

Entry, Exit, and Plant-level Dynamics over the Business Cycle*

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Abstract

This paper analyzes the implications of plant-level dynamics over the business cycle. We first 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. Second, we build a general equilibrium model of industry dynamics and compare its predictions to the data.

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.

We first 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., Chatterjee 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. Such a barrier may hurt the long-run growth of the economy.

It has long been argued that recessions have “cleansing” effects: low-productivity plants are scrapped during recessions, enhancing aggregate efficiency. Many recent papers have pro-

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

vided 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,² 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.

Based on our observations of heterogenous plant-level behavior during business cycles, we build a dynamic general equilibrium model. Our model extends the standard general equilibrium industry dynamics model of Hopenhayn and Rogerson (1993) by incorporating aggregate productivity shocks. In order to account for entrants’ productivity differences in booms and recessions, we also incorporate self-selection during the entry process. We find that the model performs well in replicating the cyclicalities of entry rates and exit rates. However, it turns out that the model with constant entry cost cannot account for the cyclical

²See, e.g., Mortensen and Pissarides (1994), Hall (2000), and Caballero, Hoshi, and Kashyap (2008).

patterns of selection in the entry process. We show that the model with cyclical entry costs can account for the observed cyclical plant-level dynamics.

Some other recent papers extend a similar style of an industry dynamics model to incorporate business cycles. Many of these papers, such as Chatterjee and Cooper (1993), Devereux, Head, and Lapham (1996), Veracierto (2002, 2008), Comin and Gertler (2004), and Jaimovich and Floetotto (2008), and Bilbiie, Ghironi, and Melitz (2012), either assume exogenous entry or exit or do not pin down gross flows of entry and exit.

Samaniego (2008) constructs a general equilibrium model of industry dynamics with endogenous entry and exit. Instead of solving a model with aggregate shocks, he characterizes the (deterministic) transition path after the change in aggregate productivity. He finds that both entry and exit respond very little to the change in aggregate productivity. The difference between his results and ours mainly stems from the specifications the entry cost.

The paper is organized as follows. In the next section, we document the empirical facts on entry, exit, and employment in U.S. manufacturing. In Section 3, we build a general equilibrium model of plant-level dynamics and compare it to the data. Section 4 concludes.

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.³

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.

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).⁴ 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

³See Online Appendix A 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.

⁴Without 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.

material inputs, TFP (s_t) can be measured from the growth accounting equation

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

We measure factor elasticities (α_k , α_n , and α_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 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

$$\ln(s_t) = \ln(y_t) - \theta \ln(n_t). \quad (2)$$

In the model of Section 3, the output y_t is interpreted as value added, and the measure of productivity from (2) directly matches our model specification.⁵

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 used to calibrate the steady state of the 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

⁵The production function $y_t = s_t n_t^\theta$ 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 , α , ϕ , 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 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.

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.⁶ 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.

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).⁷ Second, exiting plants are less productive than entering plants.

⁶By 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.

⁷Differences 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) ar-

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 $\ln(s_t) = \ln(y_t) - \theta_I \ln(n_t)$. θ_I is obtained from the four-digit SIC industry-level labor share. 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. Moreover, we use this exact form of production function in Section 3. Therefore, we mainly utilize this last measure of productivity in calibrating the model. 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.

