ELSEVIER

International Journal of Industrial Organization
13 (1995) 523–542

International Journal of Industrial Organization

The role of technology use in the survival and growth of manufacturing plants

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Abstract

This paper documents the relationship between capital intensity, the use of advanced manufacturing technology, growth rates, and exit probabilities for a sample of U.S. manufacturing plants. It utilizes data from a unique establishment survey of technology usage that allows us to control for both the quantity and heterogeneity of capital in the plant. The main findings are that capital-intensive plants and plants employing advanced technology have higher growth rates and are less likely to fail. The effects are present after controlling for plant productivity and age; however, the technology results are sensitive to the inclusion of size variables.

Keywords: Plant growth; Exit; Technology use

JEL classification: L11; L6; O33

1. Introduction

Recent examinations of producer turnover using micro data have revealed that the low rates of net entry in most industries hide substantial volatility in the composition of producers. Even in industries where the number of producers is relatively constant, there frequently exists substantial entry,

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SSDI 0167-7187(95)00503-X

exit, and movement of producers through the size distribution.[1] In order to explain this continual turnover, economists have relied on models that emphasize producer heterogeneity and market selection.[2] A number of empirical studies have documented the relationship between growth and exit rates and the observable characteristics of plants and firms, including their size and age, that are implied by these theories.[3] These studies treat producer size and age as proxies for efficiency differences that could arise from either observed or unobserved differences in managerial ability, production technologies, and experience.

In addition, several recent empirical studies have examined how total factor productivity varies among cohorts of entering, surviving, or exiting producers.[4] They thus implicitly control for differences in capital inputs among producers. The general conclusion of these papers is that higher measured productivity is correlated with higher growth rates and lower failure rates for manufacturing facilities. However, there remains considerable variation in plant-level growth and failure that is unexplained by plant-level productivity differences.

The goal of this paper is to extend the empirical literature on plant growth and failure by more fully controlling for producer heterogeneity that arises from differences in the level and type of capital equipment used in the plant. While capital usage is likely to be correlated with producer size and productivity, which earlier empirical studies have examined, it is also likely to have independent effects on growth and failure because of its fixed or sunk nature. If capital inputs are fixed in the short run they directly affect the plant's shutdown decision through their effect on average variable costs and thus differences in capital stocks can lead to variation in failure patterns among otherwise identical plants. Similarly, if capital investments have a substantial sunk cost component then plants that adopt capital-intensive technologies should exhibit more persistence in participation patterns.[5] This paper will control for variation in capital–labor ratios and differences in the

[1] These patterns of producer entry and exit have been documented in developed countries (see Dunne et al., 1988, 1989a; Baldwin and Gorecki, 1991; Geroski, 1991; Geroski and Schwalbach, 1991, and in semi-industralized countries (Roberts and Tybout, 1994).

[2] In particular, the passive learning model of Jovanovic (1982) and the active learning model of Ericson and Pakes (1989).

[3] These empirical studies include Evans (1987a,b). Dunne et al. (1989a,b), Pakes and Ericson (1990), Troske (1992), Audretsch and Mahmood (1995), and Das (1995).

[4] Bailey et al. (1992), Griliches and Regev (1992), Olley and Pakes (1992), Liu and Tybout (1993), and Bailey et al. (1994) all examine or control for productivity differences among entering, exiting, and surviving firms or plants.

[5] Recent theoretical work by Dixit (1989) demonstrates how sunk entry or exit costs affect the response of firm entry and exit to changing market conditions. The sunk costs result in less firm response to small changes in profitability and can lead to hysteresis in market-level variables.

number of advanced technologies, such as computer-controlled equipment and robotics, utilized in the plant.

To analyze these issues we utilize three establishment-level U.S. Census Bureau data sets: the 1988 Survey of Manufacturing Technology (SMT), the 1987 Census of Manufactures (CM), and the 1991 Standard Statistical Establishment List (SSEL). The data from the SMT allow us to identify which of 17 advanced computer or information technologies a manufacturing plant utilizes. This information is merged with data from the CM and SSEL to provide a detailed set of size, age, productivity, capital usage, growth, and failure variables for a sample of 6,090 plants over the 1987–1991 period.

The basic findings of this paper are: increases in the capital intensity of the input mix and increases in the use of advanced manufacturing technologies (AMTs) are negatively correlated with plant exit and positively correlated with plant growth. These correlations persist even after controlling for age, size, and productivity differences among the plants. The only qualifier to these patterns is that the effect of technology usage on exit is substantially weakened when size is included among the set of control variables. This is not surprising, since technology usage and plant size are strongly positively correlated. However, when examining patterns of plant growth, we find that the technology usage measures have larger positive effects on growth when plant size is controlled for, indicating a potentially important role for the nature of capital equipment in the growth process.

The remainder of the paper is organized as follows: Section 2 describes the empirical model of growth and failure, the third section summarizes the data sets and data construction procedures, the fourth section presents the empirical results and the fifth section concludes.

2. An empirical model of plant growth and failure

This paper will focus on two sources of producer heterogeneity: the first resulting from variation in the plant-level capital–labor ratios and the second from differences in the types of manufacturing technologies adopted by the plant. The fact that producers within the same industry differ in their capital–labor ratios, with large producers generally being more capital intensive, has been noted by many researchers. In addition, Mansfield (1968), Romeo (1975), Kelley and Brooks (1991), and Dunne (1994) provide evidence that larger plants are more likely to adopt a range of newer, more capital-intensive technologies.

