Does Productivity Growth Fall After the Adoption of New Technology?

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Abstract

A number of theoretical models of technology adoption have been proposed that imply that measured productivity growth may initially fall and then later rise after the adoption of a new technology. This paper investigates whether or not this implication is a feature of plant-level data from the Colombian manufacturing sector. We focus on technology adoption embodied in new equipment, given the emphasis put on embodied technological change in the literature. We find evidence that the effect of a large equipment purchase is initially to reduce and then to increase plant-level total factor productivity growth.

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1 Introduction

A number of theoretical models of technology adoption have been proposed with the following feature. After a production unit adopts a new technology, not all the expertise in the old technology transfers to the new technology and there is a period of technology-specific learning. One implication of these theories is that measured productivity growth may at first fall and then later rise after adopting a superior technology.[1]

In this paper we provide micro-evidence on the question of whether productivity growth falls after the adoption of new technology embodied in new equipment. We are motivated to address this question for two main reasons. First, micro-evidence on productivity growth is key for issues related to aggregate productivity growth. For example, Greenwood (1996), Hornstein and Krusell (1996) and Greenwood and Yorukoglu (1997) evaluate the hypothesis that an increase in the pace of technology adoption that is embodied in new equipment is behind the aggregate productivity growth slowdown experienced by the majority of the advanced economies since the 1970's. As another example, Klenow (1998) argues that the cyclical properties of productivity growth at the industry level are consistent with technology adoption models where new technologies are embodied in new equipment. These studies all lack micro-evidence on the key empirical issues behind their analyses (i.e. Does productivity growth fall at existing production units after the adoption of technology that is embodied in new equipment? If so, then by how much?). Second, in the data set that we have explored the vast majority of equipment investment occurs at existing rather than brand new production units. Thus, we conjecture that it is the productivity dynamics at existing production units that will prove to be crucial for issues related to aggregate productivity growth rates.

To address the question posed above, we identify the adoption of a new technology at a particular production unit with the purchase of equipment. In particular, we will say that those plants making equipment purchases that increase their real equipment stocks by more than a critical fraction are adopting new technology embodied in new equipment. A number of remarks are in order in regards to this assumption. First, equipment purchases are precisely the mechanism of technology adoption emphasized in the literatures described above. Second, the evidence in the papers by DeLong and Summers (1991, 1993) and Greenwood et al (1997) suggests that equipment investment may be a quantitatively important source of technology adoption.[2] Third, in plant-

[1] Zeckhauser (1968), Parente (1994, 1998), Klenow (1998) and Yorukoglu (1998) provide theoretical models with these features.

[2] DeLong and Summers (1991, 1993) show that the growth rate of labor productivity across countries is highly positively correlated with the fraction of equipment investment in GDP. Greenwood et al (1997)

level data it is the case that investment displays a pronounced lumpy pattern at the plant level with the bulk of plants making little or no purchases of equipment in a given year but large percentage changes in the stock of equipment in other years.[3] Thus, our measure of technology adoption has the potential to correspond to the notion that major technology adoptions embodied in equipment occur somewhat infrequently. Lastly, we realize that our measure of technology adoption may not be a perfect measure of technology adoption embodied in new equipment. Our reaction to this is twofold. First, even if this is true we will still be addressing an interesting question. This question is whether the effect of a large purchase of equipment is initially to decrease productivity growth. Second, we regard it as a key issue for future research to focus on data sets that potentially allow one to distinguish between equipment purchases reflecting technology adoption versus those reflecting the acquisition of more capital of a technology known to the plant.

Our empirical strategy is straightforward. We focus on a data set of plants from the Colombian manufacturing sector. For each plant, we calculate total factor productivity (TFP) growth rates across time periods. We then regress the productivity growth of a plant on the current and past values of our plant-level measure of technology adoption, controlling for industry and/or time effects. We find evidence that productivity growth falls after a plant makes a large equipment purchase. More precisely, we find evidence that the effect of a large increase in a plant's stock of equipment is to at first reduce productivity growth by $2-5$ percent and then increase productivity growth in the subsequent year. The point estimates indicate that with a one year lag productivity growth increases by $1-2$ percent. Thus, if plants making large equipment investments are adopting new technologies embodied in new equipment, then this is evidence that technology adoption does lead to a temporary fall in productivity growth.

This paper is organized in four sections. Section 2 presents a number of background facts about the data set, plant-level productivity growth and plant-level investment in equipment. Section 3 presents our main results. Section 4 concludes.

1.1 Related Literature

To the best of our knowledge, there is only scattered micro-evidence bearing on the question that we address. We discuss work in three separate areas. First, there is a literature consisting of case studies by Baloff (1966, 1970), Russell (1968) and oth-

argue that the bulk of postwar US growth in labor productivity can be attributed to technological change embodied in new equipment.

[3]This is documented by Doms and Dunne (1998) and Cooper et al (1995) using US data and by Ospina (1994) and Isgut (1997) using Colombian data. In section 2.3 of this paper we also provide evidence on this point.

ers in which plants from the US manufacturing sector have changed products or the production process and in which the level of productivity initially falls and then later rises. These studies are part of a large literature on learning curves. The focus of this literature has been to document the upside of the learning curve rather than any potential downside after a switch in technology. This is true, for example, of the well-known work of Bahk and Gort (1993) who estimate learning at new plants in the US manufacturing sector.[4]

Second, there is a literature on adjustment costs and on firm-level investment. Parts of these literatures have been surveyed by Chirinko (1993) and Dixit and Pindyck (1994). While some of the models presented in these literatures are potentially consistent with the findings of this paper, the empirical component of these literatures has not answered the question that we pose. With this said, we are aware of some work that is is suggestive that firm investment in physical capital may be associated with falls in productivity. In particular, Pakes and Griliches (1984) regress firm-level, accounting profits on past investments. They find that accounting profit increases more strongly to investment lagged several periods than to more recent investment.