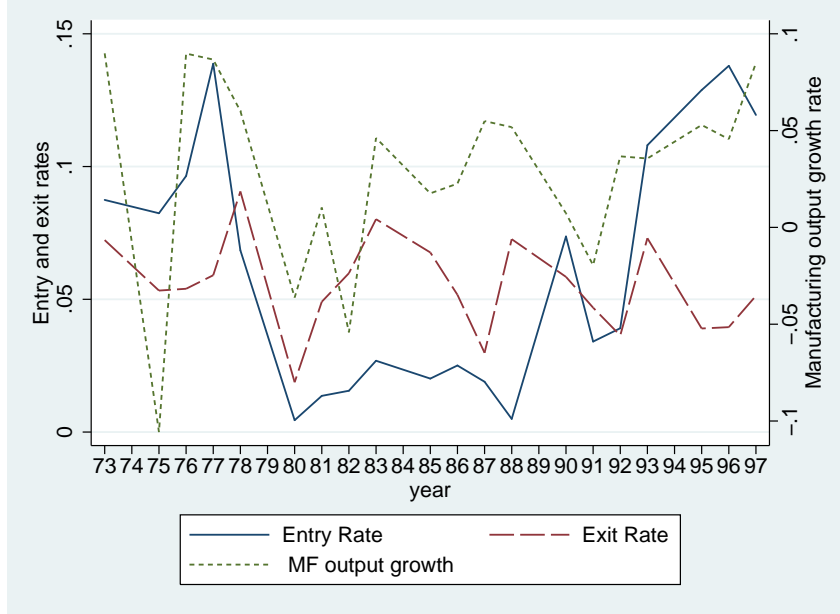
2.2.2 Business cycle patterns

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.⁸ 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

gue 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.

⁸Good 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.

Figure 1: Entry and exit rates



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.⁹ The simple correlation between entry rates and the annual

⁹The p-value associated with the t-test of the mean difference in entry rates between good and bad years is .023, while that of exit rates is .371. In order to check the robustness of our result, we also consider four alternative measures to divide booms and recessions, i) NBER business cycle dates, ii) changes in the unemployment rate, iii) growth rates of real GDP, iv) HP-filtered GDP (level). The pattern of Table 2 remains similar with these alternative divisions, with the exception of the division based on the HP-filtered GDP. See the appendix for the estimates based on the alternative divisions. 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 all first years of ASM panels to avoid the

Table 2: Entry and exit rates

	Good	Bad	Total average
Entry (birth)	8.1%	3.4%	6.2%
Exit (death)	5.8%	5.1%	5.5%

Note: Entry (exit) rate is measured by the number of entering (exiting) establishments as percentage of the total number of establishments each period.

Table 3: Job creation and job destruction rates

	Good	Bad	Total average
Job creation from startups	1.76	1.21	1.52
Job creation from continuers	8.20	6.48	7.44
Total job creation	9.96	7.69	8.96
Job destruction from shutdowns	2.52	2.27	2.41
Job destruction from continuers	6.72	8.74	7.61
Total job destruction	9.24	11.01	10.02

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.

growth rates of manufacturing output is 0.413 (p-value=.070), while the same statistic for the exit rates is 0.240 (p-value=.308).¹⁰

We also analyze cyclical patterns in annual job creation due to startups and job destruction 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).¹¹ The job creation rate from startups is measured by the number of jobs created in entering establishments as percentage of the total

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.

¹⁰Using 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.

¹¹The job flows data are available from the webpage of John Haltiwanger, <http://www.econ.umd.edu/~haltiwan/download.htm>.

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, while job destruction rate from shutdowns is only slightly higher. The simple correlation between the job creation rate due to startups and the percentage change in manufacturing output (annual) is 0.368 (p-value=.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=.977).¹² Focusing on employment flows, Davis, Haltiwanger, and 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.

The first three rows of Table 4 describe average plant size (employment) of continuing, entering, and exiting plants during booms and recessions. In general, the average size is larger during recessions. Exiting plants are of similar size across booms and recessions, but the average size of entering plants dramatically changes during recessions.¹³ Compared

¹²Using the aggregate job flows data from the earlier period (Davis, Haltiwanger, and Schuh, 1996), Campbell (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 Davis, 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 13 in Online Appendix A.

¹³There 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

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

	Good	Bad	Average
Average size, continuing	85.4	89.5	87.5
Average size, entering	45.1	59.2	50.3
Average size, exiting	34.9	35.9	35.3
Relative size, entering	0.53	0.70	0.60
Relative size, exiting	0.50	0.46	0.49

Note: Each column represents the average 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.

to entering plants in booms, entering plants in recessions start with about 30 percent more workers. In the fourth and fifth 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 smaller in recessions than in booms.¹⁴ The simple correlation between the relative size of exiting plants and the percentage change in manufacturing output is 0.066 (p-value=.782), while the simple correlation between the relative size of entering plants and the percentage change in manufacturing output is -0.241 (p-value=.320).

