THE MISSING LINK: TECHNOLOGY, INVESTMENT, AND PRODUCTIVITY

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Abstract—This paper examines the relationship between productivity, investment, and plant age for over 14,000 plants in the U.S. manufacturing sector for the period of 1972 to 1988. Productivity patterns vary significantly due to plant heterogeneity. Initially productivity increases with respect to plant age, but then it decreases. Productivity and growth in productivity are found to be systematically correlated with plant size and industry. However, there is virtually no observable relationship between investment and productivity or productivity growth. Overall the results indicate that plant heterogeneity and fixed effects are more important determinants of observable productivity patterns than sunk costs or capital reallocation.

I. Introduction

U.S. ECONOMIC policy reflects the widely held belief that there is a link between investment, productivity, and economic growth. For example, the 1995 Economic Report of the President states that “[p]roductivity can be raised by . . . investing in new private equipment and structures in public infrastructure.” In addition, federal tax policy contains many features, including provisions for investment tax credits, expensing options, and accelerated depreciation rules, which are based, at least in part, on the presumption that investment generates higher productivity and economic growth.

A substantial body of economic research attempts to establish the relationship between technology, investment, and economic progress. A recent class of macroeconomic growth models (Andolfatto and MacDonald (1993), Krusell (1991)) endogenizes the technology adoption decision in order to derive predictions concerning the evolution of these variables. The models embed technology adoption in the producers’ decisions by either assuming that new machinery incorporates the latest technology (Cooley et al. (1994)) or assuming barriers to technology adoption (Campbell (1993)) such as sunk costs. From a different perspective, models of plant dynamics (Jovanovic (1982), Pakes and Ericson (1987), Lambson (1991), Dixit (1989)) also link technology and the evolution of economic variables.

Clearly, economic theory, and major aspects of U.S. fiscal policy, explicitly or implicitly, assume a link between technology, investment, productivity, and economic growth. Yet to date there is limited empirical evidence of such a connection. A plant-level analysis of the observed relationship between productivity, investment, and plant characteristics should provide particularly valuable insight into the existence and nature of this link. The primary goal of this paper is to provide new evidence on the relative importance of investment, plant age, and other plant characteristics on productivity. A secondary goal is to explore the implications of this evidence for the theoretical models mentioned above.

The data consist of a panel constructed from the Census Bureau’s Longitudinal Research Database (LRD).1 This plant-level extract spans the period of 1972 through 1988 and consists of approximately 14,000 large manufacturing plants, which collectively account for over 60% of the investment in the U.S. manufacturing sector. The econometric model is a reduced-form production function, augmented to incorporate the notion of lumpy investment, or investment spikes.2 Lumpy investment can be explained by the presence of fixed costs, and implies differences in capital vintages across plants. The time elapsed since the plant’s most recent investment spike, or its investment age, tracks the time between investment spikes, and can also be viewed as an indicator of the plant’s capital vintage.3

In order to examine the link between investment and productivity, I estimate a number of ordinary least-squares (OLS) regressions, in which the dependent variables are productivity and growth in productivity. The right-hand-side variables are plant age, investment age, and other relevant plant characteristics. The regressions are estimated on the pooled sample, and separately by industry. Furthermore, in order to exploit both cross-plant and within-plant variations in productivity, these regressions are estimated both with and without plant-level fixed effects.

The findings of this analysis are quite surprising. In the pooled regressions there is virtually no evidence of a positive correlation between productivity and high levels of recent investment. The absence of a positive correlation, which persists across various definitions of “high recent investment,” is particularly apparent in the regressions that control fixed effects. Although a few industries exhibit some variation in productivity with respect to investment age,

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1 Previous studies have used the LRD to analyze aggregate productivity fluctuations. Some important findings are: (1) there is persistence in plant-level productivity over time (Baily et al. (1992), Bartelsman and Dhyres (1992)), and (2) firm-specific characteristics (Baily et al. (1992)) and firm-specific learning by doing (Bahk and Gort (1993)) are important for determining aggregate productivity. Other LRD studies provide evidence that reallocation of capital across plants (Olley and Pakes (1992)) and the simultaneous expansion of productive plants and failure of unproductive plants (Bartelsman and Dhyres (1992)) help explain aggregate productivity growth. The results of the present study indicate that the permanent characteristics of the plants are extremely important for explaining productivity variations, which is consistent with previous findings.

2 See Doms and Dunne (1993), Power (1994), Cooper et al. (1995), and Caballero et al. (1995) for evidence of the widespread existence and importance of lumpy investment throughout the manufacturing sector.

3 Investment age also captures the investment hazard function (Cooper et al. (1995)).
these patterns are diminished in the regressions controlling fixed effects. The results indicate that productivity varies somewhat with respect to plant age. Furthermore, I find evidence that size, industry, and plant-specific effects are important determinants of productivity.

The paper proceeds as follows. Section II provides theoretical background and motivation for the empirical strategy adopted in this paper. Section III presents the econometric model. Section IV describes the data and defines the variables. Section V discusses the results, and section VI provides some conclusions and discusses the implications of these results for further research.

II. Theoretical Grounding

Within the recent literature that endogenizes the technology adoption decision, vintage capital models offer similar hypotheses regarding why different firms use different technologies, and how technology is dispersed. Beginning with Solow (1960), some models of economic growth embody technological progress in new machinery, an assumption that is often referred to as “machine-embodied technical change” (Cooley et al. (1994)). In many vintage models, producers face fixed or sunk costs, which implies that it might not be profitable to invest in the newest technology immediately. For example, Campbell (1993) points out that since existing producers face sunk costs, new plants have a relative advantage in adopting new technology. This assumption, called plant-embodied technical change, suggests that capital reallocation and entry and exit are important factors for technological dispersion. Many of these models generate a lumpy investment pattern, which is consistent with recent empirical evidence.

Other models focus on different dynamics associated with the technology adoption decision. For example, in Jovanovic and Nyarko’s (1994) one-agent learning-by-doing model, productivity increases as firms learn about the given technology. This implies that technology adoption can be costly due to the loss of technology-specific human capital. In fact, productivity immediately following a technology switch can be lower than under the old technology.

A final class of theoretical models focuses on the importance and implications of plant heterogeneity for determining plant and industry dynamics. Modeling differences among plants generates predictions about the observable relationships between plant characteristics and other variables, as well as firm, cohort, and industry evolution (Jovanovic (1982), Pakes and Ericson (1987), Lippman and Rummelt (1992), Lambson (1991), Dixit (1989), and Frank (1988)). By analyzing the relationship between observable plant characteristics and various economic phenomena, numerous empirical studies (Dunne et al. (1989), Evans (1987a,b), Hall (1987), and Garen (1989)) document the role of differences across plants, or plant heterogeneity, in determining economic evolution.