Third, there is an empirical literature on information technology, reviewed in part by Yorukoglu (1998). Some studies in this literature presents micro-evidence consistent with low measured returns to investment in information technology. Other studies in this literature present evidence for strong learning-by-doing effects after an investment in information technology when capital vintage is controlled for. However, just as in the case study literature, this literature focuses on the upside of the learning curve rather than any potential downside after an investment in information technology.

2 Background Facts

2.1 Description of Data Set

The Colombian Statistics Department (DANE) conducts an annual survey of plants in the Colombian manufacturing sector called the *Encuesta Anual Manufacturera*. DANE surveys all firms listed in the Industry directory. These firms are then required to report on all their plants with at least 10 employees. The data set covers the period 1974-1991. In a typical year the data set has between 6,000 and 8,000 plants.[5]

[4]See Argotte and Epple (1990), Jovanovic (1997) and Greenwood and Jovanovic (1998) for surveys of a number of distinct literatures related to learning.

[5]For a discussion of the methodology of the *Encuesta Anual Manufacturera* see DANE (1991). Research based on versions of this data set, some with and some without plant identification numbers, has been conducted by Roberts and Tybout (1996) and Isgut (1996) among others.

For each plant, data is collected on (1) employment and employee compensation, (2) capital inputs, (3) intermediate input, (4) production and (5) various other information. Employment is divided in six categories: proprietors, managerial, professional, employees, technicians and apprentices. Information on capital inputs is divided into five categories: buildings, machinery, office equipment, transport equipment and land. For each capital input there is data on book value, purchases of new and used capital, own production of capital, sales of capital, depreciation and revaluation. The data on bookvalues for a particular year are end-of-period values. An important feature of the data set is that DANE assigns each plant a plant identification number. Thus, it is possible to track individual plants over time. This means that a plant-specific measure of productivity growth can be calculated.

Our analysis focuses on the collection of plants present in all years of the data set that are not excluded by any of the following two criteria.[6] First, we exclude any plant for which any of the data needed to calculate TFP growth rates are missing. This data includes employment and employee compensation for each type of labor input, bookvalue of capital for the first year a plant appears in the data, investment data for each type of capital input, intermediate input consumption and gross production. In addition, we require strictly positive values for gross production, value added, capital services, intermediate input, total employment, total compensation and the real value of the stock of machines. Second, we exclude plants for which either the plant identification number is missing or repeated or for which the industry classification code is missing. After applying the above exclusion criteria, there are a total of 2125 plants in our data set each year and 31875 total observations on plants over the years $1976 - 90$. In any year of the data about half of these plants have less than 50 employees, whereas about 5 percent of the plants have 500 or more employees.

2.2 Productivity Growth Facts

This section characterizes some features of the distribution of TFP growth rates. The measurement of TFP growth rates is described in detail in the Appendix. Figure 1 plots the distribution of TFP growth rates in each year over the period 1976-90. Figure 1 shows that in each year (i) the median TFP growth rate is close to zero and typically positive, (ii) the TFP growth rate distribution is rougly symmetric with the vast majority of the plants having a TFP growth rate between 40 and -40 percentage points and (iii) a small percentage of plants (typically less that half of one percent)

[6] We focus on the balanced panel in order to minimize on measurement error in the calculation of TFP growth rates. We conjecture that plants that partially shutdown in a given year occur less frequently in the balanced than in the unbalanced panel. We suspect that productivity growth rates for these plants may be quite sensitive to the mismeasurement of the value of goods in the process of production.

have a TFP growth rate either greater than 100 percent or smaller than -100 percent. This last finding is represented in Figure 1 by plotting all plants with a growth rate of less than -100 percent at -1 and all the plants with a growth rate exceeding 100 percent at 1.[7]

We now comment on a number of other features of productivity growth rates in Figure 1. First, the variability of TFP growth rates is substantially greater at the plant level than what is observed in more highly aggregated data (e.g. industry or sectoral data). For example, TFP growth rates are typically between 0 and 10 percent when TFP growth rates are calculated for the Colombian manufacturing sector over the period 1976-90 using aggregate measures of outputs, inputs and factor shares. Second, although intuitively implausible, a straightforward application of Solow's growth accounting equation can produce TFP growth rates smaller than -100 percent. This can occur when input growth rates are large and positive and when output growth rates are not quite so large. We have examined a number of the cases of extreme negative TFP growth rates and have found that in these cases output increased by a couple of hundred percentage points whereas intermediate input increased at much greater rates.[8] The statistical methods employed in subsequent sections of this paper have been selected with these extreme observations in mind.

Insert Figure 1 Here

2.3 Equipment Investment Facts

We now document the distribution of plants by equipment purchases in real terms as a fraction of the stock of equipment in real terms. Our measure of equipment consists only of machinery and thus does not include investment in office equipment, transport equipment or structures. Investment in machinery is by far the largest component of investment in physical capital. In particular, in all years machinery investment is between 70 and 80 percent of the combined value of the investment in machinery, office equipment, transport equipment and structures.