Relative productivity of entering and exiting plants, presented in Table 5, exhibits a similar pattern.¹⁵ The relative productivity of entering plants in recessions are about 10–20 percent higher than that of entering plants in booms.¹⁶ The simple correlation between the

support to our finding. Although the results for average employment do 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.

¹⁴We only have 19 yearly observations and the difference is not statistically significant in t-tests of comparing the means between good and bad years. The p-value of the t-test of the difference in the average size of entering plants between good and bad years is .464 and that of the relative size of entering plants is .275. However, in a similar test run at the *plant-level*, we get a statically significant difference. The p-value associated with testing the mean difference in the average size of entering plants between good years and bad years is .000. The p-value associated with the similar test for the relative size of entering plants is .000. For exiting plants, on the other hand, the difference was not statistically significant.

¹⁵We also examined cyclical changes in the relative TFP based on (1) with various assumed values of returns to scale in the appendix. The observed pattern is similar to Table 5.

¹⁶Because 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.

Table 5: Relative productivity of entering and exiting plants

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

Note: The first row reports the relative TFP based on (1). The second row reports relative TFP based on (2). Relative productivity of entering (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.

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).¹⁷

3 Model

In this section, we set up a dynamic general equilibrium model of plant employment, entry, and exit. We base our model on Hopenhayn (1992) and Hopenhayn and Rogerson (1993), departing significantly from their model in four respects.

First, we add aggregate shocks to the economy. This ingredient is essential in analyzing the business cycle implications of the model.

Second, we assume that there is a positive (and stochastic) value of exiting. This modification is necessary for the model to match the exit pattern observed in the data.¹⁸

Third, we consider entry in two steps—to enter, one first has to pay some cost and come up with an “idea.” Then, after observing the quality of the idea, one decides whether to

¹⁷We only have 19 yearly observations and the difference is not statistically significant in simple t-tests. The p-value associated with testing the mean difference in the relative TFP based on (1) between good and bad years is .156 and the p-value from the t-test of the mean difference in the relative TFP based on (2) is .148. However, the difference in the relative TFP of entering plants between good and bad years is statistically significant when the unemployment rate or the growth rate of real GDP is used to determine good and bad years. See Table 12 in Online Appendix A for the estimates based on the alternative divisions.

¹⁸Samaniego (2006, 2008) assumes a stochastic continuation value, rather than a stochastic exit value that we employ, to cope with this problem. We have also experimented with a model that assumes a stochastic continuation value. The results are essentially the same.

pay an additional cost to actually enter the market. This “two-step” process introduces the endogenous selection of the entering plants.¹⁹ In the data, we observe that the productivity of entering plants is very different across booms and recessions (see Table 5).

Finally, we introduce the cost of adjusting employment. The estimation of the employment process by Cooper, Haltiwanger, and Willis (2004) strongly indicates that there are important adjustment costs in the employment process.

3.1 Plants

The model consists of two kinds of entities: plants and consumers. Plants use labor to produce output. Consumers own plants, supply labor, and consume. There is only one type of good, which is used for entry costs and consumption; we use it as the numeraire. In our model, the only price we have to keep track of is the wage of the workers. We assume that the plants have to pay adjustment costs and the firing tax when labor input is adjusted. The specifics of the adjustment costs and the firing tax are explained later.

Here, we describe the decision of the plants. We first outline the behavior of incumbent plants. Then we illustrate entrant’s behavior.

