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Entry-Exit, Learning, and Productivity Change

Evidence from Chile

Lili Liu

The effects of plant turnover and learning on productivity growth are econometrically measured using a large panel of Chilean establishments covering the period 1979-86.

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Do competitive pressures really force inefficient producers to shut down? Does the entrance of new producers typically increase or worsen industrywide efficiency? Is there evidence of systematic learning processes? If there is, do these processes differ across plant cohorts? How do the effects of plant turnover combine to shape overall rates of industrial productivity growth?

Liu addresses these largely unexplored questions by applying econometric techniques from the efficiency frontiers and the panel data literature. She constructs plant-specific time-variant technical efficiency indices for surviving, exiting, and entering plant cohorts. She then uses these to compare productivity growth rates across plant cohorts and to examine the net effect of plant turnover and learning patterns on manufacturing-wide productivity growth.

The analysis is based on plant-level panel data for all Chilean manufacturing plants with at least 10 workers, covering eight years in the post-reform adjustment period 1979-86.

Liu finds the importance of plant turnover and different learning patterns across cohorts in driving the Chilean manufacturing-wide productivity changes. She finds that:

• The evidence supports the hypothesis that competitive pressures force less efficient producers to fail more often than others. Average technical efficiency levels are higher among surviving and entering plants than among exiting plants. These differences in productivity across cohorts are both systematic and persistent over time. The gap in productivity between incumbents and exiting plants, and between entering and exiting plants, has widened over time, while the gap between incumbents and entering plants has shrunk over time. This is because exiting plants have declining productivity over time, while entering plants gradually speed up their productivity growth. Moreover, competitive pressures have driven both incumbents and entrants to improve their productivity.

• The ratio of skilled labor to unskilled labor is higher and increasing more rapidly among incumbents and entrants than among exiting plants, providing an important source of learning and productivity growth.

• Although the economywide recession affected the productivity of each cohort to different degrees, there are steady increases in productivity over the sample period, reflecting both the replacement of inefficient producers by efficient ones and the improvement of productivity by incumbents and entrants.

These efficiency gains have not been isolated by traditional total factor productivity studies based on sectoral data. These gains suggest that microeconomic reform -- including trade liberalization, privatization, and the deregulation of markets -- have been effective in promoting efficiency improvements in the Chilean manufacturing sector.

Entry-Exit, Learning, and Productivity Change: Evidence From Chile

By
Lili Liu

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I. Introduction

Do competitive pressures really force inefficient producers to shut down? Does the entry of new producers typically improve or worsen industry-wide efficiency? Is there evidence of systematic learning processes, and if so, do these processes differ across plant cohorts? How do plant turnover effects combine to shape the overall rate of industrial productivity growth? Although theoretical studies on entry-exit and productivity growth have recently emerged (Jovanovic, 1982; Pakes and Ericson, 1988). micro empirical evidence on the linkage between entry-exit patterns and productivity in manufacturing sectors is very scant.

Most studies of industrial productivity change have been done at the sectoral level[1] and thus have been unable to capture the effects of entry, exit, and heterogeneity on productivity growth. Some micro studies of productivity change have been done, but they have been either cross-sectional or limited to selected industries or to a small sample of firms.[2] Hence they too have been unable to systematically address the issues mentioned above. Recently, as comprehensive micro data have become available, studies have emerged on the actual entry-exit patterns in manufacturing sectors (Dunne, Roberts, and Samuelson, 1989, on the U.S. manufacturing sector; Tybout, 1989, on the Chilean manufacturing sector). The substantial degree of heterogeneity in plant size, market share, and failure rates first revealed by these studies has motivated the present research to address the largely unexplored questions raised above.

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1 Much of this literature is surveyed in Chenery, Robinson, and Syrguin (1986), the World Bank (1987), Pack (1988), and Havyrlyshyn (1990).

2 See, for example, Cornwell, Schmidt, and Sickles (1990), Handoussa, Nishimizu, and Page (1986), Page (1984), and Tybout, Corbo, and De Melo (1990).

This paper applies econometric techniques from the efficiency frontiers literature and the panel data literature to construct plant-specific time-variant technical efficiency indices for surviving, exiting, and entering cohorts. These are then used to compare productivity growth rates across plant cohorts and to examine the net effect of plant turnover and learning patterns on manufacturing-wide productivity growth.

The analysis is based on plant-level panel data from Chile covering the period 1979-86. For several reasons, these data provide an excellent basis for inference. First, they include all Chilean manufacturing plants with at least 10 workers. This allows one to identify entering, exiting, and surviving plants and to look at their relative importance in driving manufacturing aggregates. Second, from 1974 to 1979 Chile underwent sweeping reform programs to liberalize its trade regime, privatize state firms, and deregulate markets. The data cover eight adjustment years following the reform, a period during which intense foreign competition, rising interest rates, and other shocks to the economy led to plant turnover rates much higher than in either developed countries (Dunne, Roberts, and Samuelson, 1989) or in other developing countries with less extensive liberalization and external shocks (Tybout, 1989; Roberts and Tybout, 1990). Finally, the removal of market distortions excludes the possible bias in estimating productivity gains because almost all prices are determined by the world market.

