Does Productivity Fall After the Adoption of New Technology?

Mark Huggett and Sandra Ospina*

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Abstract

A number of theoretical models of technology adoption have been proposed that emphasize technological switching, loss of expertise and subsequent technology-specific learning. These models imply that measured productivity 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 regress measures of productivity growth at the plant level on a plant-specific measure of technology adoption and its lagged values. We find that .... .

*Address of the authors: Centro de Investigacion Economica ITAM, Camino Santa Teresa 930, Mexico DF 10700, Mexico. E-mail: huggett@master.ster.itam.mx, ospina@smith.rhon.itam.mx
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1 Introduction

The following points have been made in the literature on technological change:

1. Technological change is key for growth in GDP per capita.[1]
2. Outside of the lead countries, technologies need only be adopted not invented. Even in the lead countries the vast majority of resources are devoted to adoption rather than invention.[2]
3. Technology adoption often requires an investment in physical capital. In this case technological change is said to be embodied or investment specific.[3]
4. 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 is that measured productivity growth may at first fall and then later rise.[4]

Building upon these points, a number of recent papers have gone on to advance as well as to examine the hypothesis that an increase in the rate of technology adoption may lead to a temporary or even long lasting slowdown in measured rates of economy-wide productivity growth. For example, Hornstein and Krusell (1996) use economy-wide and sectoral data to examine the plausibility of this hypothesis as an explanation of the slowdown in measured total factor productivity (TFP) growth that has occured in the majority of the advanced countries since the 1970's. Greenwood (1996) and Greenwood and Yorukoglu (1997) focus on historical experience with major technological innovations and argue that these were associated with labor productivity growth slowdowns at the economy-wide level as well as increases in income inequality. They also argue that this has been occuring in the US since 1974.[5]

An important point to mention is that technology adoption is a decision variable for individual production units in the economy. However, the papers by Greenwood (1996), Hornstein and Krusell (1996) and Greenwood and Yorukoglu (1997) have neither presented nor referenced micro-evidence showing that productivity growth actually falls or slows down at individual production units after the adoption of new technology.

[1] Solow (1956) provides a theoretical argument, whereas Solow (1957) provides an empirical argument.

[2] Jovanovic (1996) provides arguments for these points.

[3] Solow (1960) provides an early theoretical model of vintage capital.

[4] Zeckhauser (1968), Parente (1994), Jovanovic and Nyarko (1996), Hornstein and Krusell (1996) and Klenow (1998) provide theoretical frameworks emphasizing technological switching, loss of expertise and learning. Argotte and Epple (1990) review the large empirical literature on learning curves.

[5] Basu Fernald and Kimball (1997) consider a related hypothesis. In particular, they focus on the business-cycle implications of technology improvements within sticky-price models.

Such micro-evidence would appear to be important to assessing the above hypothesis as measures of productivity change for the whole economy are, in theory, simply complicated aggregates of productivity change at individual production units.[6]

To the best of our knowledge, there is relatively little existing micro-evidence documenting whether or not measured productivity growth rates fall or slow down at individual production units after adopting new technology. Baloff (1970) among others has presented several case studies in which plants from the US manufacturing sector have changed products, changed the product mix or adopted new ways of mechanizing the production process and in which the level of productivity initially falls and then later rises. However, the main focus of the learning literature has been to document the upside of the learning curve rather than any potential downside after a switch in technology. For example, Bahk and Gort (1993) focus on a wide selection of new plants in the US manufacturing sector and estimate the magnitude of learning effects. While quite useful for many purposes, we doubt that this evidence is the most relevant to assessing the hypothesis of Greenwood (1996), Hornstein and Krusell (1996) and Greenwood and Yorukoglu (1997).[7]

In this paper we provide evidence on the hypothesis that the adoption of new technology is associated with a fall or slowdow in the measured productivity growth rate of individual production units. To address this hypothesis, we identify the adoption of a new technology at a particular production unit with the purchase of equipment. A number of remarks are in order in regards to this choice for measuring technology adoption. First, this is exactly the mechansim of economic growth and technology adoption emphasized by Greenwood (1996), Hornstein and Krusell (1996), Greenwood and Yorukoglu (1997) as well as by economic historians such as Rostow (1958) and Mokyr (1992). Thus, even if equipment investment is not a perfect measure of technology adoption embodied in equipment, it will still be useful for addressing the related hypothesis that equipment investment is associated with a fall or slowdown in measured

[6]Hulten (1978) extends the growth accounting apparatus of Solow (1957) to allow for many final outputs, many primary inputs and many intermediate goods. Measures of the shift in the production possibility frontier arising from technological change can then be related to a weighted-sum of productivity growth rates for the production of each final good in the economy. Alternatively, if one attempts to measure productivity change using highly aggregated data, then this aggregate measure can still be related to productivity change at the sector or more finely disaggregated levels (see Massell (1961) for an early example of this type of exercise). The result is that the measure of productivity growth from aggregate data can be related, through an accounting identity, to a weighted-sum of productivity growth at disaggregated levels as well as to some additional terms.