These documented variations in input mix can arise from differences in factor prices, with larger plants having lower capital prices than small producers, or for other reasons. Lambson (1991) develops a theoretical model that shows how differences in expectations of future prices, the fixity of the capital stock, and adjustment costs among producers will generate within-industry heterogeneity in technology adoption and input use. He uses the model to explain the simultaneous entry and exit that is often observed in many industries.

In this paper we recognize the heterogeneity in capital usage among manufacturing plants and attempt to study its relationship to plant growth and failure. There are several reasons to expect them to be related. First, the use of advanced manufacturing technologies may directly increase plant productivity and thus survivability. Recent work by Griliches and Siegel (1991) and Brynjolfson and Hitt (1993) support the conjecture that productivity and the use of advanced manufacturing technologies are related. Second, the use of advanced technologies may be a proxy for unobserved managerial ability. If plants with superior management are best able to fully exploit advanced production technologies, then plants with high-quality managers will be the most likely to adopt the new production methods as well as be the most likely to grow and survive because of their efficiency advantages. This would generate a positive correlation between technology adoption, growth, and survival.

There are also several reasons why we expect the growth and exit rates of plants to vary with the capital intensity of their input mix. A basic rationale for the inclusion of this variable is that plants with higher capital–labour ratios may have a lower ratio of variable to fixed costs. Given the basic shutdown rule that a plant will remain in operation as long as it can cover variable costs, plants with low variable-cost production techniques may be more likely to withstand negative shocks than high variable-cost producers. Second, in the presence of sunk entry or exit costs and uncertain future market conditions, Dixit (1989) demonstrates there is an option value to remaining in a market even if the producer is incurring losses. If the capital intensity of the plant's technology is related to the magnitude of sunk costs then turnover rates will vary between more and less capital-intensive producers. A third reason is motivated by recent models of unobserved producer heterogeneity and active learning. Olley and Pakes (1992) develop a model that emphasizes the relationship between a producer's underlying efficiency and the incentive to invest in capital. Essentially, efficient firms generate higher levels of investment and larger capital stocks. In this case capital intensity may act as a proxy for other unobserved sources of efficiency.

The empirical model of plant exit and growth we will estimate is developed in two stages. As motivation for our exit equation we begin with the framework developed by Jovanovic (1982) and Ericson and Pakes (1989). Each of these models assumes underlying cost differences among producers which, when combined with a market selection mechanism, generates different probabilities of failure. In particular, size and age, which act as proxies for the unobserved cost differences, will be correlated with failure patterns.[6] To this standard framework we will add direct measures of productivity, capital intensity, and technology usage. To the extent that size and age generally act as proxies for productivity differences that we will control for directly, we may find less significant patterns of size or age coefficients than earlier empirical studies.

The basic empirical technique is a probit regression of the discrete variable *Exit*, which takes the value one if the plant fails over the 1988–1991 period and zero if it does not, on the observed plant characteristics in 1987.[7]

$$\mathrm{Prob}(\mathit{Exit}) = f(\mathit{Age}, \mathit{Size}, \mathit{Productivity}, \mathit{Technology}, \mathit{Capital\text{–}Labor}, \mathit{Industry})\,. \tag{1}$$

Eq. (1) is appended with a disturbance term that is assumed to be distributed normally with mean zero and constant variance. Age is modeled as a set of three dummy variables with the oldest plants (pre-1959 plants) as the omitted group. Size is also included as a set of four dummy variables, based on total plant employment, with the largest plants the omitted group. Productivity will be measured using both labor and total factor productivity. The use of advanced technologies will also be included as a set of four dummy variables that measure the number of different computer-related technologies present in the plant.[8] The technology dummy variable groupings are: plants using zero technologies, plants using one or two technologies, plants using three to five technologies, and plants using six or seven technologies. The omitted group is plants using more than seven technologies. The capital–labor ratio will be included to control for capital intensity and the model will also include a set of dummy variables to distinguish three-digit manufacturing industries.

The second part of the empirical model is an equation describing the growth in plant-level employment from 1987 to 1991 as a function of observable plant characteristics in 1987. The dependent variable is the discrete growth rate, which is measured as the change in plant employment between 1987–1991 divided by the 1987 level. In this paper we will utilize only the growth rates of surviving plants over the 1987–1991 period.[9] This

[6] Virtually every empirical study in this literature has found failure rates to decline with producer size and age, at least for plants more than a few years old.

[7] The SMT data actually come from a survey carried out at the beginning of 1988 and measure technology use at that point in time.

[8] The exact nature of these technologies is discussed in the next section.

[9] Plants that fail over the time period have 1991 employment equal to zero and a growth rate of -1. This failure results in a mass point in the distribution of growth rates at -1. Dunne et al. (1989b) summarize the relationship between the moments of the distribution of growth rates over surviving plants, the distribution over all plants present in the initial year, and the distribution of the underlying latent variable that does not admit failure.

creates a sample selection problem with only surviving (i.e. successful) plants remaining in the data set. To solve this problem we use the results from the exit equation estimated above to control for the probability of selection into the sample of plants used in the growth rate regressions. The estimated inverse Mills ratio constructed from the exit regressions is included as an additional regressor in the growth rate regressions. The complete estimating model is:

$$Exit_i = \text{Prob}(X_i\boldsymbol{\beta}_1) + \mu_{1i} \tag{2}$$

$$Growth_i = \boldsymbol{X}_i\boldsymbol{\beta}_2 + \sigma_{12}\phi(\boldsymbol{X}_i\boldsymbol{\beta}_1)/(1 - \Phi(\boldsymbol{X}_i\boldsymbol{\beta}_1)) + \mu_{2i}\,. \tag{3}$$