The timing of events for an incumbent plant at period t is as follows. In the beginning of the period, all plants observe the current aggregate state, z_t . An incumbent plant starts a period with the individual state (s_{t-1}, n_{t-1}) . s_{t-1} is the individual plant’s productivity level at period $t - 1$. n_{t-1} is the employment level at period $t - 1$. The value function of a plant at this stage is denoted as $W(s_{t-1}, n_{t-1}; z_t)$. Then, it observes its (stochastic) exit value, x_t . Here, x_t can be interpreted as the scrap value of its capital (and owned land), although we do not explicitly model capital stock or land.²⁰ After observing the exit value, the plant decides whether to stay or exit. If it exits, it has to pay the firing tax, since it has to adjust the employment level from n_{t-1} to zero. If it decides to stay, it observes this period’s

¹⁹Melitz (2003) employs a similar selection process in entry. Here, the interpretation of this process is slightly different from Melitz (2003).

²⁰The entry cost that is introduced later can be interpreted as (partially sunk) investment in new capital and land.

Here, $g(n_t, n_{t-1})$ is the firing tax. In the $\max\langle \cdot, \cdot \rangle$, the plant compares the value of staying (the first term) and exiting (the second term). $E_s[\cdot | s_{t-1}]$ denotes the expectation regarding s_t , conditional on s_{t-1} . We assume that the exit value x_t follows an i.i.d. distribution $\xi(x_t)$,²³ and that the exit value distribution does not vary over the business cycle. As we will see later, our model can match the exit pattern in the data without relying on the cyclical exit values. $E_s[V^c(s_t, n_{t-1}; z_t) | s_{t-1}]$ is the expected value of a continuing plant $V^c(s_t, n_{t-1}; z_t)$, and is calculated as

$$E_s[V^c(s_t, n_{t-1}; z_t) | s_{t-1}] = \int V^c(s_t, n_{t-1}; z_t) d\psi(s_t | s_{t-1}),$$

where

$$V^c(s_t, n_{t-1}; z_t) = \max\langle V^a(s_t, n_{t-1}; z_t), V^n(s_t, n_{t-1}; z_t) \rangle,$$

and $\psi(s_t | s_{t-1})$ is the distribution of s_t given s_{t-1} . Here, $V^a(s_t, n_{t-1}; z_t)$ is the value function when the plant adjusts employment, and $V^n(s_t, n_{t-1}; z_t)$ is the value function when it does not adjust employment.

If the plant decides to adjust employment, the current period profit is

$$\pi^a(s_t, n_{t-1}, n_t; z_t) \equiv \lambda z_t f(n_t, s_t) - w_t n_t - g(n_t, n_{t-1}),$$

where $\lambda < 1$ represents the “disruption cost” type of adjustment cost, emphasized by Cooper, Haltiwanger, and Willis (2004). This represents the cost of slowing down the production process when employment is adjusted. In Cooper, Haltiwanger, and Willis’s (2004) estimation, this cost turns out to be the most important type of adjustment cost in explaining employment dynamics observed at the plant level.

If the plant does not adjust employment, the current period profit is

$$\pi^n(s_t, n_{t-1}; z_t) \equiv z_t f(n_{t-1}, s_t) - w_t n_{t-1}.$$

²³Formulating the exit decision using i.i.d. stochastic scrap values is popular in the empirical industrial organization literature—see, for example, Doraszelski and Pakes (2007) and Weintraub, Benkard, and Van Roy (2008). Ramey and Shapiro (2001) analyze the resale prices of displaced capital. The resale prices vary substantially—see their Figure 2.

Therefore,

$$V^a(s_t, n_{t-1}; z_t) = \max_{n_t} \pi^a(s_t, n_{t-1}, n_t; z_t) + \beta E_z[W(s_t, n_t; z_{t+1})|z_t],$$

and

$$V^n(s_t, n_{t-1}; z_t) = \pi^n(s_t, n_{t-1}; z_t) + \beta E_z[W(s_t, n_{t-1}; z_{t+1})|z_t].$$

Here, $E_z[\cdot|z_t]$ takes the expectation regarding z_{t+1} , conditional on z_t .