Regardless of the particular assumptions employed, all of these models, either implicitly or explicitly, characterize some aspect of an assumed relationship between technology, investment, productivity, and economic growth. In this spirit, the present investigation attempts to examine the extent to which the different characteristics of plants can explain differences in their economic evolution, by exploring the relationship between productivity and observable plant characteristics, such as plant age, investment age, plant size, industry, and plant-level fixed effects. A distinguishing feature of this study is the inclusion of both investment age and plant age in the regressions. The results help shed light on the relative importance for productivity of “machine-embodied technical change,” “plant-embodied technical change,” and other plant characteristics. The analysis derives in part from, and provides insight into, the two classes of models mentioned above: (1) models of endogenous technology adoption and (2) models of plant dynamics.

III. Empirical Model

In this section I describe the econometric model and empirical strategy. I also discuss the advantages and disadvantages of the chosen specification and offer some cautionary notes.

The dependent variable $y_{it}$ is defined two ways: (1) labor productivity for plant $i$ in year $t$, denoted by $lp_{it}$, and (2) growth rate of productivity for plant $i$ in year $t$, denoted by $lpdif_{it}$.

The specific empirical model described by equations (1) and (2) derives from the predictions of a simple vintage model which I constructed, but which is omitted in order to focus on the empirical analysis (see Power (1994) for details). Of relevance for the present study is the fact that the model combines sunk costs, plant heterogeneity, and selection, and new technology is embodied in new machinery. Further, the model predicts that the productivity of plants that have invested recently is higher than that of plants that invested long ago; and because selection causes the less productive plants to exit, it predicts that the mean levels of productivity across plants increase with respect to plant age. Obviously these predictions are highly contingent on the specifications of this stylized model. Nevertheless, they suggest that a regression of productivity on two indicators—time elapsed since birth (plant age) and time elapsed since the last investment spike (investment age)—is a reasonable way to examine the link between productivity, investment, and other factors.

The logarithmic specification, as well as this measure of labor productivity, are common in productivity analysis. For examples, see Baily et al. (1992) and Olley and Pakes (1992). Labor productivity, rather than total factor productivity (TFP), is chosen because TFP is calculated as a residual. By nature, a residual is prone to measurement error, and this problem is exacerbated in the empirical definition of TFP. For example, if two plants have identical amounts of capital, but one plant rents the capital while the other buys it, the two plants will have different TFP measures, even though in practice they are similar. Given the other measurement issues in the analysis, labor productivity was deemed a better choice.
The estimating equation is a simple production function, augmented to incorporate capital vintage, or lumpy investment,

\[ y = \alpha + \beta X + \epsilon \]

where

\[ y = \log (lp) \] (1)

or

\[ y = lpdif \]

\[ \log (lp) = \log (tvs) - \log (tph) \]

\[ tph = \frac{ph(sal + ww + cw)}{ww} \] (2)

\[ lpdif = \log (lp) - \log (lp_{-1}). \]

The variables in equation (2) are defined as follows: \( ph \) is production worker hours for plant \( i \) in year \( t \); \( sal \) is salaries for plant \( i \) in year \( t \); \( cw \) is costs of contract workers for plant \( i \) in year \( t \); and \( ww \) is worker wages for plant \( i \) in year \( t \). The LRD contains data on production worker hours, but it does not contain data on nonproduction worker hours. Therefore total hours (i.e., production worker and nonproduction worker hours), labeled \( tph \), can be obtained by using the ratio of total wages to production worker wages to capture the relationship between total hours and production worker hours. That is, the ratio of total wages to production worker wages can be used to “scale” production worker hours up to total hours. The total value of shipments for plant \( i \) in year \( t \), \( tvs \), is adjusted for changes in inventories. All units are in constant 1972 dollars. Finally, \( X \) is a vector that includes eight year dummy variables, twenty industry dummy variables, eight birth-age dummy variables, eight investment-age dummy variables, and five size dummy variables.

The empirical model, summarized by equations (1) and (2), is estimated using OLS. The productivity level and the productivity growth rate specifications are each estimated twice—with and without plant-level fixed effects. This provides four sets of estimated coefficients, which are reported in section V (see table 7). The two productivity-level regressions are also estimated by two-digit SIC industry codes.

If there is unobserved heterogeneity across plants, then the estimated coefficients from the regressions which do not control for fixed effects will be biased. Plant-level fixed effects remove time-invariant differences in mean productivity across plants. Thus the regressions with plant-level fixed effects eliminate this potential source of bias. In addition, fixed effects reveal the patterns of productivity and productivity growth for the average plant. In other words, they represent the within-plant, as opposed to across-plant, variation in productivity and productivity growth.

The reduced-form specification and the dummy variable age categories are quite flexible. They do not impose arbitrary structure, which helps to reveal the actual correlation between investment and productivity. There are, however, certain limitations from using a reduced-form specification. Before proceeding to a description of the data and construction of the variables, a few broad caveats should be noted.

Several issues complicate an analysis of the relationship between lumpy investment and productivity, and risk obscuring the interpretation of the results. First, identifying the link between technology, investment, and productivity is complicated by the fact that technological change is also discrete, or lumpy. This suggests that even if technology is embodied in plants or in equipment, not all investments have the same impact on productivity.

Second, the reduced-form empirical specification is not derived from a particular structural model. The empirical model abstracts from the issue of causality. Therefore this exercise should not be viewed as an explicit test of the structural models discussed in section II. This study attempts to document the observed relationship between productivity, investment, and plant characteristics, and thereby provide intuition, guidelines, and empirical underpinnings for further model development and testing.

Third, there are many different types of investment, including replacement,retooling, and expansion. Each of these may have different implications for the relationship between investment and productivity. For example, the replacement of worn-out machinery with new machinery ought to be associated with increases in productivity, while this is not necessarily the case for investments that simply

\[ \begin{align*}
9 \text{If time-invariant plant characteristics exist, then failing to control for these characteristics when using pooled cross-section time-series data will cause the error term, the dependent variable, and possibly several explanatory variables to be correlated over time. This biases the results. For example, if there is unobserved heterogeneity across the plants which comprise a given investment-age category, then an apparent correlation between productivity and investment age might in truth be spurious. That is, the permanent characteristics of the plants which comprise the investment-age category, rather than the investment age itself, might explain the correlation between productivity and investment age. Differentiating the data also controls for unobserved heterogeneity. Therefore using productivity growth as the dependent variable also helps to correct any bias.}
10 \text{Depending on the chosen functional forms, theoretical models can be consistent with a variety of different productivity patterns, including, for example, a constant marginal product of labor across producers with different capital vintages.}
\end{align*} \]
increase capacity. The present study focuses on lumpy investments. However, a number of robustness tests are performed, using a variety of definitions of lumpy investment, in an effort to allow for different types of investment spikes. Unfortunately, it is quite difficult to identify these different types of investment spikes empirically, and thus this variety may not be fully captured.

Finally, since an “investment spike” is a theoretical rather than a numeric or algebraic concept, and lacks an unambiguous real-world analogue, there is some risk of measurement error, whichever definition of investment spike is employed. In order to alleviate this risk, a variety of definitions of an investment spike is used to test robustness.