This is similar to the models estimated by Evans (1987b) and Hall (1987). $\boldsymbol{\beta}_1$ is the parameter vector estimated from the exit probit, $\boldsymbol{\beta}_2$ is the parameter vector from the growth equation, and σ_{12} is the covariance between the disturbance terms of the two equations. The expression $\phi(\boldsymbol{X}_i\boldsymbol{\beta})/(1 - \Phi(\boldsymbol{X}_i\boldsymbol{\beta}_1))$ is the inverse Mill's ratio. A problem in estimating this system is identifying the second equation. In both Evans and Hall, the $\boldsymbol{X}_i$ matrices are identical in the two equations so that identification is achieved through functional form – the non-linearity of the Mill's ratio in $\boldsymbol{X}_i$. We also rely on this identification method, though ideally, plant or firm-level variables that influence exit but not growth should enter into the first-stage equation. An additional problem which occurs in these data is the presence of heteroskedasticity.[10] To control for this when drawing inferences about the growth-rate regression, we utilize White's (1980) procedure to construct standard errors that are consistent under heteroskedasticity.

3. Data and measurement issues

The data used in this study come from three establishment-level data sources: the 1987 Census of Manufactures (CM), the 1988 Survey of Manufacturing Technology (SMT), and the 1991 Standard Statistical Establishment List (SSEL). The CM provides the basic data on output and input use, disaggregated by labor, energy, capital and materials, to construct the plant-level productivity statistics and capital intensity measures in 1987. We measure the plant's capital intensity as the log of the ratio of the book value of capital to total employment.[11]

We adopt two approaches to measuring plant-level productivity. A simple formulation uses labor productivity defined as the log of value added per

[10] Jovanovic's (1982) selection model predicts that size and age will affect the conditional variance of plant growth. Dunne et al. (1989b) find empirical support for this.

[11] The book value of capital is used here in place of physical capital because physical capital is unavailable. Doms (1995) constructs capital based on the perpetual-inventory method and compares this series with the book value series. The correlation between the two series in his sample of plants is above .90. Thus, the reported book values should act as a reasonable proxy for the physical capital stock in the cross-section of plants.

worker. The advantage of this measure is that it is simple to compute and makes no assumptions concerning returns to scale or factor shares. The drawback is that it fails to control for the use of other inputs. The second measure of productivity utilized is the total factor productivity (TFP) index constructed analogously to Bailey et al. (1992). TFP is measured as plant output minus a factor-share weighted sum of inputs. The major difficulty in constructing this TFP index is that we do not observe a price of capital or the total expenditure on capital services by the plant. We assume that there are constant returns to scale and measure the expenditure on capital as plant revenue minus the expenditure on other inputs. Because they are generated from a single year's data, both the labor and TFP measures will reflect short-run differences in capacity utilization, and thus are likely to be relatively noisy measures of the permanent or long-run differences in plant efficiency that we desire.[12]

The data on technology use are taken from the SMT which provides information on each plant's usage of 17 different advanced production technologies at the beginning of 1988. These technologies include such innovations as CAD/CAM systems, robots, computers, and networks. A complete list of the technologies included in the SMT is given in Table A.1 of the appendix. For each technology, the respondent is asked whether it is in current use. Unfortunately, there is no data on intensity of use. Thus, a plant experimenting with a technology and a plant fully using a technology appear identical in the data.[13] Our measure of technology usage is based on the number of technologies that a plant reports that it uses. The data on entry cohort is also obtained from the SMT.

The final data set, the SSEL, is used to track plants over time. The 1991 SSEL is a complete list of all establishment in the United States. To identify plants that fail between 1988 and 1991, we match the SSEL to all respondents of the SMT survey using establishment identification numbers. Plants in the SMT that are not found in the SSEL are considered potential exits. A geographic screen is then performed to filter out plants which have successors but are cataloged under a different establishment identification number.[14]

[12] A preferable procedure, that would minimize the measurement error introduced by capacity utilization effects, would be to average each plant's labor productivity or TFP over a longer time period. The annual time-series data needed to do this were not available.

[13] The 1990 Survey of Manufacturing Technology provides information on the intensity of technology use. We constructed the plant-level correlations between technology intensity from the 1990 SMT and the number of technologies used in the 1988 SMT. The correlations indicated strong positive association and suggest that the number of technologies serves as a relatively good proxy for overall technology intensity.

[14] It is likely that a small number of false exits still exist in the data set with the result that we may overstate exit in the small to mid-size company size classes. However, we believe the problem is small and does not affect the general inverse relationship between size and exit that we observe.

The sample of plants studied here is restricted to plants in five two-digit standard industry classification (SIC) manufacturing industries that are covered by the SMT: fabricated metals (SIC 34), non-electrical machinery (SIC 35), electrical machinery (SIC 36), transportation equipment (SIC 37), and scientific instruments (SIC 38). The SMT is a probability sample of 10,000 plants from a population of roughly 40,000 plants. The survey includes only those plants whose total employment was greater than 20 employees in the 1987 CM. Thus, the smallest manufacturing plants are omitted from the analysis. In addition, of the 10,000 plants available for the study in the SMT, only 6,090 observations have non-imputed data in both the SMT and the CM. The main source of attrition is due to imputation of key variables in the CM. Of the 3,400 plants lost due to non-response of important variables, over 3,000 are lost due to non-response to the CM and the remaining are due to non-response to items in the SMT. Overall, the plants employ 2.5 million workers, which is roughly 15% of total manufacturing employment, and have an average plant size of 409 employees in 1987. The sample, therefore, represents both mid-size and large plants but systematically excludes smaller plants.