The entrant's value function is

$$V^e(q_t; z_t) = \int V^c(s_t, 0; z_t) d\eta(s_t|q_t),$$

where $\eta(s_t|q_t)$ is the distribution of s_t given q_t . Only the potential entrant with high enough q_t will actually enter. There is a threshold value of q_t , q_t^* , which is determined by

$$V^e(q_t^*; z_t) = c_e. \quad (3)$$

A potential entrant will enter if and only if $q_t \geq q_t^*$. A potential entrant's value function is

$$V^p(z_t) = \int \max\langle V^e(q_t; z_t) - c_e, 0 \rangle d\nu(q_t),$$

where $\nu(q_t)$ is the distribution of ideas. We impose a free-entry condition for becoming a potential entrant:

$$V^p(z_t) = c_q. \quad (4)$$

3.2 Consumers

The representative consumer maximizes the expected utility:

$$\mathbf{U} = E \left[\sum_{t=0}^{\infty} \beta^t [C_t + A v(1 - L_t)] \right],$$

where $v(\cdot)$ is the increasing and concave utility function for leisure, C_t is the consumption level, L_t is the employment level, $\beta \in (0, 1)$ is the discount factor, and A is a parameter.

Here, for simplicity, we consider linear utility for consumption.²⁴ This simplification enables

²⁴Hopenhayn and Rogerson (1993) assume a period utility function that is concave in consumption and linear in leisure.

us to discount the firm's profit by the discount factor β . Since we consider the adjustment of L_t at the extensive margin, the appropriate interpretation of the $v(\cdot)$ function is that it is the result of an aggregation of many consumers who have different preferences over consumption and leisure. The budget constraint in each period is:

$$C_t = w_t L_t + \Pi_t + R_t, \quad (5)$$

where w_t is the wage rate, Π_t is the firm's profit, and R_t is the transfer from the government. The government transfers the firing tax to the consumer in a lump-sum manner every period. We assume that there is no saving. The first-order condition in each period is:

$$Av'(1 - L_t) = w_t. \quad (6)$$

3.3 General equilibrium

Now we analyze the general equilibrium of the model. The general equilibrium is defined as a situation where (i) consumers and firms (plants) optimize and (ii) the markets clear. For (ii), it is sufficient to ensure that the labor market clears.

First, consider a situation where z_t is constant. We will use the solution of this steady-state situation for the purpose of calibration. In this case, the definition of the stationary equilibrium is similar to Hopenhayn and Rogerson (1993). In our model, the general equilibrium can be summarized in the labor market. The free-entry condition (4) characterizes the demand side of the labor market. The quantity of the labor demand in the steady state is given by

$$L^d = N \int \phi(s', n) d\mu(s', n), \quad (7)$$

where $\mu(s', n)$ is the stationary distribution of the plants with the state (s', n) when we assume that the mass of potential entry in each period is one. $\phi(s', n)$ is the labor demand for a plant with the state (s', n) . (Here, s' is the plant-level productivity at the current period and n is the plant-level employment one period before.) N is the actual mass of potential entrants at each period.

The consumer's first-order condition (6) characterizes the labor supply side. The labor demand side in effect determines the wage level at w^* (with the free-entry condition (4)). Combined with the labor-supply curve (6), the equilibrium level of labor, L^* , is determined. Once L^* is determined, the equilibrium level of N , N^* , is determined by (7).

When we introduce an aggregate shock, L^* and N^* move over time. Labor demand is now characterized by

$$L_t^d = L_{it}^d + N_t L_{et}^d, \quad (8)$$

where L_{it}^d is the labor demand from incumbents at period t and L_{et}^d is the labor demand from the entrant when the mass of potential entry is assumed to be one. The determination of the equilibrium is similar: the free-entry condition (4) determines the wage, the labor-supply equation (6) determines L , and the labor-demand equation (8) determines N .