IV. The Data

This section describes the data set used in this analysis and the construction of the variables. The data set is a pooled cross-sectional time-series extract from the Census Bureau’s LRD. The LRD is a panel containing detailed plant-level information on more than 750,000 U.S. manufacturing establishments in 1963, 1967, and 1972–1988. The extract utilized for the regression analysis contains annual information on 13,936 large manufacturing plants from 1980 to 1988. In addition, information on these plants for the period of 1972–1980 is also employed in constructing some of the variables.

Table 1 reports the number of plants and the total number of observations by industry. By comparing columns (3) and (5) we see that the distribution of plants in the data set across two-digit SIC industries is roughly comparable to the distribution for total manufacturing. Furthermore, all 20 industries are well represented in the sample.

Table 2 reports the number of plants and the total number of observations by plant size. Plants are assigned to size classes based on their average, size-weighted employment over the sample period. The size classes are 250–500, 500–1000, 1000–2500, 2500–5000, and more than 5000 employees.

Although the data set excludes small plants, the 13,936 plants include every large manufacturing plant in the United States, where large is defined to be plants with 250 or more employees. Thus the distribution of plants across these five large size classes is identical to their distribution for the total manufacturing observations are computed using LRD data for 1980–1988.

Table 1.—Number of Observations in Data Set by Industry

<table>
<thead>
<tr>
<th>Two-Digit Industry</th>
<th>Number of Plants in Data Set (1)</th>
<th>Number of Observations in Data Set (2)</th>
<th>Percent of Data Set (3)</th>
<th>Number of Observations in Total Manufacturing (5)</th>
<th>Percent of Total Manufacturing (5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Food</td>
<td>1342</td>
<td>10,220</td>
<td>9.8%</td>
<td>54,555</td>
<td>10.8%</td>
</tr>
<tr>
<td>Tobacco</td>
<td>41</td>
<td>308</td>
<td>0.3%</td>
<td>644</td>
<td>0.1%</td>
</tr>
<tr>
<td>Textile</td>
<td>941</td>
<td>6,606</td>
<td>6.3%</td>
<td>18,143</td>
<td>3.6%</td>
</tr>
<tr>
<td>Apparel</td>
<td>937</td>
<td>6,305</td>
<td>2.1%</td>
<td>30,656</td>
<td>6.1%</td>
</tr>
<tr>
<td>Lumber</td>
<td>313</td>
<td>2,233</td>
<td>2.8%</td>
<td>26,770</td>
<td>5.3%</td>
</tr>
<tr>
<td>Furniture</td>
<td>387</td>
<td>2,094</td>
<td>2.1%</td>
<td>12,097</td>
<td>2.4%</td>
</tr>
<tr>
<td>Paper</td>
<td>563</td>
<td>4,329</td>
<td>4.9%</td>
<td>20,462</td>
<td>4.1%</td>
</tr>
<tr>
<td>Printing</td>
<td>660</td>
<td>5,083</td>
<td>5.4%</td>
<td>34,857</td>
<td>6.9%</td>
</tr>
<tr>
<td>Chemicals</td>
<td>734</td>
<td>5,671</td>
<td>1.0%</td>
<td>32,312</td>
<td>6.4%</td>
</tr>
<tr>
<td>Petroleum</td>
<td>138</td>
<td>988</td>
<td>3.8%</td>
<td>7,633</td>
<td>1.5%</td>
</tr>
<tr>
<td>Rubber</td>
<td>570</td>
<td>3,981</td>
<td>1.8%</td>
<td>22,021</td>
<td>4.4%</td>
</tr>
<tr>
<td>Leather</td>
<td>286</td>
<td>1,890</td>
<td>3.2%</td>
<td>5,607</td>
<td>1.1%</td>
</tr>
<tr>
<td>Stone, clay, and glass</td>
<td>453</td>
<td>3,315</td>
<td>5.5%</td>
<td>20,343</td>
<td>4.0%</td>
</tr>
<tr>
<td>Primary metals</td>
<td>812</td>
<td>5,742</td>
<td>8.0%</td>
<td>20,280</td>
<td>4.0%</td>
</tr>
<tr>
<td>Fabricated metals</td>
<td>1201</td>
<td>8,397</td>
<td>11.4%</td>
<td>53,132</td>
<td>10.6%</td>
</tr>
<tr>
<td>Nonelectric machinery</td>
<td>1681</td>
<td>11,899</td>
<td>11.8%</td>
<td>59,816</td>
<td>12.0%</td>
</tr>
<tr>
<td>Electric machinery</td>
<td>1721</td>
<td>12,368</td>
<td>6.2%</td>
<td>36,987</td>
<td>7.4%</td>
</tr>
<tr>
<td>Transport</td>
<td>952</td>
<td>6,442</td>
<td>3.7%</td>
<td>18,370</td>
<td>3.7%</td>
</tr>
<tr>
<td>Instruments</td>
<td>546</td>
<td>3,819</td>
<td>1.7%</td>
<td>15,889</td>
<td>3.2%</td>
</tr>
<tr>
<td>Miscellaneous</td>
<td>273</td>
<td>1,771</td>
<td>6.2%</td>
<td>11,866</td>
<td>2.4%</td>
</tr>
</tbody>
</table>

Notes: a Two-digit industry is assigned on the 1972 SIC basis. b Total manufacturing observations are computed using LRD data for 1980–1988.

Table 2.—Number of Observations and Plants in Data Set by Average Plant Size

<table>
<thead>
<tr>
<th>Average Size</th>
<th>Number of Plants in Data Set</th>
<th>Number of Observations in Data Set</th>
<th>Percent of Data Set</th>
</tr>
</thead>
<tbody>
<tr>
<td>250–500 employees</td>
<td>7,750</td>
<td>59,538</td>
<td>54.2%</td>
</tr>
<tr>
<td>500–1000 employees</td>
<td>3,853</td>
<td>31,138</td>
<td>28.4%</td>
</tr>
<tr>
<td>1000–2500 employees</td>
<td>1,701</td>
<td>13,778</td>
<td>12.6%</td>
</tr>
<tr>
<td>2500–5000 employees</td>
<td>429</td>
<td>3,495</td>
<td>3.2%</td>
</tr>
<tr>
<td>5000+ employees</td>
<td>203</td>
<td>1,698</td>
<td>1.6%</td>
</tr>
<tr>
<td>All plants</td>
<td>13,936</td>
<td>109,647</td>
<td>100%</td>
</tr>
</tbody>
</table>

Note: a Plants are assigned to a size class based on their average size over the entire sample period.

This size measure captures each plant’s long-run average employment, and is chosen to avoid transitory fluctuations in size (Davis et al. (1995)). Current size (in particular, the lag of the plant’s employment) was tested, and the results were not substantially different from the average-size results.