Table 1 reports the mean values of employment, number of technologies

Table 1
Descriptive statistics

	Number of plants	Average employment	Mean number of AMTs	Mean log of KL	Mean labor productivity	Mean TFP
Growth rate class						
−1	966	143	2.79	2.97	4.27	0.05
−1 to −0.25	1069	597	4.38	3.10	4.30	0.04
−0.25 to 0	1567	594	4.69	3.30	4.38	0.05
0 to 0.30	1525	365	4.24	3.33	4.45	0.07
>0.30	963	239	4.06	3.30	4.49	0.09
Employment size class						
<50	1331	34	1.76	2.95	4.22	0.04
50 to 100	1102	72	2.57	3.05	4.30	0.06
100 to 250	1709	160	3.75	3.22	4.35	0.05
250 to 500	818	357	5.21	3.44	4.43	0.07
>500	1130	1597	8.21	3.62	4.66	0.09
Entry cohort						
1984–1988	542	159	3.14	2.96	4.42	0.10
1973–1983	1809	225	3.77	3.17	4.40	0.08
1959–1972	1926	367	4.07	3.19	4.37	0.06
pre-1959	1813	713	4.82	3.38	4.37	0.03
Total	6090	409	4.12	3.22	4.38	0.06

used, capital–ratio, labor productivity, and total factor productivity for plants in the sample disaggregated by three characteristics. The first panel disaggregates these variables by the employment growth rate of the plant, the second panel disaggregates by total plant employment, and the last panel provides an entry cohort break out. In this first panel the cells represent different growth rate groups. The top row includes plants that exit (i.e. generate discrete growth rates of −1). Failing plants are considerably smaller than average. Among the non-failing plants, the average size of plants falls as you move to higher growth rate categories. Results for the other variables indicate that growth generally increases with technology use, capital intensity, and productivity. The second panel shows that technology use, capital intensity, and productivity all increase markedly with size. The size–technology relationship is particularly evident. The number of technologies used increases from 1.67 for the smallest size group to 8.24 for the largest size group. The age panel indicates that older plants are larger, use somewhat more technology, are more capital intensive, but are generally the least productive.[15]

4. Empirical results

In this section the patterns of exit and growth are examined focusing, in particular, on the role that capital use and technology adoption play in generating the patterns. Our approach is first to estimate a set of exit equations and then estimate a set of growth equations controlling for the selection process.

Table 2 reports the results from the probit exit regressions using data pooled across all 6,090 plants. All the regressions include controls for the plant's three-digit SIC industry and standard errors are reported in parentheses. The first two columns give the results when plant size is omitted from the analysis. Column one includes a labor productivity measure while column two includes the TFP measure. The basic results indicate that younger plants and plants that use fewer of the advanced technologies have higher probabilities of exit. Higher productivity and higher capital intensity reduce the probability of exit. With the exception of the labor productivity variable, all the effects are statistically significant. The results on age and productivity are consistent with the findings of most previous empirical studies. The results indicate that the plant's capital structure has an

[15] The slight increase in technology use as plants age due to the fact that older plants are larger. Dunne (1994) reports that age generally has no effect on technology use in models where size is also included.

Table 2
Probit exit equations

Variable	(1)	(2)	(3)	(4)
Intercept	−1.198	−1.179	−1.540	−1.530
	(0.303)	(0.286)	(0.315)	(0.297)
Cohort				
1984–1988	0.515	0.518	0.342	0.347
	(0.074)	(0.074)	(0.076)	(0.076)
1973–1983	0.266	0.272	0.120	0.126
	(0.056)	(0.056)	(0.058)	(0.058)
1959–1972	0.096	0.101	0.025	0.030
	(0.056)	(0.056)	(0.057)	(0.058)
Technologies				
0 Tech	0.703	0.665	0.178	0.164
	(0.084)	(0.084)	(0.095)	(0.095)
1–2 Tech	0.526	0.497	0.080	0.071
	(0.077)	(0.078)	(0.086)	(0.086)
3–5 Tech	0.441	0.419	0.117	0.109
	(0.075)	(0.075)	(0.082)	(0.082)
6–7 Tech	0.211	0.194	0.043	0.035
	(0.088)	(0.089)	(0.093)	(0.093)
K/L	−0.070	−0.137	−0.049	−0.094
	(0.027)	(0.029)	(0.027)	(0.030)
Labor productivity	−0.051		−0.036	
	(0.034)		(0.035)	
TFP		−0.312		−0.205
		(0.081)		(0.082)
Employment size class				
< 50			0.988	0.967
			(0.098)	(0.099)
50–100			0.947	0.930
			(0.097)	(0.097)
100–250			0.675	0.659
			(0.090)	(0.091)
250–500			0.217	0.209
			(0.104)	(0.104)
Log likelihood	−2403.28	−2396.81	−2320.45	−2317.9
Likelihood ratio index[a]	0.064	0.066	0.096	0.097

Note: All probits include three-digit industry controls.
[a] The likelihood ratio index is a measure of goodness of fit similar to the R^2 measure in linear regression. The construction is described in Greene (1990).

additional effect on exit decisions with increased use of capital acting to reduce exit.[16]

These results do not control for the initial size of the plant, which has been included in earlier studies as a control for underlying efficiency differences among plants. The third and fourth columns of Table 2 report probit regressions that control for plant size. Initial size has a large, statistically significant effect on plant exit with smaller plants failing more frequently. Again, this correlation has been found in virtually all empirical studies of exit. More importantly for our purposes, the inclusion of size in the failure regressions reduces the magnitudes of the coefficients on all the other variables in the model. In particular, it sharply reduces the effect of advanced technology use on exit, with the technology dummy variables generally becoming insignificant. Total factor productivity, age and capital intensity remain statistically significant.