Figure 2 examines the distribution of equipment investment in the balanced panel. We find that the distribution of plants by equipment investment as a fraction of the equipment stock is similar across years. In a given year about 30 percent of the plants make no purchases of equipment and approximately another 30 percent make purchases

[7]The maximum TFP growth rate is 60 (6000 percent) and the minimum is -287 (-28700 percent).

[8]Output is measured by gross production which measures both the value of finished goods produced as well as changes in the value of goods in the process of production. Thus, the extreme negative TFP growth rates are not due to not measuring goods in the process of production.

of less than 10 percent of the value of their equipment stock. Due to depreciation, these plants will not in net terms expand the value of their equipment stocks. The last point that Figure 2 makes is that in any given year between $5-15$ percent of the plants make purchases that increase their equipment stock by 50 percent or more and between $2-6$ percent of the plants make equipment purchases that more than double their stock of equipment.[9] In later sections we will say that plants making an equipment investment which increases the equipment stock by $25, 50$ or 100 percent are adopting new technology embodied in equipment.

Insert Figure 2 Here

In the introduction we claimed that continuing plants account for the bulk of the aggregate equipment investment in the Colombian manufacturing sector. Figure 3 provides some evidence on this point. Here we define a plant in the data set in a specific year t to be a continuing plant if it was in the data set in year $t-1$. Otherwise a plant in a specific year t is considered to be an entering (i.e. new) plant. Clearly, this definition may understate investment at continuing plants as one could imagine defining a plant to be continuing if it were in the data set in any previous year.[10] Nevertheless, using this definition, Figure 3 shows that on average over 90 percent of investment in machinery or in the sum of all types of reproducible physical capital occurs at continuing plants.[11] [12]

Insert Figure 3 Here

3 Results

The results are organized in two subsections. First, evidence is set out that bears on the question of whether the effect of a large equipment investment is to decrease

[9]See Cooper et al (1995) for similar but less dramatic results for their sample of large plants in the US manufacturing sector. See Ospina (1997) and Isgut (1997) for a more detailed analysis of lumpy investment in Colombia. The upper tail in Figure 2 is very long with a very small fraction of plants making equipment investments that increase their equipment stocks by more than a factor of 100.

[10]Using this definition, easily more than ninety percent of the plants in any given year are continuing plants.

[11]In 1982 continuing plants accounted for 76 percent of all investment. The bulk of this drop is due to a very large investment at one new plant in a capital-intensive industry. This does not appear to be due to any obvious recording or reporting error.

[12]Gort and Boddy (1967, p. 398) report similar findings for the US manufacturing sector.

measured productivity growth. Second, theories of investment and productivity growth that are inconsistent with our findings and some others that are potentially consistent are described.

3.1 Productivity Dynamics

There are many potential sources of measured productivity growth for individual plants. Some sources are industry specific such as disembodied technological change or measurement errors that are particular to an industry. In all the results that we report, we contol for industry-specific sources of measured productivity growth by means of industry dummy variables.[13] We do not control for any other potential sources of productivity growth as there are no direct observations on these other sources. We note that one potentially important omitted variable is likely to lead us to conclude that a large equipment investment acts to increase, rather than decrease, productivity growth. In particular, suppose a plant's true output price is not picked up perfectly by the relevant 4-digit, output prices. In this case measured productivity growth increases with increases in the variable measuring the growth rate of true less measured output prices. As we argue in the Appendix, this is likely to bias upwards our estimates of the effect of equipment investment on productivity growth that we report next.

3.1.1 Evidence For A Fall

Our approach to determining whether a large equipment investment decreases productivity growth is to estimate the parameters in equation (1). In this equation the variables y_t^i, z_t^i and D_{ij} are respectively the productivity growth rate and the technology adoption decision of plant i at time t as well as a industry dummy variable. The variable z_t^i takes the value 1 if the scaled investment x_t^i of plant i at time t exceeds a critical fraction $\mathbf{x}$ of its equipment stock at time t (i.e. $x_t^i \geq \mathbf{x}$) and 0 otherwise. The variable D_{ij} takes the value 1 if plant i is in industry j and 0 otherwise. Equation (1) states that productivity growth is the result of an industry effect ($\sum_j \alpha_j D_{ij}$) plus the effect of the current technology adoption decision ($\beta_0 z_t^i$) plus an error term ϵ_t^i.

$$y_t^i = \sum_j \alpha_j D_{ij} + \beta_0 z_t^i + \epsilon_t^i \tag{1}$$

Table 1 presents the parameter estimates. The parameters are estimated both by minimizing the sum of absolute errors (i.e. least absolute deviation (LAD)) as well as by minimizing the sum of squared errors (i.e. ordinary least squares (OLS)). We note that when the error term has fatter tails than the normal distribution the statistics and

[13] Our industry dummies are at the three-digit level. In the data set there are 29 such industries.

econometrics literatures have stressed that there are non-linear estimators such as the LAD estimator that can have substantially lower variances than the OLS estimator.[14] Since the error distribution does infact have much fatter tails than the normal, our preferred estimator is the LAD estimator. This estimator is not as sensitive as the OLS estimator to the presence of a small fraction of extreme observations on the dependent variable. Previously, Figure 1 higlighted the fact that measured productivity growth rates take on extreme values for a small fraction of the plants in our sample.