Aggregate profit is given by

$$\Pi_t = Y_t - w_t L_t - R_t - N_t c_q - M_t c_e + X_t,$$

where Y_t is aggregate output, N_t is the number of potential entrants, M_t is the number of actual entrants, and X_t is the total value of exiting. Therefore, combining this with (5), in equilibrium (where labor demand equals labor supply)

$$C_t = Y_t - N_t c_q - M_t c_e + X_t.$$

3.4 Calibration

Our strategy is to use the steady state of the model with constant z (we set $z = 1$) as the benchmark for calibration, and to add the aggregate shocks later on. A large part of our calibration is based on the statistics presented in Section 2. We set one period as one year. Following Hopenhayn and Rogerson (1993), we normalize the wage rate, w , in the benchmark to 1. As in Hopenhayn and Rogerson (1993), the model exhibits a homogeneity property in the sense that given prices, all of the aggregate variables (quantities) are proportional to the number of potential entrants, N . We pin down the benchmark value of N by setting

aggregate employment, L , to 0.6 (approximate employment rate in the U.S.). The value of A is backed out from (6) and the fact that $w = 1$ and $L = 0.6$ in the benchmark. For the $v(\cdot)$ function, we use $\ln(\cdot)$.²⁵ We set $\beta = 0.94$. The production function is assumed to be $f(n_t, s_t) = s_t n_t^\theta$ with $\theta = 0.7$.²⁶

The process for idiosyncratic productivity, s , is chosen so that the model generates the employment process observed in the data (Table 15 in Online Appendix B). First, the process is assumed to be

$$\ln(s') = a_s + \rho_s \ln(s) + \varepsilon_s,$$

where

$$\varepsilon_s \sim N(0, \sigma_s^2).$$

Then, this process is approximated by a Markov process using the Rouwenhorst method (see Rouwenhorst (1995), Kopecky and Suen (2010), and Galindev and Lkhagvasuren (2010)). The constant a_s is set so that the (cross-sectional) average size of continuing plants in the steady-state of the model matches the corresponding value in the data. ρ_s is set to 0.97, which matches the autocorrelation parameter for the AR(1) process for employment (simulated in the model) to the empirical value of 0.97.²⁷ σ_s is set so that the variance of the growth rate of n is close to the empirical value of 0.14. The resulting values are $a_s = 0.040$ and $\sigma_s = 0.112$. The adjustment factor λ is set at 0.983, following Cooper, Haltiwanger, and Willis (2004).²⁸

The exit value is assumed to be zero with probability x_0 . With probability $(1 - x_0)$, the exit value is uniformly distributed over $[0, \bar{x}]$. We set x_0 and \bar{x} so that the exit rate and the size of the exiting plants are similar to the empirical values. We choose $x_0 = 0.9$ and

²⁵Online Appendix I performs a robustness check with an alternative form of preferences.

²⁶Online Appendix J performs a robustness check with $\theta = 0.85$.

²⁷See Online Appendix B. In the model, we also experimented with lower values of ρ_s . The problem with lower values of ρ_s is it is impossible to replicate the steady-state distribution of plant size (in particular, there are too few large plants). One remedy for this would be to incorporate a plant-level fixed effect in s_t , reflecting the heterogeneity in the “planned size” of the plants. We did not explore this direction due to computational complexity.

²⁸This is their point estimate with a small quadratic adjustment cost. Their point estimate for λ with no other adjustment cost is 0.988. Although we do not have a quadratic adjustment cost in our model, we prefer the former number because it produces a more reasonable job reallocation rate.