Overall, the results in Table 2 indicate an important role for plant size, age, total factor productivity and capital intensity as correlates of plant exit. The signs of the correlations indicate that plants that are more efficient or more capital intensive have a lower probability of failing. The correlation of failure with advanced technology adoption is more ambiguous. Because the use of advanced manufacturing technologies tends to be highly correlated with plant size (Dunne (1994)), its role in the exit equations is greatly reduced when initial size is included. As a result, in this data set, we are unable to confirm an independent effect of the adoption of advanced technologies on the plant's exit decision.

In addition to the pooled runs, the appendix reports separate probits for each two-digit industry (Tables A.2 and A.3). The basic findings are similar to those reported in Table 2 except that the statistical significance of many of the coefficients is reduced. When size is not included in these exit equations, the results are quite similar to column two of Table 2. Increased technology use lowers the probability of exit, as does increased TFP and higher capital-labor ratios. With size included, the effects of technology, productivity, age and capital on exit are all considerably less systematic.

Table 3 presents the results of the growth rate regressions controlling for sample selection. To conserve on space, three-digit industry controls are not reported. White standard errors are reported in parentheses. The first column provides basic size, age and productivity results. In general, these findings support previous research which finds that producer growth declines as age increases, holding size constant, and that size and growth are

[16] Audretsch (1991) examines the relationship between industry exit rates and industry capital–labor ratios. He also finds that exit rates are lower in capital-intensive industries.

Table 3
Plant growth rate regressions

Variable	(1)	(2)	(3)	(4)	(5)
Cohort					
1984–1988	0.105	0.169	0.172	0.108	0.110
	(0.039)	(0.038)	(0.038)	(0.039)	(0.038)
1973–1983	0.079	0.116	0.116	0.068	0.066
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
1959–1972	0.016	0.035	0.037	0.014	0.015
	(0.016)	(0.015)	(0.015)	(0.015)	(0.015)
Technologies					
0 Tech		0.024	0.025	−0.145	−0.144
		(0.030)	(0.029)	(0.031)	(0.031)
1–2 Tech		0.055	0.058	−0.085	−0.082
		(0.024)	(0.023)	(0.027)	(0.027)
3–5 Tech		0.040	0.043	−0.060	−0.057
		(0.025)	(0.024)	(0.026)	(0.026)
6–7 Tech		0.015	0.016	−0.029	−0.026
		(0.026)	(0.026)	(0.026)	(0.026)
K/L		0.037	0.087	0.041	0.102
		(0.012)	(0.015)	(0.012)	(0.015)
Labor productivity		0.108		0.123	
		(0.027)		(0.027)	
TFP	0.073		0.160		0.201
	(0.027)		(0.032)		(0.032)
Employment size class					
<50	0.137			0.284	0.290
	(0.024)			(0.032)	(0.031)
50–100	0.193			0.310	0.313
	(0.027)			(0.032)	(0.032)
100–250	0.113			0.200	0.204
	(0.018)			(0.024)	(0.024)
250–500	0.053			0.106	0.108
	(0.019)			(0.021)	(0.021)
Mills ratio	−0.109	0.157	−0.051	0.200	−0.034
	(0.059)	(0.056)	(0.058)	(0.056)	(0.056)
R^2	0.052	0.054	0.052	0.081	0.080

Note: All regressions include three-digit industry controls. White (1980) standard errors are reported.

inversely related. The size effect is not monotonic in this instance.[17] The next two columns provide the results when the technology adoption variables are included but size is not. In general the coefficients are not

[17] Dunne et al. (1989) also find that the effect of size on growth is non-monotonic and varies by whether or not the plant is a multi- or single-plant producer.

highly significant and the pattern that is present indicates that plants with fewer technologies have higher growth. Both the capital–labor ratio and the productivity terms correlate positively with plant growth.

The final two columns of Table 3 report regression results that include plant size. These results are very straightforward to interpret. Younger plants, higher productivity plants and smaller plants all have higher rates of growth. The age effect is monotonic across age groups but the size effect is not. The smallest size group is found to have slightly lower average growth than the next smallest group. The coefficients on the capital variables indicate a statistically significant role for capital even after controlling for plant size. The technology dummies indicate that technology use is positively related to employment growth while the capital-labor ratio indicates that more capital intensive plants have higher growth.

Comparing the three sets of estimates using the TFP variables, columns one, three, and five, two results are striking. First, the size coefficients are substantially larger when the capital variables are included (column five vs. column one). Second, the technology effects are substantially larger and their sign is reversed when size is included (column five) than when it is deleted (column three). Our interpretation is that initial size and technology use have differential effects on growth. Holding size fixed, the use of a larger number of advanced technologies is positively correlated with growth. When the technology variables are included without controlling for size the technology parameters pick up part of the negative size effect thus biasing the coefficients toward zero. Overall, the growth rate regressions provide fairly strong evidence that technology use is positively correlated with growth after differences in size, age, and productivity are controlled for.