The results in Table 1 show that productivity growth is lower for the group of plants adopting technology (i.e. making equipment investments above a critical fraction of the equipment stock). In particular, this holds when the critical fraction $\mathbf{x}$ is set at .25, .50 or 1.0 times the stock of equipment. The LAD regression results indicate that the effect of a large equipment investment is to reduce plant-level productivity growth by from 2 to 5 percent. All point estimates are different from zero at standard significance levels. The fall in productivity growth is larger for larger values of the critical fraction $\mathbf{x}$. Virtually the same results are obtained when industry dummies are eliminated and replaced with a common intercept term for all plants. Thus, the correction for industry-specifc productivity effects is not critical to these findings.[15]

Insert Table 1 Here

3.1.2 Evidence For A Fall And A Rise

We now determine whether there is evidence that the effect of a large equipment investment is to at first decrease and then later increase productivity growth. To investigate this issue we posit in equation (2) that a plant's productivity growth y_t is the sum of an industry effect ($\sum_j \alpha_j D_{ij}$), the effect of current and past technology adoption decisions ($\sum_k \beta_k z^i_{t-k}$) and an error term (ϵ^i_t).

$$y^i_t = \sum_j \alpha_j D_{ij} + \sum_{k=0}^{K} \beta_k z^i_{t-k} + \epsilon^i_t \tag{2}$$

The findings are presented in Table 2. The contemporaneous effect of a large equipment investment on productivity growth is negative and significantly different

[14] See Koenker and Bassett (1978) and the large literatures on robust estimation and quantile regression. Koenker and Bassett provide conditions under which quantile estimators, of which the LAD estimator is an example, are asymptotically unbiased and normally distributed. This result makes use of the assumption that errors are independent and that the errors have positive density at the desired quantile. We use the S-Plus program rq to calculate point estimates and standard errors. This program implements the procedures described in Koenker and D'Orey (1987) and Koenker (1994).

[15] The OLS regressions results were not sensitive to eliminating industry dummies or to allowing industry dummies to be time varying.

from zero at the one percent level for all lag lengths we consider. The magnitude of the fall in productivity growth ranges from 2 to 5 percent depending on the setting of the critical fraction of investment which constitutes technology adoption. The higher this critical value the larger is the fall in productivity growth. The point estimates indicate that the effect of a large equipment investment one year in the past is to increase current productivity growth by 1 to 2 percent. These estimates are all significantly different from zero at the one perent level. The point estimates for lag lengths longer than a year are smaller in absolute value than the one year lagged effect and are typically negative.

Insert Table 2 Here

3.1.3 Two Robustness Checks

We focus on two questions: (1) Do the findings in Tables 1-2 hold within specific industries? and (2) Are the findings in Tables 1-2 sensitive to the presense of plausible magnitudes of unmeasured quality improvements in equipment?

To address the first question, we look at the four largest industries in our balanced panel as measured by the number of plants in that industry. For each of these industries we estimate by least absolute deviations (LAD) the effect of a large equipment investment on productivity growth, controlling for year effects by means of time dummies, D_{it}. The four largest industries are Food (311), Apparel (322), Other Chemical (352) and Metal Products (381). The findings in Table 3 are consistent with those previously noted in Tables 1 and 2 in that the point estimates for the contemporaneous effect of a large equipment investment on productivity growth is negative and that the one year lagged effect is positive. The magnitudes of these effects are of the same order of magnitude as those obtained previously. However, the standard errors of these estimates are larger than those in Table 1-2 due to the smaller number of observations.

Insert Table 3 Here

To address the second question, we note that the investment price index for equipment in Colombia makes no attempt to adjust for quality improvements. Substantial quality improvements in equipment have been documented by Gordon (1990). Thus, there is the issue of whether unmeasured quality improvements might be important. To examine this issue, the equipment capital for each plant in the data set is adjusted for quality improvements as follows. We let q_t index the quality level of investment in period t equipment. The old measure K_t and the new measure $\hat{K}_t$ of equipment capital stocks are calculated from the old measure of real investment I_t using the perpetual inventory method: $K_{t+1} = K_t(1-\delta) + I_t$ and $\hat{K}_{t+1} = \hat{K}_t(1-\delta) + I_t q_t$. All other aspects of the TFP growth calculations are as described in the Appendix.

Our series for unmeasured quality improvements q_t is based on work by Gordon (1990, Table 12.2). He calculates that his measure of the price of producer's durable equipment grows on average 3 percent slower over the period 1947-83 than the official US government price series that, like the Colombian data, does not attempt to adjust for quality improvements. We assume that q_t grows at 3 percent per year. Gordon's work is based on US rather the Colombian data. Thus, the findings on this point should be viewed as being very provisional and as providing potential magnitudes of the effects of unmeasured quality improvements on our results.

The findings in Table 4 show that the main conclusions from Tables 1-3 continue to hold. In particular, the contemporaneous effect of a large equipment purchase is to decrease productivity growth and the one year lagged effect is to raise productivity growth. The magnitude of the fall in productivity growth is now from 1 to 3 percent rather than from 2 to 5 percent as in Tables 1-2. Intuitively, the magnitude of the fall may be less since after adjusting for quality improvement many more plants have equipment purchases raising their equipment stocks by 25, 50 or 100 percent.

Insert Table 4 Here

3.2 Models of Investment and Productivity Growth

3.2.1 Two Models at Odds with the Evidence

We present two models at odds with the data. In models 1 and 2 output is produced according to a constant returns to scale production function: $Y_t = A_t F(X_t)$. Here, Y_t, A_t, X_t are respectively the output, technology level and the input vector. In models 1 and 2 there is neutral technological change A_t that is industry specific. In model 2 there is also a component of technological change that is embodied in new equipment. However, the production function in model 2 is the same as in model 1 after measuring the capital input to adjust for quality differentials in capital of different vintages.[16]

Model 1 implies that within an industry all plants should have the same productivity growth rate regardless of whether an equipment investment is made in a period. In terms of the regression results in Tables 1-4 this means that $\beta_0 = 0$. This is because no investment is needed to take advantage of technological change. The evidence in Tables 1-4 shows a significant negative contemporaneous effect of a large equipment investment on productivity growth (i.e $\beta_0 < 0$) after controlling for industry effects. Thus, the above model is at odds with the evidence.