Because the Census Bureau samples “small” plants (i.e., plants with less than 250 employees) in five-year time-varying panels, data for most “small” plants are incomplete. Construction of the age variables for this additional robustness test, I construct a balanced panel containing both large and “small” plants. (There are approximately 7300 large plants and 4004 “small” plants in existence for the entire 1972–1988 time period.) The pooled productivity and productivity growth regressions, with and without fixed effects, are run for two different definitions of investment age (specifically, the RIS and the CIS; see section IV for details). The results from these eight regressions are qualitatively identical to those using the original data set. However, most of the coefficients from the regressions using the balanced panel are statistically insignificant.
manufacturing sector. All size classes are well represented in the sample, though plants are concentrated in the “smaller” of these large-size classes.

Finally, table 3 reports the distribution of plants over time. While many plants are active for the entire sample period, there are 969 entrants and 2592 exitors in the sample.\(^1\)

A. Variable Construction

I proceed with a description of the construction of several important variables: plant age, investment spike, and investment age.

**Plant Age:** Data from 1972 through 1980 are used. Starting in 1980 and looking back to 1972, plant age is defined as the difference between the current year and the first year the plant is recorded in the data set, until the plant reaches age 8. In subsequent years, the plant is assigned an age of eight (8\(^+\)). The range of plant age is 0 to 8\(^+\), creating nine plant-age categories.\(^4\) Thus the regressions include eight plant-age dummy variables. Table 4 reports the number of observations in these age categories. Although all ages have a substantial number of observations, the majority of observations in the sample is in the oldest category.

**Investment Spike:** The time elapsed since the occurrence of a “large” investment, or investment age, provides a measure of a plant’s capital vintage. In order to determine a plant’s investment age, I must first identify “lumpy” investment episodes, or investment spikes, and then track the time elapsed between those episodes. Thus the definition of investment age requires a precise definition of an investment spike.

Let \(\beta_t\), or the rate of investment in period \(t\), equal the ratio of the plant’s nominal new machinery purchase \(n_m\) in year \(t\) to the nominal book value of machinery assets at the end of period \(t\), \(m_a\).\(^5\) Define \(\beta_{\text{norm}}\) as the plant’s median investment, or normal investment, over the sample period.\(^6\)

**Definition:** A relative investment spike occurs in year \(t\) if \(\beta_t > \alpha \beta_{\text{norm}}\).

The scaling parameter \(\alpha\) attempts to satisfy the concept of “large.” However, any parameterization is admittedly ad

<table>
<thead>
<tr>
<th>Year</th>
<th>Number of Plants in Data Set</th>
<th>Percent of Data Set</th>
</tr>
</thead>
<tbody>
<tr>
<td>1980</td>
<td>13,004</td>
<td>12.0%</td>
</tr>
<tr>
<td>1981</td>
<td>12,883</td>
<td>11.7%</td>
</tr>
<tr>
<td>1982</td>
<td>12,634</td>
<td>11.5%</td>
</tr>
<tr>
<td>1983</td>
<td>12,442</td>
<td>11.3%</td>
</tr>
<tr>
<td>1984</td>
<td>12,254</td>
<td>11.2%</td>
</tr>
<tr>
<td>1985</td>
<td>12,118</td>
<td>11.1%</td>
</tr>
<tr>
<td>1986</td>
<td>11,891</td>
<td>10.8%</td>
</tr>
<tr>
<td>1987</td>
<td>11,310</td>
<td>10.3%</td>
</tr>
<tr>
<td>1988</td>
<td>11,111</td>
<td>10.1%</td>
</tr>
</tbody>
</table>

Note: From 1980 to 1988, 969 plants are born and 2592 plants die.

<table>
<thead>
<tr>
<th>Year</th>
<th>Number of Plants in Data Set</th>
<th>Percent of Data Set</th>
</tr>
</thead>
<tbody>
<tr>
<td>Just born</td>
<td>971</td>
<td>0.9%</td>
</tr>
<tr>
<td>1 year old</td>
<td>1,218</td>
<td>1.1%</td>
</tr>
<tr>
<td>2 years old</td>
<td>1,335</td>
<td>1.2%</td>
</tr>
<tr>
<td>3 years old</td>
<td>1,329</td>
<td>1.2%</td>
</tr>
<tr>
<td>4 years old</td>
<td>1,298</td>
<td>1.2%</td>
</tr>
<tr>
<td>5 years old</td>
<td>1,124</td>
<td>1.0%</td>
</tr>
<tr>
<td>6 years old</td>
<td>1,405</td>
<td>1.3%</td>
</tr>
<tr>
<td>7 years old</td>
<td>2,875</td>
<td>2.6%</td>
</tr>
<tr>
<td>8+ years old</td>
<td>98,092</td>
<td>89.5%</td>
</tr>
</tbody>
</table>

1 The observed relationship between productivity and plant age is in part a result of selection, that is, exit of “failures” presumably causes the mean productivity of a given cohort to rise with age. To allow for this effect, no Heckman correction for sample selection bias is performed. However, to understand the impact of exiting plants on the results, several diagnostic tests are performed. In particular, (1) the distribution of observations across investment-age categories is tabulated, (2) a probit analysis is performed, and (3) the pooled productivity-level regression without fixed effects is run (and descriptive statistics are tabulated) separately for surviving and failing plants. The results are as follows. First, a noticeably smaller percentage of failing plants has investment-age 0 (1%), and a noticeably larger percentage has investment age 8. In subsequent years, the plant is assigned an age of eight (8\(^+\)). The range of plant age is 0 to 8\(^+\), creating nine plant-age categories.\(^4\)

13 The range of plant age is 0 to 8\(^+\), creating nine plant-age categories.\(^4\) Thus the regressions include eight plant-age dummy variables. Table 4 reports the number of observations in these age categories. Although all ages have a substantial number of observations, the majority of observations in the sample is in the oldest category.

14 While many plants are active for the entire sample period, there are 969 entrants and 2592 exitors in the sample.\(^1\)

15 See Baily et al. (1992) for evidence that the book value of capital provides an accurate proxy for capital stock. Cooper et al. (1995) define \(\beta\) as each plant’s new machinery investment divided by its capital stock (rather than by \(m_a\)), and the identification of investment spikes is not meaningfully altered. Note that end-of-period machinery assets \(m_e\), rather than the traditional beginning-of-period machinery assets \(m_b\), are used because the nature of Census data is such that beginning-of-period assets do not exist in 1972, and they are imputed in 1986 and 1988. Therefore using \(m_a\) allows the most information possible to be used. The investment rate \(\beta\) captures gross investment, because it is not net of depreciation. Finally, note that the investment rate \(\beta\) is used for the absolute and the combined spike definitions.

16 The plant’s mean investment was also tested as a measure of \(\beta_{\text{norm}}\). However, most plants have \(\beta\) distributions that are skewed to the left, but which have a long, wide right-hand tail, indicating the periodic occurrence of unusually large investments. This is consistent with empirical observations, and consistent with the existence of fixed costs. It further implies that the mean of \(\beta\) can be substantially higher than the typical \(\beta\). On average, the mean definition results in fewer investment spikes. Several of the regressions were run on the mean specification to test for robustness, and the results were largely unaffected. Therefore the median was deemed to be the better measure of typical.
Furthermore, the spike definition captures the absolute, as opposed to relative, investment spikes using an absolute criterion. The absolute spike definition is often assumed to embody technical change (i.e., machinery, structures, and therefore reflects the type of investment that is suited for capturing smooth, potentially large expansions. A combined investment spike occurs in year \( t \) if either the absolute or the relative spike criteria are satisfied.