The findings support the hypothesis that competitive pressures force less efficient producers to fail more frequently than others. Average technical efficiency levels are higher among surviving and entering plants than among exiting plants. These differences in productivity across plant cohorts are both systematic and persistent over time. The gap in productivity between surviving and exiting plants and between entering and exiting plants has widened over time, while the gap between surviving and entering plants has narrowed. This occurred because the productivity of exiting plants declined over time while that of entering plants increased. Moreover, competitive pressures have driven both surviving plants and entrants to improve their productivity. The ratio of skilled labor to unskilled labor is higher and increasing more rapidly among incumbents and entrants than among exiting plants, providing an important source of learning and productivity growth. Although the economy-wide recession affected the productivity of each cohort to different degrees, productivity increased steadily over the sample period, reflecting both the replacement of inefficient producers by efficient ones and productivity improvements among surviving and entering plants. These efficiency gains have not been isolated by traditional total factor productivity studies based on sectoral data. These gains suggest that microeconomic reforms--including trade liberalization, privatization, and market deregulation--have been effective in promoting efficiency improvements in the manufacturing sector.

The rest of the paper is organized as follows. Section II reviews the literature on productivity and entry-exit studies. Section III specifies the models to be estimated, and section IV analyzes both descriptive evidence and the results from fitting the econometric models. Section V concludes the paper by pointing out the potential problems in the estimation models and possible corrections.

II. Review of Productivity and Entry-Exit Studies

The issue of industrial productivity growth has long interested development economists since efficient resource use helps to promote successful industrialization. Numerous empirical studies of productivity in developing countries are summarized by Chenery, Robinson, and Syiquin (1986), the World Bank (1987), Pack (1988), and Havyrlyshyn (1990).

However, empirical research on industrial productivity has suffered from two major shortcomings. First, the majority of the studies employ the traditional measure of productivity: total factor productivity (TFP).[3] This measure is based on strong assumptions, such as constant returns to scale and competitive markets, yet most studies completely ignore the possible bias of estimates if those assumptions are violated. Second, even if these problems are solved, the problem of aggregation remains. Most studies have been at the macro or sectoral levels, and have been unable to capture the effects of entry, exit and heterogeneity on productivity growth. Tybout (1990a), after discussing possible approaches for dealing with violated assumptions, concludes that the aggregate studies assume a well-defined production technology for all plants within the industrial, sectoral, or country analysis, completely ignoring plant heterogeneity: "if technological innovation takes place through a gradual process of efficient plants displacing inefficient ones, and/or through the diffusion of new knowledge, approaches to productivity measurement based on 'representative plant' behavior are at best misleading. At worst, they fail to capture what is important about productivity growth altogether, as Nelson (e.g., 1981) has long argued" (pp. 28-29).

Despite the recent advances in theoretical work on entry-exit, learning, and productivity (Jovanovic, 1982; Pakes and Ericson, 1987), micro empirical evidence on the linkage between entry-exit and plant productivity in manufacturing sectors is still very scant. This study draws on two lines

[3] See, for example, Nishimizu and Robinson (1984), and Nishimizu and Page (1982).

of recent micro empirical research, each of which has a different focus: entry-exit analysis and efficiency frontiers for panel data.

A. Entry-Exit Analysis

One line of micro empirical research attempts to identify actual patterns of entry-exit in manufacturing sectors. To delineate manufacturing-wide patterns of entry-exit, plant-specific time series data covering all plants in the manufacturing sector are needed. Plant identification codes and Standard Industrial Classification (SIC) codes for each observation allow files to be merged into a single panel-data base sorted by plant, year, and product type. The inter-temporal patterns of missing values for each plant can thus be used to identify entering, exiting, and surviving plants.

As comprehensive micro-level panel data have become available, studies have been done on actual entry-exit patterns in manufacturing sectors. For example, Baldwin and Gorecki (1987) provide a summary of entry-exit patterns in Canadian industries; Dunne, Roberts, and Samuelson (1989) analyze the actual patterns of entry-exit in the U.S. manufacturing sector; and Tybout (1989) does the same for the Chilean manufacturing sector. These studies were the first to reveal the substantial degree of heterogeneity in plant size, market share, and failure rates, which was largely unexplored in previous theoretical and empirical work. The performance measures used in these studies are typically output share and relative plant size. What is entirely missing in the entry-exit literature is an examination of how plant cohorts differ in efficiency levels and total factor productivity and how this heterogeneity, together with turnover effects, systematically helps to shape overall productivity performance and growth.

B. Traditional Efficiency Frontier Analysis

Another line of micro empirical research focuses on the measurement and estimation of firm-specific technical efficiency, entirely omitting the issue of entry-exit and learning. The common approach used in these studies is based on the framework of production frontier and technical efficiency models first proposed by Farrell (1957). The production function f(**x**) defines the maximum possible output a firm can produce given input bundles **x**, constituting the efficiency frontier or the best-practice frontier. Technical inefficiency is the amount by which a firm's actual output falls short of the efficiency frontier, reflecting non-minimized costs due to excessive use of inputs. Once the frontier (or the "best-practice") production, rarely known a priori, is estimated, an efficiency index for an economic unit can be derived from the deviation of its actual output from the frontier.