Table 6: Benchmark parameters

β	θ	a_s	ρ_s	σ_s	λ	c_e	c_q
0.94	0.7	0.040	0.97	0.112	0.983	941.2	14.1

Table 7: Data and model statistics in the steady-state

	Data	Model
Average size of continuing plants	87.5	87.5
Average size of entering plants	50.3	47.4
Average size of exiting plants	35.0	35.3
Entry rate	6.2%	5.5%
Exit rate	5.5%	5.5%
AR(1) coefficient ρ for employment	0.97	0.97
Variance of growth rate for n	0.14	0.14
Job reallocation rate	19.4%	27.4%

$\bar{x} = 2700$. We assume the entry transition function to be identical to the transition function for the incumbents: $\eta(s'|q) = \psi(s'|s)$. The entry costs, c_q and c_e , are backed out from the model. Given the value function $V^c(s', n)$, conditions (3) and (4) pin down the values of c_q and c_e , given $\nu(q)$ and the equilibrium value of q^* that we target. We assume that $\nu(q)$ follows $\nu(q) = B \exp(-q)$ over the lower part of the grids on s (B is the scale parameter to make $\nu(q)$ sum to one).²⁹ We select the value of c_e so that the target value of $\ln(q^*)$ is 0.5. As we see below, this choice of $\nu(q)$ and q^* brings the size distribution of young plants close to the data. In the benchmark, we set the firing cost, $g(n', n)$, to zero. Table 6 lists the main parameter values for the benchmark case. Note that c_e and c_q are measured in annual wages, because we normalize to $w = 1$ in equilibrium.

3.5 Steady-state results

First, we compute the model without aggregate shocks to establish the steady-state behavior of the model. The details of the computation of the steady-state model are described in

²⁹We set 200 grids on x and 50 grids on q . The results do not change when we increase the number of x grids to 1000 or when we use interpolation to approximate the continuous x distribution.

Online Appendix C. Table 7 compares the output of our model to the data.³⁰ Everything except for the job reallocation rate is our “target” for calibration, and we can see that we are able to get close to the empirical values. The job reallocation rate is not one of the calibration targets, and it is somewhat higher in the model than in the data. Online Appendix D provides some additional comparisons of the data and the model outcome.

3.6 Adding aggregate shocks

To analyze business cycles, we assume that z_t fluctuates between two values. We assume that z_t takes either 1.01 or 0.99. This results in a 1% standard deviation in z_t . z_t follows a symmetric Markov process. We calibrate the transition probabilities so that the average duration of each state is three years.³¹

The computation turns out to be much simpler than standard heterogeneous-agent models, such as Krusell and Smith (1998), since the wage depends only on z (this is thanks to the utility function that is linear in consumption and the free entry assumption). From this property, we can perform the optimization by plants and determine $w(z)$ without considering the labor-market equilibrium. After $w(z)$ is determined, the labor-market equilibrium determines the equilibrium quantities, in particular the mass of entrants, N . The details of the computation are in Online Appendix E.

The results of the model with aggregate shocks are summarized in Table 8. Here, “Good” corresponds to the periods with $z_t = 1.01$ and “Bad” corresponds to the periods with $z_t = 0.99$. First, notice that the wage fluctuates substantially. While the cyclicalities of wages is empirically controversial, in Cooley and Prescott (1995) the wages are procyclical and have a standard deviation of less than 1% (see their Table 1.1). In our model, a procyclical wage is necessary to make employment procyclical—in (6), for L to increase when A stays the same, we need w to increase. Somewhat surprisingly, in Table 8, the equilibrium value of q^* does

³⁰The job reallocation rate is taken from Davis, Haltiwanger, and Schuh (1996, Table 2.1).

³¹The average duration of the post-war (1945-2009) NBER contraction (peak to trough) is 11 months and NBER expansion (trough to peak) is 59 months. Thus, overall, the average duration of each state is 35 months.

Table 8: Results with aggregate shocks

	Good	Bad
Wage	1.014	0.986
q^*	0.5000	0.5000
Entry rate	7.2%	3.7%
Exit rate	5.5%	5.5%
Average size of all plants	83.8	86.8
Relative size of entrants	0.54	0.54
Relative size of exiting plants	0.41	0.40
Relative productivity of entrants	0.85	0.85
Relative productivity of exiting plants	0.85	0.85

not change with the change in z .