A further complication arises in the definition of an investment spike. Some investment projects are so large that they last more than one year. Thus a single, annual accounting period would not necessarily reflect the total expenditures necessary to complete the project. Furthermore, even a year-long project need not start at the beginning of an accounting year, nor reach completion by the end of an accounting year. Thus the expenditure necessary to complete an investment project could be distributed over two consecutive years. In those instances, the actual investment spike is the total investment recorded in the relevant years.

In an effort to capture such events, adjacent years of relatively intense investment activity are grouped into a single investment event. This grouping is labeled a multiyear spike and is defined as follows.\(^{19} \)

**Definition:** A multiyear investment spike occurs over periods \( t, \ldots, t + i \) if \( \beta_j > \eta \beta_{\text{norm}} \) and \( \beta_{t+j} > \eta \beta_{\text{norm}} \), where \( j = 1, \ldots, i \).

The scaling parameter \( \eta \) reflects the fact that if an investment project spans several years, the amount of investment in any particular year might be low (relative to an investment project concentrated in one year). However, as with \( \alpha \), the chosen value of \( \eta \) is ad hoc. Therefore three alternative values of \( \eta \) are employed: 0.90, 0.85, and 0.80.

With the definitions of plant age and investment spike in hand, I can now turn to the construction of investment age, which measures the time elapsed since a plant’s most recent investment spike.

**Investment Age:** The analysis is initialized in 1980, but data from 1972 through 1980 are used to construct eight

\(^{17}\) As discussed more fully below, the qualitative results appear to be essentially invariant to the value of the scaling parameter employed. Therefore I focus the discussion on the least stringent criterion, where \( \alpha \) equals 1.75.\(^ {18} \)

\(^{18}\) In order to maintain consistency in the definition of an investment spike, \( \alpha \) is restricted to be the same for every plant.

\(^{19}\) For absolute spikes, if \( \beta_j > 0.2, \ldots, \beta_{t+n} > 0.2 \), a multiyear spike occurs in the years \( t, \ldots, t + n \). An investment spike occurs under the combined spike definition if either the absolute or the relative spike criteria are satisfied. That is, if \( \beta_j > 0.2 \) or \( \beta_{t+n} > \alpha \beta_{\text{norm}} \), then a combined spike occurs in year \( t \); and likewise for a multiyear combined spike, if \( \beta_j > 0.2 \) or \( \beta_{t+n} > \alpha \beta_{\text{norm}} \), then a combined spike occurs in years \( t, \ldots, t + n \).
precise investment-age categories. Starting in 1980 and looking back to 1972, a plant’s investment age is equal to its plant age until a plant has its first investment spike. Thereafter investment age is set equal to the difference between the current year and the year of a plant’s most recent investment spike, until the plant reaches investment age 8. In each subsequent year, the plant is assigned an investment age of 8+ until it experiences another investment spike. Plants that never experience an investment spike have investment ages equal to their plant age for the entire sample period. The range of investment age is 0 to 8+, creating nine investment-age categories. Thus the regressions include eight investment-age dummy variables. Table 6 reports the distribution of plants across investment ages. The distribution is fairly uniform, with a slight downward trend, until age 8+.

V. Results

As noted previously, investment age is constructed, and the empirical model estimated, using three different definitions of an investment spike: (1) a relative investment spike (RIS), (2) an absolute investment spike (AIS), and (3) a combined investment spike (CIS). Furthermore, since there are three values of $\alpha$ and three values of $\eta$, there are nine different definitions of an RIS. The four specifications of the regression equation (using productivity as the dependent variable estimated with and without fixed effects, and productivity growth with and without fixed effects) are estimated on the pooled sample using the nine RIS criteria, the AIS criterion, and the CIS criterion. In order to make the discussion of the results tractable, the pooled estimates are discussed under the RIS criterion with $\alpha = 1.75$ and $\eta = 0.90$. The qualitative results are very similar across the different definitions of an investment spike when the regressions are estimated on the pooled data set. To the extent that differences occur, they are most often relatively minor differences in magnitude, although there are a few changes in statistical significance. Discussion of meaningful differences in the results obtained under these various specifications is provided.

The discussion of the results proceeds as follows. First, I discuss the pooled plant-age results; then I turn to the pooled investment-age results. I conclude this section with a discussion of the by-industry results.

A. Pooled Plant-Age Results

Table 7 provides the estimated coefficients and associated standard errors for the four specifications of the pooled results in columns (1) through (4). Figure 1 plots the plant-age coefficients and figure 2 the investment-age coefficients. Figures 1 and 2 are divided into four panels (A) through (D), representing columns (1) through (4) of table 7.

Consider first the productivity-level regression without plant fixed effects (Figure 1, panel (A), which plots the plant-age coefficients from column (1) in Table 7). The pattern illustrates the cross-plant variation in productivity with respect to age. The hump-shaped pattern offers some evidence that the exit of low-productivity plants causes the mean productivity across plants to increase with age: selection is important. It could also reflect learning by doing and, possibly, life-cycle effects (Grabowski and Mueller (1972)).

The lower productivity of older plants, relative to newer plants, is consistent with Campbell (1993), in which sunk costs give new plants an advantage in acquiring the most recent technology. However, productivity increases with plant age until age 4, which is not as consistent with this theory.

The results from the regression controlling for plant-level fixed effects (figure 1, panel (C)) show productivity increasing monotonically with plant age. Controlling for plant-level fixed effects implies that the variation in productivity with respect to plant age is within plant variation. This monotonic increase may indicate that learning is an important systematic patterns with respect to one particular age group. The results were robust to the alternative definitions.

In the regressions both with and without fixed effects there is some sensitivity to the investment spike specification in the magnitude and statistical significance of the plant-age coefficients. In particular, the quantitative magnitudes (particularly of the age 8+ coefficients) are reduced in the AIS and CIS specifications. This discrepancy is somewhat perplexing. Perhaps when investment age is defined in terms of the AIS and the CIS, it absorbs some of the variation in productivity with respect to plant age. Note, however, that the pattern of productivity with respect to plant age under all three investment spike specifications is the same. Because the fixed-effects regressions measure the within-plant variation of productivity, the plants that are always age 8+ are effectively dropped from the fixed-effects regressions.
Table 7.—Regression Results Describing the Relationship Between Productivity and Age