[7]If technology adoption primarily occurs at new plants, then the Bahk and Gort evidence would be very important. However, we conjecture that existing plants account for the bulk of technology adoption. We make this conjecture as in the data set that we explore the vast majority of the expenditures on either equipment investment or total investment occur at existing plants rather than new plants.

productivity growth rates. Second, there is some evidence that equipment investment may be a quantitatively important source of growth. For example, 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. In addition, Greenwood et al (1997) argue that the bulk of postwar US growth in labor productivity can be attributed to technological change embodied in new equipment. Third, in plant-level data it is the case that investment, and especially equipment 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 and large percentage changes in the stock of equipment in other years.[8] Thus, our measure of technology adoption has the potential to correspond to the casual notion that major technology adoptions occur somewhat infrequently. Fourth, we do not take the position that our measure of technology adoption will pick up all instances of measured productivity growth at individual plants. Clearly, we will miss all productivity growth that is unrelated to the purchase of equipment and the subsequent learning process. For example, changes in labor laws, changes in managerial techniques and reorganizations of the production process may be unrelated to equipment investment and yet result in measured productivity growth. There may also be productivity growth resulting from a similar mechanism to the one we investigate but arising from the purchase of other types of physical capital. As a last example, some portion of measured productivity growth may arise from measurement error. This could happen as errors in measuring inputs and output or the corresponding prices will be reflected in our measures of productivity growth.

Our empirical strategy is straightforward. We focus on a data set of plants from the Colombian manufacturing sector. For each plant present in our data set for two consecutive years, we calculate a measure of productivity growth. We consider both labor productivity and total factor productivity (TFP) growth as both of these have been stressed in the literatures cited above. We then use equipment purchases as a fraction of the stock of equipment as our measure of the degree of technological updating of each particular plant in a given year. By regressing our measure of productivity growth on our measure of technology adoption and its own lagged values, we address the question posed in the title of the paper.

Discussion of results.

This paper is organized in four sections. Section 2 presents features of our data set, properties of plant-level productivity growth and properties of our measure of technology adoption. Section 3 presents our main results. Section 4 concludes.

[8]Doms and Dunne (1998) and Cooper et al (1995) document this fact with US data, whereas Ospina (1994) and Isgut (1997) document this fact with Colombian data. In section 2.3 of this paper we also provide some evidence for the lumpy behavior of equipment investment.

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. Our data set covers the period 1974-1991. In a typical year our data set has between 6,000 and 8,000 plants. Over this period we have data on 14,181 distinct plants.

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. Professionals are skilled workers in charge of managing production. Employees are administrative managers, secretarial workers, accountants, drivers and others who are not directly in charge of production. Technicians are directly in charge of the production process. The data indicates the number of employees of each of the above six types listed in the payroll as of (or nearest to) November 15. This measure includes those employees temporarily absent from work during the year.

Capital inputs are 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 capital, purchases of 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.

There are two different output measures in our data set: gross production and value added. Gross production is measured as the sum of the value of the production of finished goods, changes in the value of goods in the process of production, value of raw materials or electricity sold, income received for services performed for others and indirect taxes caused during the year. Value added is measured as gross production less intermediate consumption. Intermediate consumption is measured as the sum of the value of raw materials consumed, energy consumed, materials sold without transformation, services performed by others and indirect taxes caused during the year. All of these data are reported on an annual basis.[9]

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 measures of productivity growth are total factor productivity growth and labor productivity

[9]See DANE (1991, pp. 16-17) for more explanation of these definitions.

growth, where labor productivity is measured using real value added per unit of labor input.[10]

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.[11] First, we exclude any plant for which any of the data needed to calculate TFP or labor productivity 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 expenditure 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 and office equipment. Second, we exclude plants for which either the plant identification number is missing or repeated or for which the industry classification code is missing.

Figure 1 describes the size distribution of plants that are in our balanced panel after applying the above exclusion criteria. There are a total of 2158 plants in our data set each year. 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.

Insert Figure 1 Here

2.2 Productivity Growth Facts

This section characterizes some features of the distribution of TFP and labor productivity growth rates. The measurement of TFP growth rates is described in detail in the Appendix. Figure 2 plots the distribution of TFP growth rates in each year of our data. Figure 2 shows that in each year (i) the median TFP growth rate is about zero, (ii) the TFP growth rate distribution is rougly symmetric about a value of zero with the vast majority of the plants having a TFP growth rate lieing between 40 and −40 percentage points and (iii) there are a small percentage of plants (typically less that half of one percent) that have a TFP growth rate either greater than 100 percent or smaller than −100 percent. This last finding is represented in Figure 2 by plotting all

[10]For a discussion of the methodology of the *Encuesta Anual Manufacturera* see DANE (1991). For a detailed examination of properties of this data set see Huggett, Ospina and Torres (1998). Research based on versions of this data set has been conducted by Roberts and Tybout (1996), Isgut (1996) and Kugler (199?) among others.