Table A.4 in the appendix reports separate growth rate regressions for each two-digit industry using the specification that is reported in column five of Table 3.[18] In general, the results are similar to those reported in Table 3; however, the statistical significant of many of the coefficients is reduced. Focusing only on the capital variables we see that higher capital–labor ratios are positively correlated with plant growth and the effect is significant in every industry. The technology dummies indicate that growth is increasing in the number of technologies adopted in all industries although the pattern is statistically significant in only the fabricated metals (34) and instrument (38) sectors.

5. Summary and conclusions

Recent research on entry, exit and growth has increasingly emphasized the role of producer heterogeneity as a key determinant of these evolution-

[18] The selection equations for these models are the exit models reported in Table A.3.

ary processes. With this in mind, this paper examines one particular facet of producer heterogeneity, namely, the heterogeneity of the capital stock. The paper extends earlier empirical studies, which have quantified the effect of size, age, and productivity, by examining the additional impact which variation in capital intensity and capital quality have on plant-level growth and failure patterns. It takes advantage of a new manufacturing survey that examines the extent to which individual plants have adopted a range of advanced manufacturing technologies.

The basic conclusion is that size, age and productivity are not sufficient statistics for characterizing the growth and failure patterns, but that capital has an independent role to play. In particular, the capital intensity of the plant, measured as the capital–labor ratio, is negatively correlated with plant failure and positively correlated with plant growth. This correlation exists even after controlling for a range of other plant characteristics. We also find that plants that have adopted a larger number of advanced manufacturing technologies, such as robots, lasers, or computer-controlled machinery, have higher subsequent growth rates and lower failure rates. The latter conclusion is sensitive to whether or not the regressions control for plant size with this control diminishing the relationship between technology use and failure.

The exact mechanism by which capital affects the plant's expansion, contraction, or shutdown decision cannot be determined from the pattern of correlations reported in this paper. Several mechanisms are possible as a result of either the short-run fixity of the capital input or the sunk nature of many capital investments. A further possibility is that the quantity or type of capital input acts as a proxy for some unobserved component of plant of firm-level productivity, such as managerial efficiency. Distinguishing these different effects requires structural empirical models of industry evolution that recognize both the many sources of plant heterogeneity and the inter-temporal effects of plant investment decisions. The empirical findings in this paper simply suggest that explicit recognition of the role of capital as a determinant of an industry's pattern of evolution is a useful path for future work.

Acknowledgements

This paper represents the views of the authors and does not reflect the opinions of the U.S. Census Bureau. The authors would like to thank an anonymous referee, David Audretsch, and participants at the conference on The Post-Entry Performance of Firms for helpful comments.

Appendix

Table A.1
Description of technologies

Technology	Description
Computer aided design (CAD)	Use of computers for drawing and designing parts or products for analysis and testing of designed parts and products.
CAD controlled machines	Use of CAD output for controlling machines used to manufacture the part or product.
Digital CAD	Use of digital representation of CAD output for controlling machines used to manufacture the part or product.
Flexible manufacturing systems/ cell	Two or more machines with automated material handling capabilities controlled by computers or programmable controllers, capable of single path acceptance of raw materials and delivery of finished prod.
Numerically controlled machines/computer controlled machines	NC machines are controlled by numerical commands punched on paper or plastic mylar tape while CNC Machines are controlled through an internal computer.
Materials working lasers	Laser technology used for welding, cutting, treating, scribing, and marking.
Pick/place robots	A simple robot with 1–3 degrees of freedom, which transfers items from place to place.
Other robots	A reprogrammable, multifunctional manipulator designed to move materials, parts, tools or specialized devices through variable programmed motions.
Automatic storage/retrieval systems	Computer controlled equipment providing for the automatic handling and storage of materials, parts, and finished produces.
Automatic guided vehicle systems	Vehicles equipped with automatic guidance devices programmed to follow a path that interfaces with work stations for automated or manual loading of materials, parts, tools, or products.
Technical data network	Use of local area network (LAN) technology to exchange technical data within design and engineering departments.
Factory network	Use of LAN technology to exchange information between different points on the factory floor.

Table A.1 (*Continued*)

Inter-company computer network	Intercompany computer network linking plant to subcontractors, suppliers, and/or customers.
Programmable controllers	A solid state industrial control device that has programmable memory for storage of instructions, which performs functions equivalent to a relay panel or wired solid state logic control system.
Computers used on factory floor	Exclude computers used solely for data acquisitions or monitoring. Include computers that may be dedicated to control, but which are capable of being reprogrammed for other functions.
Automated sensors used on inputs	Automated equipment used to perform tests and inspections on incoming or in process materials.
Automated sensors used on final product	Automated equipment used to perform tests and inspections on final products.

Source: U.S. Department of Commerce, Bureau of the Census (1989).