In the model, exiting plants compare the value of staying with the value of exiting when making exit decisions. Since the distributions of the value of staying and the value of exiting are both quite dispersed, a 1% difference in z does not make a large difference for this comparison.³² Thus the exit rate and the size and productivity of exiting plants are similar throughout the business cycle in Table 8. This fits well with the pattern we observe in the data.

The entry rate fluctuates significantly in Table 8, as we see in the data.³³ The mechanism here is simple: since the wage increases during booms, the average size of incumbent plants shrinks (we observe in the data as well). The labor that is released from the incumbents can be hired by the entrants. At the same time, the labor supply increases because of the wage increase. As a result, the entry rate goes up. Here, again, the procyclicality of wages plays an important role.

Since q^* does not move across cycles, the selection of ideas is similar across booms and recessions, and the model cannot generate the cyclical relative productivity and the cyclical

³²If both values are concentrated around one value and there are many “marginal” plants around that value, it is possible that these plants exit with a small change in z .

³³Note that the entry rate at time t is measured as the number of entering plants from $t - 1$ to t divided by the total number of plants at time $t - 1$. The exit rate at time t is measured as the number of exiting plants between $t - 1$ and t divided by the total number of plants at time t .

Table 9: The case of a countercyclical c_e and procyclical c_q

	Good	Bad
Wage	1.010	0.990
q^*	0.3216	0.6259
Entry rate	7.1%	3.9%
Exit rate	5.5%	5.5%
Average size of all plants	80.5	83.4
Relative size of entrants	0.47	0.65
Relative size of exiting plants	0.40	0.40
Relative productivity of entrants	0.78	0.93
Relative productivity of exiting plants	0.84	0.84

relative size of entrants that we see in the data. The main reasons are that (i) the wages are very cyclical and the effect of the wage change offsets the effect of the aggregate productivity shocks³⁴ and (ii) the effect of aggregate productivity shocks is too small to generate significant changes in selection.

It turns out that once we allow for entry costs to be cyclical, the model generates the right degree of fluctuations in both w and q^* .³⁵ Table 9 describes the result of an experiment where c_e is 0.7 percent higher during recessions and 0.7 percent lower during booms, and c_q is 3.2 percent lower during recessions and 3.8 percent higher during booms. This generates a large selection effect, and the differences in the relative size and productivity of entrants in booms and recessions are comparable to the data.

4 Conclusion

This paper explores the business-cycle implications of plant-level dynamics, particularly the entry and exit behavior of plants. First we documented patterns of plant entry, exit, employ-

³⁴Online Appendix F explains the intuition of why these two effects offset each other using a simple static version of the model.

³⁵We have experimented with many other specifications. Online Appendix G considers a model with a fixed pool of entrants at each period, Online Appendix H looks at a model where exit values are cyclical, Online Appendix I analyzes a different specification of the utility function, Online Appendix J considers a case with $\theta = 0.85$, and Online Appendix K makes exit exogenous.

ment, and productivity 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. Then we constructed a general equilibrium model of plant dynamics by extending Hopenhayn and Rogerson's (1993) model. Our model accounts for the properties that we found in the data, when certain assumptions are made about the cyclicity of entry costs.

We found that a countercyclical "implementation cost" and a procyclical "idea cost" are important in matching our model to the data. In this paper, we did not explicitly model why these costs exhibit such cyclical patterns. An important research topic for the future will be to uncover the nature of these costs theoretically (by modeling the microeconomic foundations of these costs) and empirically (by looking into the microeconomic process of entry).³⁶

We employed a stationary model and abstracted from the secular productivity growth. Foster, Haltiwanger, and Krizan (2001) show that a significant part of the productivity growth in the U.S. manufacturing sector comes from entry and exit of plants. Extending our analysis to incorporate secular productivity growth may open up a new possible link between aggregate fluctuations and aggregate growth, as in Barlevy (2004).

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

³⁶Explicitly modeling the limited enforceability of contracts, as in Cooley, Marimon, and Quadrini (2004), is one possible direction.

patterns is beyond the scope of this paper, but we believe that these are also very important topics for future research.

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