[16]This assumes that different vintages are perfectly substitutable after correcting for quality differences.

Allowing for errors in measuring inputs or outputs does not seem promising for reconciling model 1 with the results in Tables 1-4. One possibility is that there are in reality several industries within our 4-digit industry classifications. In this case output will be mismeasured when true output prices have heterogeneous growth rates within a 4-digit industry. Following the line of argument in the Appendix, this type of measurement error biases the parameter estimates of β_0 in Table 1-4 upward not downward. Thus, measurement error of this type only further strengthens the case against model 1.

Model 2 is also inconsistent with the data in Tables 1-4, provided that the capital input is measured to adjust for quality change due to technological change embodied in new equipment, for precisely the same reason that model 1 fails. However, the investment price index for equipment in Colombia makes no attempt to adjust for quality improvements. Given an estimate of quality improvements in machinery and office equipment, capital inputs can be recalculated to adjust for quality change. Such an exercise was carried out previously in Table 4. The findings were qualitatively consistent with the findings in Tables 1-3. Thus, models 2 is also at odds with the evidence even allowing for plausible amounts of unmeasured quality improvement embodied in new equipment.

3.2.2 Two Models Potentially Consistent with the Evidence

The models from the previous section all fail as there is no reason for productivity growth to be lower for those plants making a large equipment investment. What is needed is a reason why equipment investment is usually small and sometimes very large as well as why plants with large equipment investments have lower productivity growth than plants in the same industry making no investment. Next, we consider two specific models with these features.

Zeckhauser-Parente Type Models

Zeckhauser (1968) and Parente (1994, 1998) posit that an immortal craftsman periodically adopts superior technology. A version of their model is presented below, where (Y, X, A, Z_A) denote output, an input vector, the technology level and experience with the current technology and where F is constant returns to scale. When the craftsman adopts a superior technology (higher A) two things happen: first there is an immediate fall in expertise Z_A as not all the previous expertise transfers to the new technology and second Z_A increases over time due to learning as long as the craftsman sticks to technology A. This story can easily be modified so that adopting a technology involves a purchase of capital specific to that technology.

$$Y = AZ_AF(X)$$

Following the standard Solow (1957) growth accounting argument described in the Appendix, total fator productivity growth is $(\Delta AZ_A + A\Delta Z_A)/AZ_A$. Total factor productivity growth in this model (i) could fall after a switch in technology when the fall in exertise is sufficiently great to offset the technology improvement and (ii) rises thereafter due to learning as $\Delta Z_A/Z_A > 0$. Thus, in terms of the results in Tables 1-4, this model is consistent with $\beta_0 < 0$ and $\beta_1, ..., \beta_K > 0$. This is qualitatively consistent with the evidence in Tables 1-4 in that $\beta_0 < 0$ and $\beta_1 > 0$.

Machine Replacement Models

Recently the machine replacement problem (Cooley et al (1997) and Cooper et al (1995)) has been advanced as an explanation of plant-level investment patterns and of lumpy investment in particular. A version of the model presented by Cooper et al (1995), which emphasizes equipment investment at existing plants, is presented below. Here (Y, X, A) denote output, an input vector and an industry-specific technology shock. The function F is constant returns to scale. Adjustment costs come in two types: a proportional cost Z and a fixed cost C. In periods where a machine is replaced $Z_t < 1$ and $C_t > 0$. In periods without a machine replacement $Z_t = 1$ and $C_t = 0$.

$$Y_t = A_tZ_tF(X_t) - C_t$$

The total factor productivity growth implications of this model are as follows. First, for all plants making no machine replacements in two consecutive periods, total factor productivity growth within an industry is given by the amount of technological change at the industry level $\Delta A/A$. Second, plants replacing machines have lower productivity growth than plants not replacing machines due to both proportional costs (i.e. $\Delta Z/Z < 0$) and fixed costs of replacement. One period after a replacement decision, productivity growth is higher than for plants making no replacement in the last two periods as $\Delta Z/Z > 0$. In terms of the results of Tables 1-4, this type of model is consistent with $\beta_0 < 0, \beta_1 > 0$ and $\beta_2, ..., \beta_K = 0$, when a model period corresponds to a year.

In summary, both machine replacement models and Zeckhauser-Parente technology adoption models are consistent with the results in Tables 1-4 in that $\beta_0 < 0$ and $\beta_1 > 0$. These models differ in their predictions for further lags of the response of productivity growth to a large equipment investment. Neither model predicts that further lagged effects are negative (e.g. $\beta_2 < 0$). We note that the point estimates in Tables 1-4 on lagged effects beyond one year are typically negative but often are not siginificantly differrent from zero.

4 Conclusion

The main findings of the paper are as follows: (1) The contemporaneous effect of a large equipment investment is to decrease a plant's total factor productivty growth by 2 to 5 percent in annual data. This decrease is larger for larger critical values for what constitutes a large equipment investment, (2) Total factor productivity growth increases by 1 to 2 percent for plants making a large equipment investment one year in the past, (3) The previous findings hold within industries and are robust to plausible amounts of unmeasured quality improvements in equipment, (4) The bulk of investment in either equipment or all reproducible physical capital occurs at existing plants rather than at new plants.