<table>
<thead>
<tr>
<th>Investment age</th>
<th>Productivity Growth (1)</th>
<th>Productivity Controls Plant Effects (2)</th>
<th>Productivity Growth Controls Plant Effects (3)</th>
<th>Productivity Growth Controls Plant Effects (4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>8 years old</td>
<td>-0.052</td>
<td>0.002</td>
<td>0.010</td>
<td>0.001</td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.004)</td>
<td>(0.005)</td>
<td>(0.006)</td>
</tr>
<tr>
<td>7 years old</td>
<td>-0.029</td>
<td>-0.012</td>
<td>0.017</td>
<td>-0.008</td>
</tr>
<tr>
<td></td>
<td>(0.012)</td>
<td>(0.006)</td>
<td>(0.006)</td>
<td>(0.007)</td>
</tr>
<tr>
<td>6 years old</td>
<td>-0.017</td>
<td>0.001</td>
<td>0.000</td>
<td>0.006</td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(0.006)</td>
<td>(0.006)</td>
<td>(0.006)</td>
</tr>
<tr>
<td>5 years old</td>
<td>-0.029</td>
<td>-0.003</td>
<td>-0.003</td>
<td>0.002</td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(0.005)</td>
<td>(0.005)</td>
<td>(0.006)</td>
</tr>
<tr>
<td>4 years old</td>
<td>-0.027</td>
<td>0.001</td>
<td>-0.002</td>
<td>0.005</td>
</tr>
<tr>
<td></td>
<td>(0.010)</td>
<td>(0.005)</td>
<td>(0.005)</td>
<td>(0.005)</td>
</tr>
<tr>
<td>3 years old</td>
<td>-0.017</td>
<td>0.001</td>
<td>-0.001</td>
<td>0.003</td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.005)</td>
<td>(0.005)</td>
<td>(0.005)</td>
</tr>
<tr>
<td>2 years old</td>
<td>-0.010</td>
<td>0.002</td>
<td>0.001</td>
<td>0.004</td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.005)</td>
</tr>
<tr>
<td>1 year old</td>
<td>-0.012</td>
<td>0.006</td>
<td>-0.005</td>
<td>0.008</td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.005)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Plant age</th>
<th>Productivity Growth (1)</th>
<th>Productivity Controls Plant Effects (2)</th>
<th>Productivity Growth Controls Plant Effects (3)</th>
<th>Productivity Growth Controls Plant Effects (4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>8 years old</td>
<td>-0.116</td>
<td>-0.012</td>
<td>0.103</td>
<td>-0.023</td>
</tr>
<tr>
<td></td>
<td>(0.030)</td>
<td>(0.012)</td>
<td>(0.019)</td>
<td>(0.019)</td>
</tr>
<tr>
<td>7 years old</td>
<td>-0.062</td>
<td>-0.005</td>
<td>0.078</td>
<td>-0.027</td>
</tr>
<tr>
<td></td>
<td>(0.033)</td>
<td>(0.011)</td>
<td>(0.020)</td>
<td>(0.019)</td>
</tr>
<tr>
<td>6 years old</td>
<td>0.069</td>
<td>-0.008</td>
<td>0.062</td>
<td>-0.035</td>
</tr>
<tr>
<td></td>
<td>(0.036)</td>
<td>(0.016)</td>
<td>(0.020)</td>
<td>(0.019)</td>
</tr>
<tr>
<td>5 years old</td>
<td>0.111</td>
<td>0.003</td>
<td>0.055</td>
<td>-0.022</td>
</tr>
<tr>
<td></td>
<td>(0.037)</td>
<td>(0.017)</td>
<td>(0.020)</td>
<td>(0.019)</td>
</tr>
<tr>
<td>4 years old</td>
<td>0.131</td>
<td>0.013</td>
<td>0.039</td>
<td>-0.008</td>
</tr>
<tr>
<td></td>
<td>(0.037)</td>
<td>(0.016)</td>
<td>(0.019)</td>
<td>(0.018)</td>
</tr>
<tr>
<td>3 years old</td>
<td>0.100</td>
<td>0.027</td>
<td>0.008</td>
<td>0.015</td>
</tr>
<tr>
<td></td>
<td>(0.036)</td>
<td>(0.016)</td>
<td>(0.018)</td>
<td>(0.017)</td>
</tr>
<tr>
<td>2 years old</td>
<td>0.062</td>
<td>0.054</td>
<td>-0.007</td>
<td>0.042</td>
</tr>
<tr>
<td></td>
<td>(0.036)</td>
<td>(0.016)</td>
<td>(0.018)</td>
<td>(0.017)</td>
</tr>
<tr>
<td>1 year old</td>
<td>-0.003</td>
<td>0.000</td>
<td>-0.059</td>
<td>—</td>
</tr>
<tr>
<td></td>
<td>(0.037)</td>
<td>(0.000)</td>
<td>(0.018)</td>
<td>—</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Size</th>
<th>Productivity Growth (1)</th>
<th>Productivity Controls Plant Effects (2)</th>
<th>Productivity Growth Controls Plant Effects (3)</th>
<th>Productivity Growth Controls Plant Effects (4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>250–500</td>
<td>-0.534</td>
<td>-0.040</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>employees</td>
<td>(0.019)</td>
<td>(0.010)</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>500–1000</td>
<td>-0.466</td>
<td>-0.036</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>employees</td>
<td>(0.019)</td>
<td>(0.010)</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>1000–2500</td>
<td>-0.340</td>
<td>-0.031</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>employees</td>
<td>(0.020)</td>
<td>(0.010)</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>2500–5000</td>
<td>-0.122</td>
<td>-0.019</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>employees</td>
<td>(0.023)</td>
<td>(0.011)</td>
<td>—</td>
<td>—</td>
</tr>
</tbody>
</table>

Note: Standard errors are in parentheses.

Now consider the productivity growth rate regressions, which demonstrate how plant-level productivity growth varies with respect to plant age. The without fixed-effects growth rate regression (figure 1, panel (B)) suggests that, across plants, productivity growth decreases with respect to age, which suggests the presence of learning. Defining a plant less than 2 years old as a “new” plant, the lower productivity of older plants, relative to “new” plants, suggests the existence of plant-embodied technical change.

The results from the fixed-effects growth rate regression (figure 1, panel (D)) also suggest that productivity growth within a plant decreases, and in some cases becomes negative, with respect to plant age. Like the level regressions, this might support the concept of learning. However, the quantitative magnitudes are small, and most of the growth rate coefficients are not statistically significant. Nevertheless, F-tests were performed for all regressions, and, as a whole, plant age is significant.

Overall, these results offer some support for the notion that differences across plants, which are manifested through selection and learning, are important determinants of observed productivity patterns. The statistical significance of the coefficients for plant size, permanent plant characteristics, and industry, as well as the importance of permanent differences across plants (captured in plant-level fixed effects) further strengthen this point.

In certain respects, a combination of theories best explains the results. That is, sunk costs imply that new plants have a relative advantage in acquiring the most recent technology. Therefore new plants have higher productivity than older plants. Furthermore, there is evidence that productivity increases for several years following birth, which suggests that learning and selection are also important.