[11]We focus on the balanced panel in order to minimize on measurement error in the calculation of labor productivity and TFP growth. 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.

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.

We now comment upon the extreme growth rates in the tails of Figure 2. 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 we calculate TFP growth rates for the Colombian manufacturing sector over the period 1975-90 using aggregate measures of outputs, inputs and factor shares. Second, although intuitively implausible, a straightforward application of a discrete-time version of Solow's growth accounting equation can produce TFP growth rates smaller than -100 percent. We have individual cases with growth rates as low as $-50,000$ 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 out that in these cases output increased by a couple of hundred percentage points whereas intermediate input increased at much greater rates.[12]

Insert Figure 2 Here

Figure 3 plots the distribution of labor productivity growth rates. Labor productivity is calculated by dividing te real value of value added by labor input. Our measure of labor input is described in the Appendix. Labor productivity growth rates display the following patterns: (i) the median labor productivity growth rate each year is close to zero, (ii) the distribution is skewed to the right in each year and (iii) a small fraction of plants in each year have a productivity growth rate exceeding 100 percent. One important difference between Figure 2 and Figure 3 is that by the construction of labor productivity it is impossible to have a labor prductivity growth rate of less than -100 percent when a plant produces positive output. Interestingly, it is the case that in each year a small fraction of plants experiences labor productivity growth rates close to -100 percent. This reflects the dramatic fluctuations occuring in plant-level data. We note that both the dramatic positive and negative productivity growth rates are smoothed out when one analyzes more highly aggregated data.

Insert Figure 3 Here

[12]Output is measured by gross production which measures both changes in the value of finished goods as well as changes in the value of goods in the process of production. Thus, the negative residuals are not due to not measuring goods in the process of production, although potentially the problem may have to do with poor measurement of the value of these goods.

2.3 Equipment Investment Facts

This section describes the pattern of plant-level gross equipment purchases as a share of the stock of equipment. This variable is the key explanatory variable that we use as a measure of technology adoption. 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 of our data machinery investment makes up between 70 and 80 percent of the combined investment in machinery, office equipment, transport equipment and structures.

We now focus on documenting the lumpy behavior of equipment investment. Figure 4 presents for several years the distribution of plants by equipment purchases as a fraction of the stock of equipment. Figure 4 shows that that the distribution is quite similar in all the years examined. Figure 4 also shows that in a given year about 25 percent of the plants make purchases of equipment of less than 10 percent of the value of their equipment stock and more than 50 percent of the plants make purchases of less than 20 percent of their equipment stock. Due to depreciation, many of these plants will in net terms not expand the value of their stocks of machinery. The last point that Figure 4 makes is that in any given year between $5-20$ percent of the plants make purchases that increase their equipment stock by 50 percent or more and between $2-8$ percent of the plants make equipment purchases that more than double their stock of equipment.[13]

Insert Figure 4 Here

3 Results

We attempt to answer the question posed in the title of the paper by means of a regression which highlights the impact of current and past technology adoption decisions on current, plant-level productivity growth. The equation that we estimate is provided below in equation (1). In this equation y_t^i is productivity growth of plant i at time t, whereas x_t^i is our measure of technology adoption of plant i at time t. Equation (1) states that productivity growth of a specific plant is the result of a time-varying industry effect $(\sum_{j,t} \alpha_t^j D_{ijt})$ plus the effect of current and past technology adoption decisions embodied in equipment investment $(\sum_k \beta_k x_{t-k}^i)$ plus an additional term ϵ_t^i

[13]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.

picking up all other sources of variation in measured productivity growth. The time-varying industry effect is captured by time-specific industry dummies D_{ijt} taking the value 1 if plant i is in industry j at time t and the value 0 otherwise. The parameter β_k describes the effect on current productivity growth due to equipment purchases k periods ago.

$$y_t^i = \sum_{j,t} \alpha_t^j D_{ijt} + \sum_{k=0}^{n} \beta_k x_{t-k}^i + \epsilon_t^i \tag{1}$$

We will now discuss our thinking about our choice of controling for other sources of productivity growth through a time-varying industry effect. First, we argue that the inclusion of an industry-specific fixed effect is warranted. The basic argument is that many of the measured changes in plant-level productivity growth are likely to be specific to particular industries and arise from either disembodied technological change or from industry-specific errors in the measurement of plant-level productivity growth. The first type of effect could arise from changes in labor laws affecting labor efficiency that are specific to a particular industry or to disembodied innovations either in product quality or in the production process that are specific to an industry. The second type of effect could arise from unmeasured changes in the quality of factor inputs that are specific to a particular industry or from changes in industry output prices that are not picked up perfectly in our 4-digit, industry-level price indicies. As many of these effects may be largely one-time effects rather than filtering out evenly through time, this suggests that we allow for industry effects that are time varying.