Table A.2
Two-digit industry exit equations: no size controls

Variable	SIC 34	SIC 35	SIC 36	SIC 37	SIC 38
Cohort					
1984–1988	0.358	0.567	0.730	0.663	0.174
	(0.166)	(0.155)	(0.151)	(0.203)	(0.205)
1973–1983	0.215	0.229	0.374	0.208	0.362
	(0.105)	(0.117)	(0.130)	(0.151)	(0.155)
1959–1972	0.026	0.231	−0.018	0.051	0.255
	(0.102)	(0.113)	(0.137)	(0.149)	(0.161)
Technologies					
0 Tech	0.543	0.733	0.743	0.982	0.407
	(0.181)	(0.186)	(0.171)	(0.230)	(0.209)
1–2 Tech	0.422	0.561	0.528	0.636	0.411
	(0.173)	(0.165)	(0.154)	(0.225)	(0.181)
3–5 Tech	0.398	0.373	0.362	0.696	0.394
	(0.171)	(0.158)	(0.151)	(0.210)	(0.177)
6–7 Tech	0.077	0.335	0.265	0.382	−0.193
	(0.206)	(0.183)	(0.171)	(0.245)	(0.229)
K/L	−0.164	−0.181	−0.013	−0.207	−0.174
	(0.062)	(0.066)	(0.056)	(0.077)	(0.080)
TFP	−0.254	−0.328	−0.183	−0.382	−0.490
	(0.181)	(0.169)	(0.160)	(0.246)	(0.186)
n	1499	1574	1283	845	889
Log likelihood	−591.56	−543.9	−530.0	−334.9	−375.2
Likelihood ratio index[a]	0.051	0.062	0.096	0.102	0.051

Note: All probits include three-digit industry controls.
[a] The likelihood ratio index is a measure of goodness of fit similar to the R^2 measure in linear regression. The construction is described in Greene (1990).

Table A.3
Two-digit industry exit equations: no size controls

Variable	SIC 34	SIC 35	SIC 36	SIC 37	SIC 38
Cohort					
1984–1988	0.218	0.414	0.554	0.544	−0.011
	(0.168)	(0.160)	(0.154)	(0.210)	(0.214)
1973–1983	0.092	0.109	0.248	0.071	0.134
	(0.110)	(0.121)	(0.137)	(0.159)	(0.167)
1959–1972	−0.035	0.158	−0.091	−0.036	0.198
	(0.105)	(0.116)	(0.141)	(0.154)	(0.171)
Technologies					
0 Tech	0.137	0.241	0.261	0.566	−0.364
	(0.200)	(0.214)	(0.193)	(0.259)	(0.244)
1–2 Tech	0.084	0.151	0.087	0.363	−0.271
	(0.189)	(0.188)	(0.176)	(0.250)	(0.217)
3–5 Tech	0.183	0.070	0.040	0.490	−0.128
	(0.183)	(0.177)	(0.166)	(0.229)	(0.207)
6–7 Tech	0.030	0.141	0.084	0.311	−0.417
	(0.217)	(0.196)	(0.180)	(0.257)	(0.255)
K/L	−0.144	−0.144	0.043	−0.175	−0.078
	(0.185)	(0.067)	(0.058)	(0.078)	(0.084)
TFP	−0.140	−0.214	−0.114	−0.207	−0.340
	(0.063)	(0.172)	(0.162)	(0.254)	(0.194)
Employment size class					
<50	1.201	0.799	0.846	0.842	1.633
	(0.265)	(0.208)	(0.192)	(0.247)	(0.302)
50–100	1.287	0.826	0.730	0.521	1.616
	(0.264)	(0.207)	(0.187)	(0.230)	(0.300)
100–250	0.795	0.502	0.660	0.503	1.270
	(0.257)	(0.196)	(0.170)	(0.211)	(0.284)
250–500	0.706	0.189	−0.074	−0.171	0.614
	(0.276)	(0.224)	(0.196)	(0.256)	(0.315)
n	1499	1574	1283	845	889
Log likelihood	−569.33	−531.1	−510.8	−323.2	−349.4
Likelihood ratio index	0.087	0.084	0.129	0.133	0.116

Note: All probits include three-digit industry controls.

Table A.4
Two-digit industry plant growth rate regressions

Variable	SIC 34	SIC 35	SIC 36	SIC 37	SIC 38
Cohort					
1984–1988	−0.030	0.233	0.185	0.116	0.061
	(0.062)	(0.085)	(0.081)	(0.145)	(0.078)
1973–1983	0.046	0.060	0.120	−0.028	0.159
	(0.032)	(0.033)	(0.041)	(0.075)	(0.042)
1959–1972	0.027	−0.022	0.100	−0.093	0.086
	(0.026)	(0.025)	(0.035)	(0.059)	(0.039)
Technologies					
0 Tech	−0.157	−0.099	0.095	−0.163	−0.319
	(0.065)	(0.064)	(0.060)	(0.094)	(0.069)
1–2 Tech	−0.113	−0.022	−0.012	−0.143	−0.238
	(0.065)	(0.049)	(0.049)	(0.081)	(0.065)
3–5 Tech	−0.110	−0.028	0.034	−0.123	−0.141
	(0.061)	(0.048)	(0.051)	(0.067)	(0.058)
6–7 Tech	−0.086	0.004	0.051	−0.077	−0.089
	(0.063)	(0.053)	(0.047)	(0.069)	(0.054)
K/L	0.089	0.140	0.117	0.063	0.090
	(0.018)	(0.046)	(0.028)	(0.029)	(0.029)
TFP	0.072	0.299	0.238	0.074	0.217
	(0.049)	(0.079)	(0.062)	(0.090)	(0.073)
Employment size class					
<50	0.260	0.263	0.341	0.339	0.299
	(0.050)	(0.051)	(0.106)	(0.078)	(0.067)
50–100	0.293	0.250	0.288	0.333	0.476
	(0.051)	(0.059)	(0.061)	(0.116)	(0.095)
100–250	0.190	0.163	0.164	0.318	0.246
	(0.053)	(0.045)	(0.044)	(0.061)	(0.056)
250–500	0.115	0.091	0.065	0.228	0.074
	(0.039)	(0.042)	(0.042)	(0.059)	(0.051)
Mills ratio	−0.077	−0.077	0.080	−0.248	0.072
(0.075)	(0.075)	(0.094)	(0.168)	(0.140)	(0.085)
n	1279	1383	1063	709	743
R^2	0.064	0.095	0.075	0.074	0.173

Note: All regressions include three-digit industry controls. White (1980) standard errors are reported.