We attach the following significance to these findings. First, the findings are inconsistent with models where all plants within an industry are affected by a common disembodied technology shock and/or by technological improvements embodied in new equipment, in the absense of "adjustment" costs. However, the findings are potentially consistent with a wide variety of what could be called adjustment cost models, including machine replacement and Zeckhauser-Parente style technology adoption models among others. Second, if a large equipment investment is associated with the adoption of new technology embodied in new equipment, then the findings imply that the adoption of new technology contemporaneously reduces total factor productivity growth. Third, we believe that the finding that the bulk of equipment investment occurs at existing plants has implications for future work. This finding suggests that the literature which attempts to quantify the importance of microeconomic models of equipment investment for aggregate productivity growth should concentrate on models where equipment investment occurs not only at new plants but also at existing plants. The findings in Tables 1-4 should be useful in future attempts at quantification.

We mention two directions to explore in future work. First, what is the effect on productivity growth of equipment purchases that reflect technology adoption versus those that merely reflect the acquisition of more capital of a technology known to the plant? This is a key question as an answer would be informative as to the precise mechanism behind the falls in total factor productivity growth documented here. To address this question a data set that allows such a distinction to be measured is needed. Doms Dunne and Trotske (1997) describe a data set that is potentially promising in this regard. Second, it would be useful to see if the findings presented here are confirmed in data sets for other countries and time periods.

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A Appendix

A.1 Measuring Productivity Growth Rates

Following Solow (1957), we assume that at each point in time a plant operates a constant returns to scale production function $Y_t = F(X_t, t)$ and that plants behave competitively in input markets. In this formulation, plants produce Y_t units of output using a vector of inputs X_t. Under the assumptions stated above, Solow derived the following growth accounting equation for calculating what is now called total factor productivity growth $\dot{F}/F$.[17] The equation states that at time t the rate of shift of the production function $\dot{F}/F$ at the current input vector equals output growth less a weighted average of the growth rates of the factor inputs, where the weights are given by factor shares $(\omega^1, ..., \omega^N)$. Solow's factor shares are shares of output, whereas our factor shares are cost shares. The cost share approach requires only competition in input markets rather than competition in input and output markets (see Hall (1991)).

$$\dot{F}/F = \dot{Y}_t/Y_t - \sum_n \omega_t^n \dot{X}_t^n / X_t^n$$

To calculate productivity growth at the plant level we first approximate growth rates with yearly growth rates as indicated below:

$$\dot{F}/F \doteq \Delta Y_t/Y_{t-1} - \sum_n \omega_t^n \Delta X_t^n / X_{t-1}^n$$

Next, we describe measurement. We measure Y by the value of nominal gross production measured in the data set divided by the industry-specific output price index.[18] We measure three separate factor inputs: labor, capital and intermediate input. We measure the real value of intermediate input by the nominal value of intermediate input measured in the data set divided by the price index for intermediate input. As we do not have a price series for intermediate input we use the GDP deflator for this purpose.

Our measure of labor input L_t at a particular plant at time t is the weighted sum of the number of employees L_t^j of type j at that plant at time t: $L_t = \sum_j w_t^j L_t^j$. The weights are chosen so as to measure the efficiency of labor input type j at the particular plant at time t. Thus, w_t^j is the wage per type j worker at the particular plant at time t divided by the average wage per type 1 worker in the economy at time t. We choose "unskilled workers" to be the type 1 worker. We measure wages by total compensation

[17] A dot over a variable denotes a time derivative.

[18] We deflate with four-digit output deflators. We have 51 distinct four-digit deflators. In some years four of these deflators have a zero price change. As we regard this as suspect, for these industries we set the price change equal to that of the GDP deflator in years where no price change is reported.

per worker per year. We note that this way of measuring labor input allows for plant-specific variation in the weight of each worker type while fixing the weight of type 1 workers in the entire economy at at value of 1 each year. This allows us to capture potential differences in labor efficiency of different worker types across plants arising from (i) differences in hours worked or (ii) differences in human capital.

We measure total capital services KS_t at a particular plant at time t as the sum of the capital serivices of each type of capital: $KS_t = \sum_j .5[K_t^j + K_{t+1}^j](\delta_j + r)$. This is the standard way that capital services is constructed from an underlying measure of the real capital stock of each capital type K_t^j (see Griliches and Jorgenson (1968)). Note that we use the average of the real value of the capital stock at the beginning of period t and period $t+1$ in order to calculate the measure of the capital stock most relevant for computing capital services during period t. We can distinguish five types of capital in our data set: structures, equipment, office equipment, transportation equipment and land. We will indicate how we calculate K_t^j for each capital type in the next section. We set the interest rate at $r = .05$ and the depreciation rates (δ_j) of structures, machinery, office equipment, transport equipment and land at $(4.61, 12.56, 13.32, 18.92, 0)$. With the exception of land which we have assumed does not depreciate, these estimates come from the work of Pombo (1998, Table 3.1) for the Colombian manufacturing sector.

We measure the weights ω_t^n as the average share of input n in total costs of a particular plant in period t and $t+1$. As we observe the nominal cost of all inputs except capital services, some assumption needs to be made to calculate cost shares. We construct a common nominal price of capital services each year so that at this price the nominal value of gross production in a given year for all plants equals the nominal value of all input costs for all plants. This amounts to assuming that there are no aggregate profits each year for the entire manufacturing sector.