3.1 Productivity Dynamics: Baseline Results

In this section we estimate the technology adoption parameters $(\beta_0, ..., \beta_n)$ as well as the time-varying industry effects. As theoretical considerations do not put any restrictions on the maximum lag length n, we provide estimates of the technology adoption parameters for several lag lengths. The lag lengths we consider vary from $n = 0$ where only current period technology adoption decisions impact current period productivity growth to $n = 4$ where technology adoption decisions four years in the past still impact current period productivity growth.[14]

We begin by focusing on the ordinary least squares estimators of the technology adoption parameters and industry effects. Under the usual assumptions of the linear

[14]Bahk and Gort (1993) present evidence for plant-specific learning effects related to capital investments of up to $5-6$ years after a plant begins operations for plants in the US manufacturing sector. This suggests that several lags may be needed to capture the effects of technology adoption and learning.

model (i.e. errors ϵ_t^i are (1) zero mean, (2) uncorrelated cross-sectionally and over time, (3) uncorrelated with the regressors and (4) homoscedastic) it is known that the least squares estimators are the linear unbiased estimators with the smallest variance. If the errors are normally distributed, then this estimator is minimum variance among all unbiased estimators. The results of the ordinary least squares (OLS) estimates are provided in Tables 1 and 2 below.[15]

Table 1:
TFP Dynamics

$$y_t^i = \sum_{j,t} \alpha_t^j D_{ijt} + \sum_{k=0}^{n} \beta_k x_{t-k}^i + \epsilon_t^i$$

Lag Length	β_0	β_1	β_2	β_3	β_4	R^2	Number of Observations
$n=0$	-.010					.005	30375
	(.14)						
$n=1$	-.011	.002				.005	28350
	(.14)	(.75)					
$n=2$	-.015	.003	.002			.005	26325
	(.10)	(.73)	(.78)				
$n=3$	-.021	.005	.002	.005		.005	24300
	(.06)	(.58)	(.78)	(.94)			
$n=4$	-.022	.006	.002	.000	.001	.005	22275
	(.07)	(.58)	(.83)	(.98)	(.92)		

p-values are indicated in parenthesis below the point estimates

[15] We allow for industry dummies up to the 3-digit level of the ISIC code.

Table 2:
Labor Productivity Dynamics
$y_t^i = \sum_{j,t} \alpha_t^j D_{ijt} + \sum_{k=0}^{n} \beta_k x_{t-k}^i + \epsilon_t^i$

Lag Length	β_0	β_1	β_2	β_3	β_4	R^2	Number of Observations
$n = 0$	-.151					.013	30375
	(.93)						
$n = 1$	-.171	-.015				.013	28350
	(.93)	(.99)					
$n = 2$	-.228	-.014	.283			.013	26325
	(.92)	(.99)	(.89)				
$n = 3$	-.348	-.016	.323	-.164		.013	24300
	(.91)	(.99)	(.88)	(.94)			
$n = 4$	-.379	-.027	.435	-.187	-.009	.013	22275
	(.91)	(.99)	(.87)	(.94)	(.99)		

p-values are indicated in parenthesis below the point estimates

Summary:

1. For the TFP growth regressions, the point estimates of the contemporaneous effect is small and negative. The estimates suggest that doubling the stock has a contemporaneous effect of lowering TFP growth by $1 - 2$ percent. None of the point estimates are different from zero at standard significance levels (i.e. 1 or 5 percent levels).

2. For the TFP growth regressions, the point estimates of the lag effects are small and not significantly different from zero.

3. For the labor productivity regressions, the point estimates of the contemporaneous effect are large negative numbers but are not significantly different from zero.

4. For the labor productivity regressions, the lag effects vary widely in magnitude but are not significantly diferent from zero.

3.2 Productivity Dynamics: Robustness

The main issues to investigate are described in the following questions:

1. Are the previous estimates sensitive to "extreme" observations?

2. Are the results sensitive to controling for productivity growth due to investment in structures or office equipment?

3. Is there evidence for heterogeneity in productivity dynamics across industries?

4. Is there evidence for a non-linear response of productivity growth to our measure of technology adoption?

3.2.1 Sensitivity to Extreme Observations

The reader will recall from Figures 2 and 3 in section 2.2 that measured productivity growth rates take on extreme values in all the years of the data. One way to examine the sensitivity of the results in the previous section is simply to remove some of these observations without changing the regression methodology. We do this below by removing all plants from the data set that have a TFP growth rate exceeding 1 in absolute value in any period. Tables 3 and 4 report the results of this exercise.

