The simple correlation between the relative productivity of exiting plants and the percentage change in manufacturing output is 0.176 (p-value=.458), whereas the simple correlation between the relative productivity of entering plants and the percentage change in manufacturing output is −0.277 (p-value=.251). Overall, our finding suggests that the selection at the entry (or "creation") margin may play an important role in explaining firm dynamics over the business cycle.

Table 7: Correlations of entry and exit rates with cyclical indicators

| | Entry rate | Exit rate |
|---|---|---|
| MF output growth | 0.413 (0.070) | 0.240 (0.307) |
| Unemployment rate | −0.409 (0.073) | 0.071 (0.766) |
| GDP growth | 0.322 (0.167) | 0.413 (0.070) |
| HP filtered GDP | −0.033 (0.889) | 0.156 (0.512) |

Note: The p-values of the estimated correlations are reported in parentheses.

### 2.2.3 Robustness to alternative classifications for good and bad years

In order to assess the robustness of the results, we report entry and exit statistics for good and bad years based on alternative measures of business cycles. In Table 6 we consider four alternative measures of cyclical indicators.[18] In the first row we use the NBER business cycle dates. Because the NBER dates are specified in months, we give weights according to the number of months that are in booms/recessions. For example, because there is a trough in March 1991, we count 2.5 months of 1991 as in a recession and 9.5 months of 1991 as in a boom. The statistics for 1991 receive the weights of 2.5/12 for bad times and 9.5/12 for good times. In the second row, we divide good and bad years based on the the unemployment rate change. If the unemployment rate decreased in a given year, we call it a good year. In the third row, the division is based on the growth rate of real GDP, i.e., whether the growth rate is above or below the average of GDP growth rates. In the fourth row, we use HP-filter to detrend the real GDP (level). We call a good year if the cyclical component is positive. We find that the entry rates are higher in good years based on the first three methods. In contrast, the entry rate is higher in bad years based on the HP-filter. However, as discussed before, the division based on the (HP-filtered) level does not match the conventional boom-

[17] Because we use a revenue-based productivity measure, caution is needed in interpreting the finding of higher productivity for entering plants in recessions. The productivity difference may reflect differences in the price.

[18] We also divided good and bad years after dropping years in which growth rates are close but the average entry and exit rates did not change much from the results in Table 2. When we dropped years with the manufacturing output growth rates between 2% and 4% (i.e., good years if the growth rate is greater than 4% and bad years if it is lower than 2%), the average entry rates were 8.3% in good years and 3.5% in bad years. The average exit rates were 5.9% and 5.1%, respectively.

recession division. For example, according to the HP-filter method, the expansion period in the early and mid-1990s (e.g., 1992, 1993,...,1997) are all classified as bad years.

Table 7 displays the correlations of entry and exit rates with alternative measures of cyclical indicators. Overall, the entry rate is procyclical: it is positively correlated with the manufacturing output growth and real GDP growth but negatively correlated with the unemployment rate. On the other hand, the correlations suggest that exit rate is mildly procyclical.

Table 8: Relative size and productivity of entering and exiting plants

| | | Entering plants | | | Exiting plants | | |
|---|---|---|---|---|---|---|---|
| Cyclical indicator | | Good | Bad | p-value | Good | Bad | p-value |
| [1] NBER | Rel. Size | 0.59 | 0.74 | 0.017 | 0.49 | 0.45 | 0.044 |
| | Rel. TFP | 0.95 | 1.01 | 0.054 | 0.86 | 0.88 | 0.186 |
| [2] Unemp. rate change | Rel. Size | 0.55 | 0.70 | 0.000 | 0.49 | 0.48 | 0.159 |
| | Rel. TFP | 0.92 | 1.06 | 0.000 | 0.86 | 0.86 | 0.787 |
| [3] GDP growth rate | Rel. Size | 0.64 | 0.52 | 0.000 | 0.50 | 0.47 | 0.000 |
| | Rel. TFP | 0.91 | 1.05 | 0.000 | 0.87 | 0.85 | 0.001 |
| [4] HP-filtered GDP | Rel. Size | 0.62 | 0.58 | 0.000 | 0.47 | 0.50 | 0.000 |
| | Rel. TFP | 0.95 | 0.97 | 0.081 | 0.87 | 0.86 | 0.019 |

Note: This table reports the relative size and the relative TFP of entering and exiting plants for good and bad years. The determination of good and bad years are based on four alternative measures of business cycles. First, we divide good and bad years based on the NBER business cycle reference dates ([1] NBER). Second, the division is based on the unemployment rate change, i.e., whether the unemployment rate has increased or not ([2] Unemp rate change). Third, the division is based on the growth rate of real GDP, i.e., whether the growth rate is above or below the average of growth rates ([3] GDP growth rate). Fourth, the division is based on the HP-filtered level ([4] GDP HP filter). The p-values from the t-test of comparing the means are reported.

Table 8 reports the relative size and the relative TFP of entering and exiting plants for good and bad years, based on the four alternative measures of cyclical indicators described in Table 6. Although the magnitude of the difference between good and bad years varies depending on the measure of cyclical indicators, the pattern of cyclical fluctuations in the relative size and the relative productivity of entering and exiting plants remains the same in most cases.[19] The relative productivity of exiting plants is similar across booms and recessions. While the difference is statistically significant in the divisions based on GDP growth rate and HP-filtered GDP, the magnitude of the difference is relatively small. In contrast, the relative productivity of entering plants is substantially different in the two phases of the cycle, with the exception of the division based on the HP-filtered GDP. The difference is statistically significant in most cases, at 1% in the divisions based on the unemployment rate and the GDP growth rate and at 10% in the division based on the NBER business cycle dates.

## 3 Conclusion

This paper explores the the entry and exit behavior of plants. We documented patterns of plant entry and exit in U.S. manufacturing, utilizing the Annual Survey of Manufactures. We found that the entry rate is much more cyclical than the exit rate, and entering plants' average size and productivity vary significantly over the business cycle.

Our finding that the productivity of entrants varies over the business cycle may have important asset pricing implications. In a recent paper, Gourio (2011) argues that, in his putty-clay investment model, the relative labor productivity (which is determined by the capital intensity) of new production units has to be countercyclical in order to account for the procyclical stock prices. This cyclical pattern of new production units is consistent with our finding.

Finally, we would like to emphasize that our study focuses only on the U.S. manufacturing sector in a particular time period. Investigating whether other sectors in the U.S., manufacturing sectors in other countries, or economies in other time period exhibit the same patterns is beyond the scope of this paper, but we believe that these are also very important topics for future research.

[19] We find the relative size of entering plants is larger in good years when the GDP growth rate or HP-filtered GDP was used for the division. This inconsistent result is driven by the fact that these divisions classify certain expansion periods as bad years (e.g., 1993 and 1995 for the division based on the GDP growth rates and the early and mid-1990s for the division based on the HP-filtered GDP).

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