B. Pooled Investment-Age Results

This section provides a discussion of the pooled investment-age results. First, consider the productivity regression without fixed effects (figure 2, panel (A), which plots the investment-age coefficients from column (1) in table 7). The small decrease in productivity with respect to investment age offers minor evidence that high levels of recent investment are associated with relatively higher productivity.24

24 These coefficients exhibit some minor sensitivity to the specification of an investment spike. For the RIS definition, , , productivity is almost constant across investment ages until age 8+, where it decreases slightly. For , it is positive and increases moderately until age 8+. However, any difference is very small in magnitude, and differences disappear in the fixed-effects regressions. The estimates from the AIS and CIS regressions are almost identical to the coefficients, but the decline in productivity is slightly more pronounced. (For the AIS the coefficients decline slowly from 0.009 at age 1 to −0.03 at age 7; the coefficient for age 8+ is −0.09, and two more of the age coefficients are statistically significant.) However, the differences, and nearly all the statistical significance, disappear in the fixed-effects regressions. The sensitivity of both sets of results suggests that unobserved differences across plants affect the composition of plants in each investment-age category. The fact that the sensitivity is absent in the regressions with fixed effects supports this interpretation. For a more complete discussion of cross-sectional heterogeneity in general, and as it relates to investment spikes, see Power (1994).
However, even this minor variation essentially disappears in the remaining three regressions: specifically, the productivity regression with plant fixed effects (figure 2, panel (C)), the growth rate regression without fixed effects (panel (B)), and the growth rate regression with fixed effects (panel (D)). Most of the individual coefficients are statistically insignificant.

Plants that are replacing worn-out, depreciated capital are likely to experience increases in productivity after a large investment. In an attempt to isolate such investments more precisely, the CIS, AIS, and RIS productivity and productivity growth regressions are also performed on the subset of observations that occur after a plant’s first “true” (i.e., nonbirth) investment spike. For this subsample, plants that never have an investment spike are excluded, and only those spikes that are unrelated to plant birth are included. Thus investment age is distinct from plant age in this subsample.

The qualitative results for this experiment are similar to those for the full sample: any observable relationship between the level of productivity and investment age, to the extent that there is one, disappears in the regressions that control fixed effects. However, the expected relationship between productivity and investment does appear, although only to a limited extent, in the productivity growth regressions which control fixed effects. The investment-age coefficients are somewhat larger than those for the full sample, and the coefficients are statistically significant in some cases. In every case, however, the increase remains quite small.

For example, in the “strongest” case (RIS and $\alpha = 3.25$) the coefficients are 0.019 for investment ages 1, 2, and 4; 0.018 for investment age 3; 0.024 for investment age 5; 0.021 for investment age 6; 0.026 for investment age 7; and 0.031 for investment age 8+. Although small is in the eye of the beholder, the implied increases in productivity again appear surprisingly modest, particularly given the nature of this subsample and given the magnitude of the investment required to qualify as an investment spike ($\alpha = 3.25$).

The fact that it is so difficult to observe a positive correlation between high productivity and high levels of
recent investment in such a large sample of plants casts at least some doubt on the assumption that is implicit in much of U.S. fiscal policy—that investment is the primary agent of productivity growth. Rather, the importance of plant fixed effects suggests that unique characteristics of plants, such as their management or location, might be more important determinants of their productivity. The importance of plant-level fixed effects is consistent with predictions of models of plant dynamics, as well as some of the empirical results described above (Baily et al. (1992), Olley and Pakes (1992), and Bartelsman and Dhrymes (1992)).

A few related results help to corroborate the importance of plant characteristics. For example, the coefficients on the size dummy variables indicate that, for all regression specifications, productivity and productivity growth increase monotonically with size (see table 7). All of the coefficients are statistically significant. In general, large plants are more capital intensive than small plants, which is consistent with this result. The significance of plant size may also reflect selection: successful plants survive and grow, whereas unsuccessful plants shrink and fail. The importance of plant-level fixed effects provides further evidence of the importance of differences across plants, as does the importance of both industry and year effects.

However, as mentioned earlier, there are many different types of investment projects, and not all of them are necessarily associated with increases in productivity. Thus one possible explanation for the weak correlation between investment and productivity could be that the bulk of the investment occurring in U.S. manufacturing plants is expansion investment, performed by successful plants which are trying to increase capacity, rather than replacement investment, performed by less productive plants attempting to boost productivity.

The RIS and AIS specifications distinguish among types of investment to a limited extent (i.e., recall that the RIS focuses somewhat more precisely on replacement and retooling investment, whereas the AIS focuses more on smooth, expansion investment). In this sense, the fact that both AIS and RIS specifications for the full sample reveal
almost no correlation between productivity and investment age (and, furthermore, to the extent that there is an observable pattern it is more evident in the AIS specification) casts some doubt on the above-mentioned explanation of the weak correlation between productivity and investment age.

Finally, although substantial variation in investment spike and productivity patterns occurs across industry, size class, age, and year, the patterns exhibit at least as much variation within a given sector. Observable plant characteristics only capture underlying differences to a limited extent: the importance of the unexplained idiosyncratic component must therefore be acknowledged.

C. By-Industry Results

In an effort to get a better sense of the microeconomic structure underlying the pooled investment-age results, the empirical model, described in equations (1) and (2), is estimated by two-digit SIC industry codes. Overall there are no striking results in the separate industry regressions, particularly in the regressions that control fixed effects. Most industries exhibit only modest, if any, variation in productivity with respect to either plant age or investment age, and most of the estimated coefficients are statistically insignificant. However, a careful review of these results does offer some useful insights. A summary of the highlights follows.

To assist in the discussion, figure 3 plots the estimated coefficients for four representative industries (SIC 23, 26, 28, and 36), which are discussed below. Each panel plots the coefficients for a distinct industry. In each panel, four

25 The by-industry regressions were run using the level of productivity as the left-hand side variable, with and without fixed effects. These two regressions were run for the AIS definition, the CIS definition, and one of the RIS definitions.

26 The coefficients from the AIS regressions are plotted because they most obviously exhibit the relevant patterns.
sets of coefficients are plotted: the plant-age coefficients from the regression without fixed effects, the plant-age coefficients from the regression with fixed effects, the investment-age coefficients from the regression without fixed effects, and the investment-age coefficients from the regression with fixed effects.

First, in many of the separate industry regressions, the plant-age coefficients are not always positive, nor are they statistically significant. This is true both in the regressions that omit plant-specific controls and in those that include plant-specific controls. This suggests that plant age does not explain the variation in productivity in every industry.

Second, in a few industries (e.g., the paper industry (SIC 26, panel (A)) and the chemicals industry (SIC 28, panel (B))) some investment-age coefficients are statistically significant in the across-plant regressions, although plant age is not. Thus in a few industries investment age appears to be somewhat more important than plant age in explaining variation in productivity. However, the variation in productivity with respect to investment age is modest. Furthermore, this variation is less pronounced, and many of the coefficients are statistically insignificant in the fixed-effects regressions.

Third, the pattern of productivity with respect to investment age and plant age is not identical across industries. For example, some industries exhibit very modest decreases in productivity with respect to investment age across plants (e.g., the apparel industry (SIC 23, panel (C)) and the electric machinery industry (SIC 36, panel (D)), while others exhibit very modest increases in productivity with respect to investment age (e.g., paper and chemicals).