Table 3:
TFP Dynamics -Excluding plants with Extreme TFP Growth Rates

$$y_t^i = \sum_{j,t} \alpha_t^j D_{ijt} + \sum_{k=0}^{n} \beta_k x_{t-k}^i + \epsilon_t^i$$

Lag Length	β_0	β_1	β_2	β_3	β_4	R^2	Number of Observations
$n = 0$	-.005					.203	26535
	(.00)						
$n = 1$	-.005	.002				.210	24766
	(.00)	(.01)					
$n = 2$	-.004	.003	.000			.206	22997
	(.00)	(.00)	(.62)				
$n = 3$	-.005	.003	.001	.001		.205	21228
	(.00)	(.00)	(.50)	(.14)			
$n = 4$	-.005	.003	.000	.000	.000	.212	19459
	(.00)	(.01)	(.68)	(.89)	(.32)		

p-values are indicated in parenthesis below the point estimates

Table 4:
Labor Productivity Dynamics -Excluding Plants with Extreme TFP Growth Rates

$$y_t^i = \sum_{j,t} \alpha_t^j D_{ijt} + \sum_{k=0}^{n} \beta_k x_{t-k}^i + \epsilon_t^i$$

Lag Length	β_0	β_1	β_2	β_3	β_4	R^2	Number of Observations
$n=0$	.004					.023	26535
	(.67)						
$n=1$	.006	.000				.023	24766
	(.59)	(.98)					
$n=2$	.006	.002	.006			.022	22997
	(.60)	(.84)	(.52)				
$n=3$	.012	.002	.010	.000		.020	21228
	(.44)	(.83)	(.38)	(.98)			
$n=4$	.007	.007	.011	-.001	.000	.018	19459
	(.68)	(.65)	(.31)	(.93)	(.98)		

p-values are indicated in parenthesis below the point estimates

Another way to deal with extreme observations is to use a regression methodology that is much less sensitive to such observations than ordinary least squares. One such methodology is the quantile regression methodology described by Koenker and Bassett (1978). One advantage of quantile estimators relative to OLS estimators is that when the regression error terms are drawn from a distribution with fatter tails than the normal distribution, then quantile estimators can have substantially lower variances than OLS estimators. An examination of the error terms indicates that they are far from being normal.

3.2.2 Sensitivity to Expanding the Controls

3.2.3 Heterogeneity Across Industries

3.2.4 Presence of Non-linear Response

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4 Appendix

4.1 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 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 $\dot{F}/F$.[16] 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 the factor shares used here are shares of cost. The cost share approach is slightly more general in that one need assume only competition in input markets rather than competition in input and output markets (see Hall (1991)).

$$TFPGrowth_t \equiv \dot{F}/F = \dot{Y}_t/Y_t - \sum_j \omega_t^j \dot{X}_t^j / X_t^j$$

To measure productivity growth at the plant level we have to empirically implement the growth accounting equation from the previous section. The first step is to approximate the growth rates in the equation with yearly growth rates as indicated below:

$$TFPGrowth_t = \Delta Y_t / Y_{t-1} - \sum_j \omega_t^j \Delta X_t^j / X_{t-1}^j$$

The second step is to indicate how we measure each of these variables. We measure Y by the value of nominal gross production measured in the data set divided by the industry-specific output price index. 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

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

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 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 eqiupment, 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^j as the average share of input j 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 in our sample equals the nominal value of all input costs for all plants in our sample. This amounts to assuming that there are no aggregate profits each year for the entire manufacturing sector.

4.2 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 as follows. The first year a plant appears in our data set we define the real value of capital of a particular type as the bookvalue divided by the investment price deflator of that type of capital. In all subsequent years we set the real value of capital equal to the previous year's value of capital after depreciation plus the deflated net purchases of capital. If a plant temporarily shuts down operations in year $t+1$, then net purchases of capital are assumed to be zero. Our procedures are summarized by the following 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 and transport equipment. The GDP deflator is used to deflate office equipment and land. Depreciation rates are set at the values calculated in Pombo (1998) that were described previously in the Appendix. We note that our procedure for assigning real capital values in the first year of the data set may introduce large errors. In particular, bookvalues for older plants may measure the nominal value of capital poorly even though the accounting procedures attempt to account for price changes through a revaluation term. This should be less of a problem for later years. 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 to measure capital services during period t is that we can construct the basic data on inputs and outputs only for 1975-90.