References

Audretsch, D., 1991, New firm survival and the technological regime, Review of Economics and Statistics 73, 441–450.

Audretsch, D. and T. Mahmood, 1995, New firm survival: New results using a hazard function, Review of Economics and Statistics 77, 97–103.

Bailey, M.N., C. Hulten and D. Campbell, 1992, Productivity dynamics in manufacturing plants, Brookings Papers: Microeconomics (Brookings Institute, Washington, DC) 187–249.

Bailey, M., E. Bartelsman and J. Haltiwanger, 1994, Downsizing and productivity growth: Myth or Reality?, Mimeo (unpublished).

Baldwin, J.R. and P.K. Gorecki, 1991, Firm entry and exit in the Canadian manufacturing sector, Canadian Journal of Economics 24, 300–323.

Brynjolfson, E. and L. Hitt, 1994, New Evidence on the returns of information systems, Sloan School of Management Working Paper, #3571-93.

Das, S., 1995, Size, age and firm growth in an infant industry: The computer hardware industry in India, International Journal of Industrial Organization 13, 111–126.

Dixit, A., 1989, Entry and exit decisions under uncertainty, Journal of Political Economy 97, 620–638.

Doms, Mark, 1995, Estimating capital efficiency schedules within production functions, Economic Inquiry, in press.

Dunne, T., 1994, Plant age and technology usage in U.S. manufacturing industries, Rand Journal of Economics 25, 488–499.

Dunne, T., M.J. Roberts and L. Samuelson, 1988, The patterns of firm entry and exit in the U.S. manufacturing sector, 1963–1982, Rand Journal of Economics 19, 495–515.

Dunne, T., M.J. Roberts and L. Samuelson, 1989a, Firm entry and post-entry performance in the U.S. chemical industries, Journal of Law and Economics 32, S233–S272.

Dunne, T., M.J. Roberts and L. Samuelson, 1989b, The growth and failure of U.S. manufacturing plants, Quarterly Journal of Economics 104, 671–698.

Ericson, R. and A. Pakes, 1989, An alternative theory of the firm and industry dynamics, Discussion Paper 445 (Columbia University).

Evans, D., 1987a, The relationship between firm growth , size and age: Estimates for 100 manufacturing industries, Journal of Industrial Economics 35, 567–582.

Evans, D., 1987b, Tests of alternative theories of firm growth, Journal of Political Economy 95, 657–674.

Geroski, P., 1991, Market dynamics and entry (Blackwell, Oxford).

Geroski, P. and J. Schwalbach, 1991, Entry and market contestability (Blackwell, Oxford).

Greene, W., 1990, Econometric analysis (Macmillan, New York).

Griliches, Z. and H. Regev, 1992, Productivity and firm turnover in Israeli Industry: 1979–1988, NBER Working Paper 4059.

Griliches, Z. and D. Siegel, 1991, Purchased services, outsourcing, computers, and productivity in manufacturing, NBER Working Paper 3678.

Hall, B., 1987, The relationship between firm size and firm growth in the U.S. manufacturing sector, Journal of Industrial Economics 35, 583–606.

Jovanovic, B., 1982, Selection and the evolution of industry, Econometrica 50, 649–670.

Kelley, M.R. and H. Brooks, 1991, External learning opportunities and the diffusion of process innovations to small firms, Technological Forecasting and Social Change 39, 103–125.

Lambson, V.E., 1991, Industry evolution with sunk costs and uncertain market conditions, International Journal of Industrial Organization 9, 171–196.

Liu, L. and J.R. Tybout, 1993, Productivity growth in Colombia and Chile: Panel-based evidence on the role of entry, exit and learning, Working Paper (Georgetown University).

Mansfield, E., 1968, Industrial research and technological innovation (Norton, New York).

Olley, G.S. and A. Pakes, 1992, The dynamics of productivity in the telecommunications equipment industry, Working Paper no. 92-2 (Center for Economic Studies).

Pakes, A. and R. Ericson, 1990, Empirical implications of alternative models of firm dynamics, Working Paper no. 8803 (SSRI, University of Wisconsin–Madison).

Roberts, M.J. and J.R. Tybout, 1994, Producer heterogeneity and performance in the semi-industrialized countries, Manuscript.

Romeo, A.A., 1975, Interindustry and interfirm differences in the rate of diffusion of an innovation, Review of Economics and Statistics 57, 311–319.

Troske, K.R., 1992, The time-series pattern of firm growth in two industries, Working Paper 92-10 (Center for Economic Studies, U.S. Census Bureau).

U.S. Department of Commerce, Bureau of the Census, 1989, Manufacturing Technology 1988 (U.S. Government Printing Office, Washington, D.C.).

White, H., 1980, A heteroscedasticity-consistent covariance matrix estimator and a direct test for heteroscedasticity, Econometrica 48, 817–838.