A.2 Measuring the Real Value of Capital

Our procedure for creating a series for each plant measuring the real value of type j capital stock at the beginning of the period is summarized in two equations:

1. First Year in Sample: $K_t^j = BV_t^j / p_t^j$
2. Subsequent Years: $K_{t+1}^j = K_t^j(1 - \delta_j) + (PN_t^j + PU_t^j + OP_t^j - S_t^j)/p_t^j$

K_t - real beginning of period value of capital
BV_t - beginning of period book value
PN_t - purchases of new capital
PU_t - purchases of used capital
OP_t - own production of capital

S_t - sales of capital
δ_j - depreciation rate of type j capital
p_t^j - Investment price deflator of type j capital

We have price deflators for structures, equipment (machines and office equipment) and transport equipment. The GDP deflator is used to deflate land. Depreciation rates are set at the values calculated in Pombo (1998) that were described previously in the Appendix. Since our data for a given year on bookvalues are end-of-year values, we use this end-of-year value as a beginning-of-period measure of the bookvalue for the following year. This means that we only measure the capital stock in the year immediately after the first year that a plant appears in the data set. An implication of this fact and the fact that we use period t and period $t+1$ capital stocks to measure capital services during period t is that we can construct the basic data on inputs and outputs only for 1975-90. Thus, growth rates can be calculated for all series starting in 1976.

A.3 Omitted Variable Bias- An Example

We show how mismeasured output prices bias can upwards the estimated effect of a large investment on productivity growth.

Step 1:

Let $\dot{A}/A$ and $\dot{\hat{A}}/\hat{A}$ denote true and measured productivity growth when the growth rate of gross production is measured correctly $\dot{Y}/Y$ and incorrectly $\dot{\hat{Y}}/\hat{Y}$. From Appendix A.1 we have the following:

$$\dot{A}/A \equiv \dot{Y}/Y - \sum_n \omega^n \dot{X}^n/X^n$$

$$\dot{\hat{A}}/\hat{A} \equiv \dot{\hat{Y}}/\hat{Y} - \sum_n \omega^n \dot{X}^n/X^n$$

When (i) $(p, \hat{p})$ denote different price indices, (ii) GP denotes nominal gross production and (iii) $Y = GP/p$ and $\hat{Y} = GP/\hat{p}$, then these measures are related as in equation (3) below. Now let (i) $y = \dot{\hat{A}}/\hat{A}$, (ii) $\dot{A}/A$ be a linear function of z as posited in section 3 of the paper (i.e. $\dot{A}/A = \alpha + \beta z$) and (iii) $w = (\dot{p}/p - \dot{\hat{p}}/\hat{p})$. Then equation (4) below follows from equation (3).

$$\dot{\hat{A}}/\hat{A} = \dot{A}/A + (\dot{p}/p - \dot{\hat{p}}/\hat{p}) \tag{3}$$

$$y = \alpha + \beta z + \gamma w \tag{4}$$

Step 2:

Let productivity growth y_t^i, technology adoption (i.e. a large equipment investment) z_t^i and an omitted variable w_t^i be related as follows: $y_t^i = \alpha + \beta z_t^i + \gamma w_t^i + \epsilon_t^i$. The least squares estimate of β (the effect of technology adoption on growth) when w_t^i is omitted is given by β_1 below (see Greene (1993, p. 247)):

$$\beta_1 \equiv Cov(y, z)/Var(z) = \beta + \gamma Cov(w, z)/Var(z)$$

Clearly, the estimate is biased upwards when $\gamma > 0$ and $Cov(w, z) > 0$. Since from step 1 $\gamma = 1$, the positive bias rests on the covariance between w_t^i and z_t^i. A positive covariance seems a plausible conjecture given the notion that big investments covary more strongly with true growth in industry price than with growth in a 4-digit measure of output prices.

Given that true output price is not observable, it is not possible to explore this last conjecture much further. However, we have calculated $Cov(\hat{w}, z)/Var(z)$ using a variable $\hat{w}$ that may have some bearing on this conjeture. The variable $\hat{w}$ is the growth in 4-digit industry prices less the growth in 3-digit industry prices. We calculate that $Cov(\hat{w}, z)/Var(z)$ within 4-digit industries is typically positive in the balanced panel.

Table 1:

$$y_t^i = \sum_j \alpha_j D_{ij} + \beta_0 z_t^i + \epsilon_t^i$$

Independent Variable	Estimator	β_0	Number of Observations
$z_t^i \equiv 1_{\{x_t^i \geq .25\}}$	LAD	-.022*	31875
		(.002)	
	OLS	-.098*	31875
		(.032)	
$z_t^i \equiv 1_{\{x_t^i \geq .50\}}$	LAD	-.034*	31875
		(.003)	
	OLS	-.162*	31875
		(.042)	
$z_t^i \equiv 1_{\{x_t^i \geq 1.0\}}$	LAD	-.046*	31875
		(.006)	
	OLS	-.367*	31875
		(.062)	

standard errors are indicated in parenthesis

* indicates that coefficient is significantly different from 0 at the 1 percent level

Table 2:

$$y_t^i = \sum_j \alpha_j D_{ij} + \sum_{k=0}^{K} \beta_k z_{t-k}^i + \epsilon_t^i$$