Figure 1

Distribution of Plants by Employees

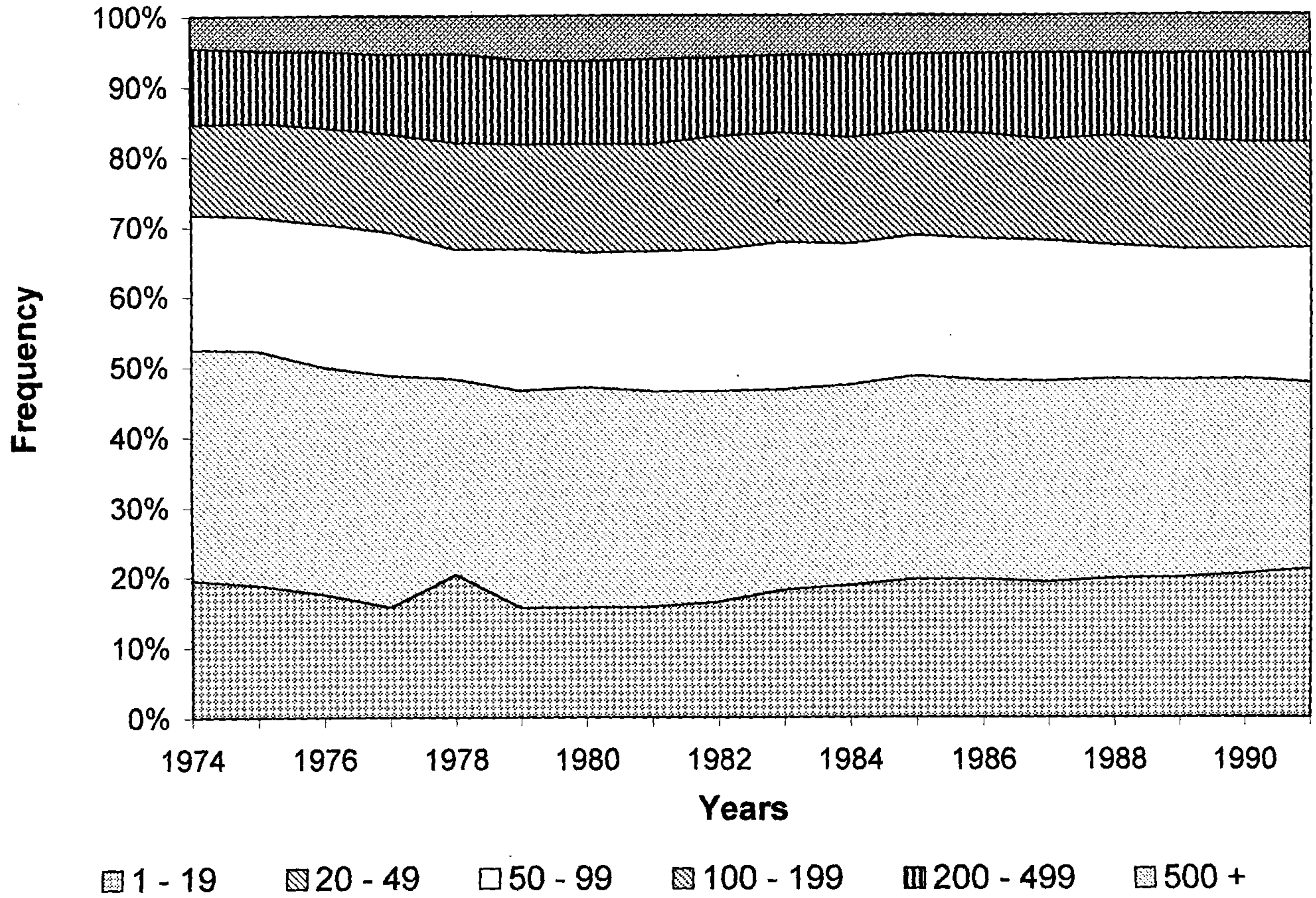