The absence of a consistent relationship between productivity and investment age across industries may indicate that some industries are characterized by infrequent reinvestment and expansion, coupled with long learning curves associated with new investment. Other industries may be characterized by more rapid technological progress, which requires frequent reinvestment in order to remain competitive. The mild increase in productivity is also suggestive of investment-based selection. However, in nearly every case there is virtually no variation in productivity with respect to investment age in the regressions that control fixed effects. This, in turn, suggests that unobserved heterogeneity across plants causes variation in productivity with respect to investment age in the cross-plant regressions.

Finally, although the results across investment spike definitions are qualitatively similar, there is some evidence of sensitivity in the magnitude of the estimated coefficients, as well as their statistical significance, to the definition of an investment spike. This is particularly evident in the nonelectric machinery industry (SIC 35).27

Although the variation, sensitivity, and patterns discussed above are interesting, I should reiterate that the magnitudes of these patterns are very small, and (with the exception of nonelectric machinery (SIC 35)) most of the coefficients are statistically insignificant in the regressions controlling for fixed effects. Thus, plant age and investment age explain only a modest amount of the variation in productivity. Again, we are left to conclude that the idiosyncratic component (i.e., individual plant characteristics) is by far the most important determinant of plant productivity.

VI. Conclusions

This investigation is designed to provide insight into the relationships between investment age, plant age, and productivity. The investigation was conducted using plant-level data, containing information on nearly 14,000 plants over an 18-year period. I find little evidence of a robust, economically meaningful correlation between high productivity and high recent investment. This cautions against the efficacy of fiscal policy that is based on the premise that investment causes high productivity.

The results offer several additional interesting insights. First, the importance of plant-level fixed effects, and the finding that productivity increases with respect to plant age, suggest that observed and unobserved plant heterogeneity may influence economic evolution. The relationship between productivity and plant age also suggests that selection and learning could be important determinants of the pattern of productivity across plants. Thus, theoretical models that incorporate such heterogeneity may help characterize and understand it. Empirical research which utilizes plant-level data and explores inherent plant dynamics may provide investment age for the RIS specification, while it decreases substantially with respect to investment age for the AIS specification. However, in the fixed-effects regressions for both RIS and the AIS specifications, productivity is virtually constant with respect to investment age. Second, productivity increases and then decreases with respect to plant age for the regressions without fixed effects, and increases monotonically for the regressions with fixed effects. However, the magnitudes of the plant-age coefficients are much smaller in the AIS regressions than in the RIS regressions. Taken together, these regressions illustrate three important lessons. First, particular patterns of investment behavior (e.g., frequent, large investments versus sporadic, restructuring investments) might be more prevalent in particular industries. For example, the presumably high obsolescence rate in the nonelectric machinery industry probably requires frequent, large expansions. This might explain why the AIS criterion better explains productivity variation across plants in this industry than the RIS criterion. Second, although the magnitudes of the investment-age coefficients are not large, the sensitivity of the plant-age coefficients to the investment-age variable suggests that vintage effects do matter, and therefore it is wise to control for both plant age and investment age when analyzing productivity. Finally, the difference in the investment-age coefficients in the regressions with fixed effects versus those without fixed effects again suggests that it is the unobserved differences across plants, or, equivalently, cross-sectional heterogeneities in the various investment-age categories, that cause the decreasing pattern in the regressions without fixed effects. If “winner” plants invest more than “loser” plants in the nonelectric machinery industry, this would cause the across-plant productivity–investment-age relationship to be decreasing, but the within-plant productivity–investment-age relationship to be fairly constant.

27 The nonelectric machinery industry includes the computer industry. The volatility of this rapidly changing industry mandates a more in-depth analysis before sound conclusions can be drawn. However, the results from this study provide an interesting introduction. First, in the regressions without fixed effects, productivity is virtually constant with respect to
insight into plant and industry performance. Generally speaking, the results are consistent with the notion that sunk costs have an impact on the diffusion of new technology. Perhaps a model that combines these two concepts will provide better predictions.

Second, the results provide almost no evidence of a strong positive relationship between productivity and investment age. This raises many questions regarding the role of investment in the dissemination of technology. An alternative explanation for the weak relationship between productivity and investment is that higher productivity is simply not the primary motivation for investment. For example, overinvestment, poor-quality investments, and low productivity can result if managers are maximizing their own utility rather than firm profits (Grabowski and Mueller (1972)). If, as some industrial organization theories suggest, incumbents in an industry use investment as a strategic device to deter entry, then cost minimization is not the only incentive for investment.  

Furthermore, tax policy potentially contributes to overinvestment. The influence of tax policy on investment decisions is apparent in the 1985 investment surge, which preceded the 1986 repeal of the investment tax credit. Rather than targeting investment as a whole, perhaps some criteria for targeting efficient producers ought to be explored. One important direction for future research is to explore the relative productivity of investments made under differing tax regimes.

Another direction for future research is to attempt to identify the occurrence and implications of different types of investments more precisely. As mentioned above, if investment is expansionary, then increases in investment need not be associated with increases in productivity. Some of the results from this study could suggest that expansionary investment is more prevalent than replacement investment for U.S. manufacturing plants. Further exploration and understanding of the impact of different forms of investment on productivity could be enlightening for policy makers, economists, and even investment analysts.

Finally, as well as those mentioned earlier, an additional caveat should be noted. Any attempt to decompose the complex, interconnected world into simple cause and effect relationships incurs a risk that elements of the investigation itself precipitate the results. This investigation is no exception. The presence of so many forms of heterogeneity in the data make the identification of investment heterogeneity problematic, and this problem is exacerbated because it is difficult to define the theoretical construct of an investment spike empirically.

28 See von Stackelberg (1934), Spence (1979), and Dixit (1980). In these theories, since investment is irreversible, overinvestment in capital by incumbents can have the strategic effect of deterring entry by opponents, or at least of reducing their scale. In this case the incumbent, rather than the entrant, has the advantage, and the investment decision involves more than pure cost minimization.

The caveats notwithstanding, this analysis provides a simple, straightforward test for any reduced-form relationship between productivity and investment. Strikingly, despite a thorough exploration of alternative variable definitions and econometric specifications, no strong relationship between productivity and investment can be discerned. Given that major aspects of economic theory and fiscal policy place a strong emphasis on investment as the vehicle for productivity and output growth, these findings obligate us to continue investigating the cherished link between investment and productivity.

In his 1960 paper on technical progress, Solow concluded that “[c]apital formation is not the only source of growth in productivity. Investment is at best a necessary condition for growth, surely not a sufficient condition.” His insight should remind us that there are other factors, perhaps even more important than investment, which may determine productivity. The role of human capital, research and development, communications, and management should not be ignored. In fact, these factors have probably become more important over time. Some recent research has begun to investigate these variables. Hopefully future studies will continue to analyze these factors.

REFERENCES