Independent Variable	Estimator	β_0	β_1	β_2	β_3	β_4	Number of Observations
$z_t^i \equiv 1_{\{x_t^i \geq .25\}}$	LAD	-.023*	.009*				31875
		(.002)	(.002)				
		-.023*	.009*	-.007			29750
		(.003)	(.002)	(.003)			
		-.025*	.009*	-.008*	-.003		27625
		(.002)	(.002)	(.002)	(.002)		
		-.025*	.008*	-.008*	-.004	.001	25500
		(.003)	(.002)	(.002)	(.002)	(.002)	
$z_t^i \equiv 1_{\{x_t^i \geq .50\}}$	LAD	-.034*	.012*				31875
		(.003)	(.003)				
		-.033*	.012*	-.005			29750
		(.003)	(.003)	(.003)			
		-.035*	.010*	-.008*	-.004		27625
		(.004)	(.003)	(.003)	(.003)		
		-.039*	.010*	-.009	-.005	-.002	25500
		(.004)	(.003)	(.004)	(.003)	(.003)	
$z_t^i \equiv 1_{\{x_t^i \geq 1.0\}}$	LAD	-.049*	.020*				31875
		(.006)	(.005)				
		-.047*	.025*	-.008			29750
		(.007)	(.007)	(.005)			
		-.052*	.019*	-.015*	-.008		27625
		(.007)	(.006)	(.005)	(.005)		
		-.057*	.018*	-.017	-.012	.000	25500
		(.005)	(.006)	(.006)	(.005)	(.004)	

standard errors are indicated in parenthesis

* indicates that coefficient is significantly different from 0 at the 1 percent level

Table 3:

$$y_t^i = \sum_t \alpha_t D_{it} + \sum_{k=0}^{K} \beta_k z_{t-k}^i + \epsilon_t^i$$

Independent Variable	Industry	β_0	β_1	β_2	β_3	β_4	Number of Observations
$z_t^i \equiv 1_{\{x_t^i \geq .25\}}$	311	-.015*	.014	-.009	-.012	-.003	4020
		(.006)	(.006)	(.005)	(.006)	(.005)	
	322	-.019	.009	-.006	-.002	-.006	1764
		(.008)	(.007)	(.007)	(.008)	(.007)	
	352	-.007	.005	-.014	.007	.005	1860
		(.010)	(.013)	(.009)	(.011)	(.010)	
	381	-.024*	.025	-.006	.005	-.007	2208
		(.008)	(.006)	(.008)	(.009)	(.007)	
$z_t^i \equiv 1_{\{x_t^i \geq .50\}}$	311	-.026*	.021	-.010	-.012	.003	4020
		(.007)	(.009)	(.009)	(.007)	(.007)	
	322	-.038*	.004	-.017	.004	-.012	1764
		(.014)	(.007)	(.016)	(.009)	(.009)	
	352	-.032*	.005	.002	.004	.012	1860
		(.011)	(.017)	(.015)	(.011)	(.016)	
	381	-.018	.015*	.008	-.006	-.007	2208
		(.008)	(.005)	(.015)	(.012)	(.017)	
$z_t^i \equiv 1_{\{x_t^i \geq 1.0\}}$	311	-.036*	.033	-.013	-.008	.008	4020
		(.014)	(.015)	(.018)	(.010)	(.014)	
	322	-.006	.001	-.032	.009	.001	1764
		(.047)	(.016)	(.014)	(.028)	(.011)	
	352	-.026	.001	-.014	.002	.010	1860
		(.026)	(.028)	(.022)	(.020)	(.027)	
	381	-.034	.018	.016	-.009	-.007	2208
		(.020)	(.013)	(.014)	(.017)	(.013)	

standard errors are indicated in parenthesis

* indicates that coefficient is significantly different from 0 at the 1 percent level

Table 4:

$$y_t^i = \sum_j \alpha_j D_{ij} + \sum_{k=0}^{K} \beta_k z_{t-k}^i + \epsilon_t^i$$

Independent Variable	Estimator	β_0	β_1	β_2	β_3	β_4	Number of Observations
$z_t^i \equiv 1_{\{x_t^i \geq .25\}}$	LAD	-.014					31875
		(.007)					
		-.014	.008				31875
		(.006)	(.005)				
		-.013*	.009*	-.008			29750
		(.004)	(.004)	(.004)			
		-.014*	.008*	-.008*	-.003		27625
		(.003)	(.003)	(.002)	(.003)		
		-.013*	.007*	-.009*	-.004	.002	25500
		(.003)	(.002)	(.002)	(.002)	(.002)	
$z_t^i \equiv 1_{\{x_t^i \geq .50\}}$	LAD	-.019*					31875
		(.006)					
		-.020*	.009				31875
		(.006)	(.005)				
		-.018*	.009	-.007			29750
		(.005)	(.005)	(.005)			
		-.021*	.010*	-.009*	-.004		27625
		(.004)	(.003)	(.003)	(.004)		
		-.020*	.010*	-.010*	-.004	.000	25500
		(.003)	(.003)	(.003)	(.003)	(.003)	
$z_t^i \equiv 1_{\{x_t^i \geq 1.0\}}$	LAD	-.028*					31875
		(.006)					
		-.028*	.015				31875
		(.007)	(.007)				
		-.027*	.018	-.012			29750
		(.007)	(.007)	(.008)			
		-.026*	.013	-.014*	-.007		27625
		(.009)	(.008)	(.005)	(.004)		
		-.029*	.014	-.016*	-.009	.001	25500
		(.007)	(.007)	(.006)	(.006)	(.005)	

standard errors are indicated in parenthesis

* indicates that coefficient is significantly different from 0 at the 1 percent level