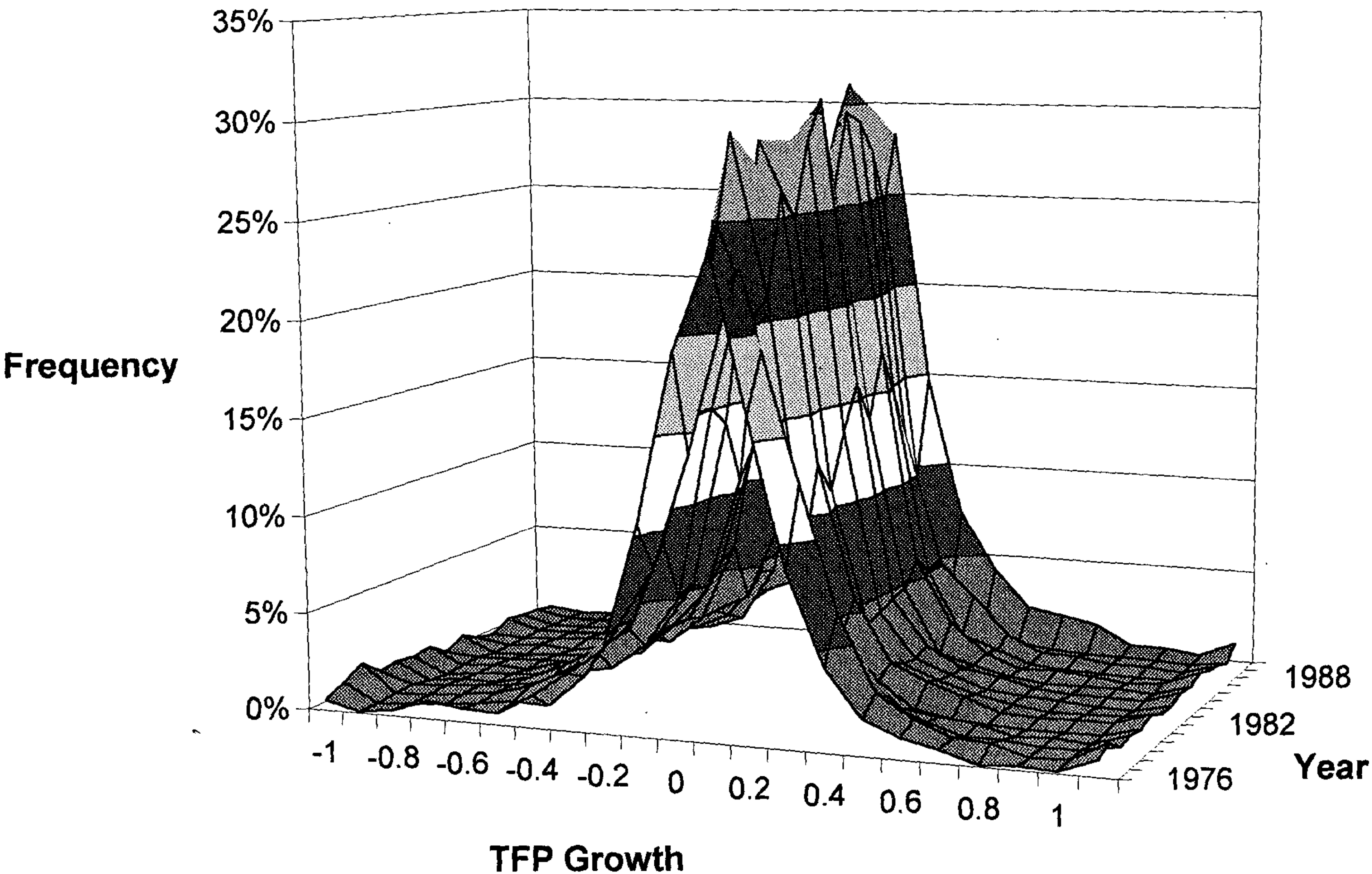
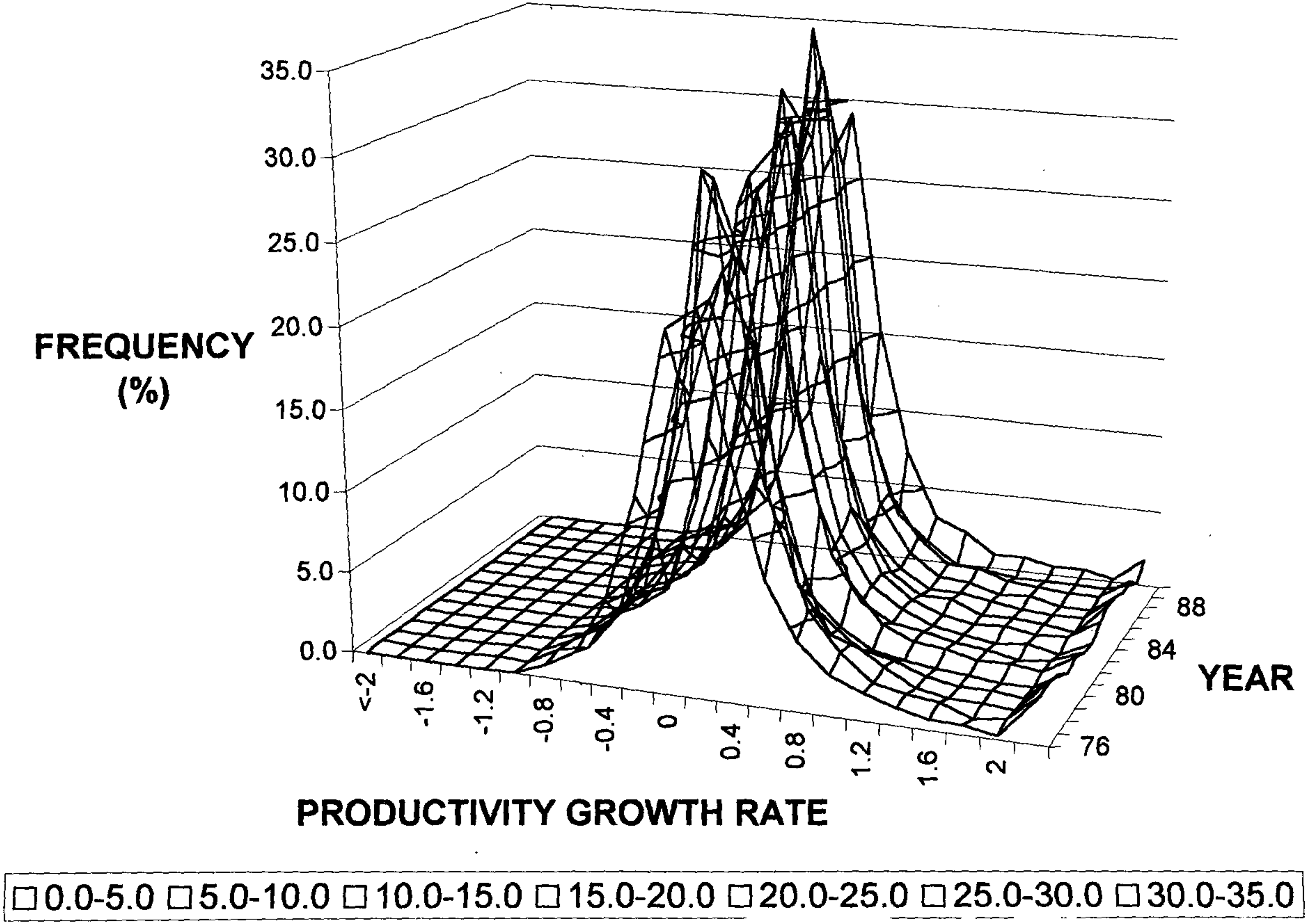


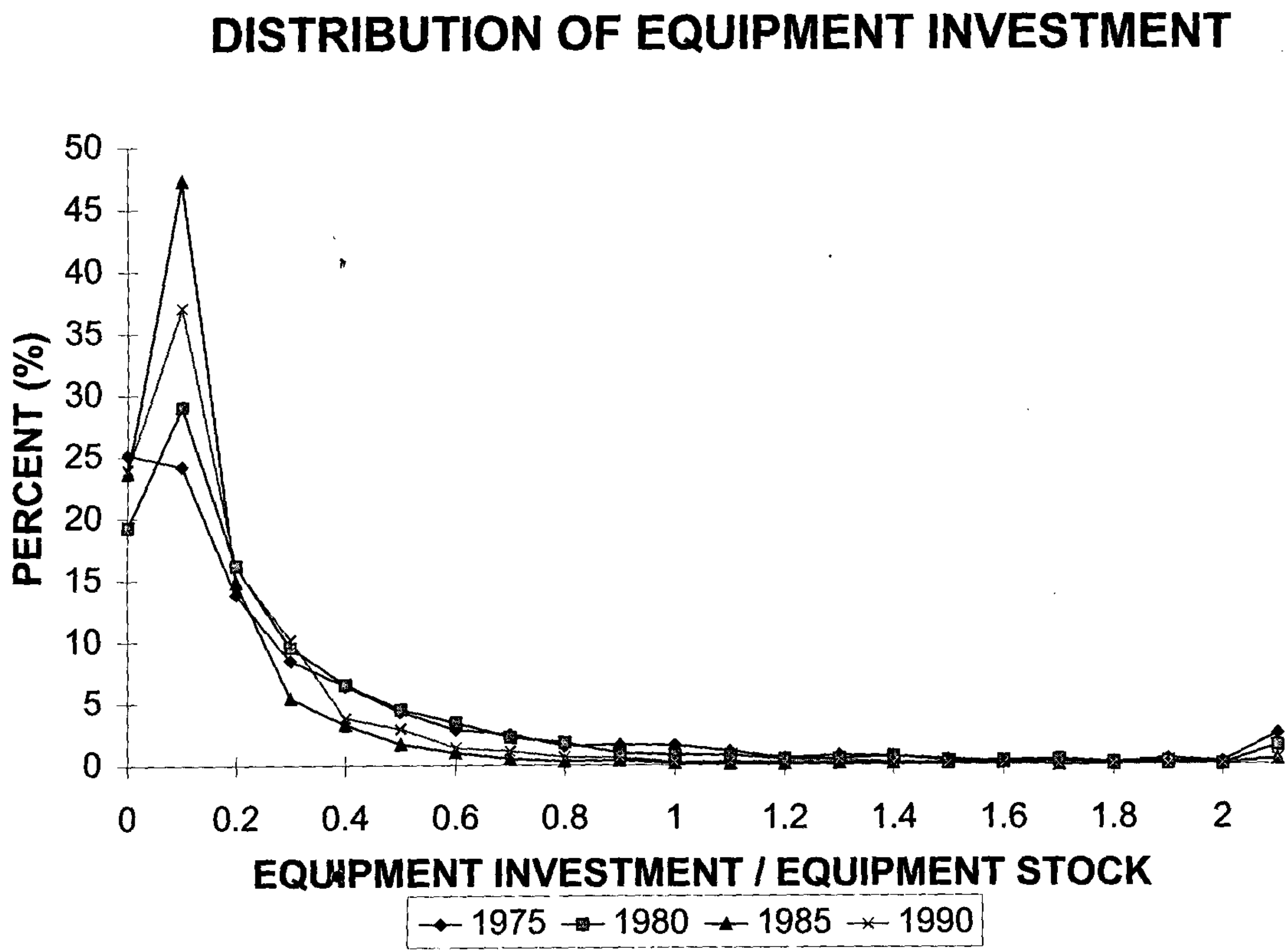
Figure 2

Distribution of TFP Growth Rates



DISTRIBUTION OF LABOR PRODUCTIVITY GROWTH RATES




DISTRIBUTION OF EQUIPMENT INVESTMENT
50
45
40
35
30
25
20
15
10
5
0
PERCENT (%)
0
0.2
0.4
0.6
0.8
1
1.2
1.4
1.6
1.8
2
EQUIPMENT INVESTMENT / EQUIPMENT STOCK
1975
1980
1985
1990