Various estimation techniques, and their strengths and weaknesses are summarized in Forsund, Lovell, and Schmidt (1980), Schmidt (1985), and Bauer (1990). Most studies on efficiency frontiers have been cross-sectional, imposing limitations on the econometric estimation of efficiency itself. Consider the following econometric model of a Cobb-Douglas efficiency frontier,

$$y_i = \beta' \mathbf{x}_i + v_i - u_i, \quad u_i \geq 0 \qquad i=1,\dots,N$$

where y_i and $\mathbf{x}_i$ are the logarithm of output and the vector of inputs, respectively, v_i is the random error term and u_i represents technical inefficiency. There are several shortcomings with the estimation of the efficiency frontier using cross-sectional data. First, to obtain estimates of plant-specific technical efficiency, one must specify probability distributions for both statistical random errors and technical inefficiency terms, and it is unclear how robust the results are for those assumptions. Second, technical efficiency has to be assumed to be independent of inputs, leading to biased estimates if inefficiency is known a priori by firm managers. Finally, firm-specific inefficiency indices can be estimated, but they cannot be estimated consistently.

When panel data are available, there is a potentially better alternative to estimation of the efficiency frontier. The repeated observations over time for a given firm provide information on its efficiency that is unavailable from cross-sectional data. Hence the estimation of firm-specific technical efficiency does not require strong distributional assumptions about composed error terms. In addition, the assumption that technical efficiency is independent of factor inputs does not have to be imposed. The panel data estimation of efficiency frontiers was introduced by Pitt and Lee (1981) and Schmidt and Sickles (1984).

The issue that concerns us here is whether a competitive environment is conducive to higher efficiency. Limited evidence suggests a positive linkage between competitive pressures and higher productivity. Using cross-sectional data, Tybout, Corbo, and de Melo (1990) derive industry-specific technical efficiency indices for Chilean industries for 1967, when an import-substitution regime was in place, and for 1979, when trade liberalization policies had been implemented. Although overall industrial efficiency did not improve between the two census years, the industries (at the three-digit classification level) that experienced relatively large reductions in protection improved relative to others. Cornwell, Schmidt, and Sickles (1990) found higher productivity in U.S. airlines during the deregulated period than during the regulated period.

This paper attempts to bring together the two bodies of literatures on entry-exit and productivity and thereby to shed light on the largely unexplored issues raised in the introduction.

III. Empirical Methodology

A. Defining Entering, Exiting, and Surviving Plants

The data cover all plants in the Chilean manufacturing sector with at least 10 workers. Plant identification codes and SIC codes for each observation allow us to merge files into a single panel-data base sorted by plant, year, and product type. The intertemporal patterns of missing values for each plant can thus be used to identify entering, exiting, and surviving plants.

Plants are divided into cohorts in three categories: surviving plants, exiting plants, and entrants. Surviving plants stay in the sample for the entire 1979-1986 period, so there is no change in their sample size. There are six exiting cohorts and each exits the data base consecutively between 1978+i and 1979+i (i=1,...,7), respectively. For example, the 1979 exiting cohort produced only in 1979, the 1980 exiting cohort produced only in 1979 and 1980, the 1981 exiting cohort produced only from 1979 through 1981, and so forth. Entrants enter the data base between 1979+i and 1980+i (i=1...., 7), respectively. For example, 1980 entrants entered the data base in 1980 and stayed through the rest of the sample years, 1981 entrants entered the data base in 1981 and stayed through the remaining sample years, and so on.[4]

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[4] Since our data cover only plants with 10 or more workers, entry-exit may also reflect an adjustment in labor around the cut-off point. However, this problem can be minimized by excluding plants which entered and exited repeatedly during the sample period (in addition, capital stock variables cannot be constructed from the perpetual inventory method for these plants). Since the data cover the cyclical period (growth-recession-growth), fluctuation in labor adjustment will likely be reflected by these plants. They account for 10% of plants but only 3% of total output.

Unfortunately, capital stock variables were reported only in 1980 and 1981, so capital stock variables derived from the perpetual inventory method could not be constructed for entrants after 1981 or for exiters in 1979. Those plants are, therefore, excluded in the econometric estimation of total factor productivity[5]. These plants do report data on other factor inputs and on output, so they can be included in the analysis of simple performance measures like labor productivity. This will be done to augment the efficiency frontier analysis.

B. Efficiency Analysis

We begin with a Cobb-Douglas representation of technology relating factor inputs and output for a given industry[6]:

$$y_{it} = \alpha + \beta' x_{it} + v_{it} - u_i \qquad (1)$$

$$i = 1, 2, \ldots, N$$

$$t = 1, 2, \ldots, T$$

$$u_i \geq 0$$

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5 A tiny portion of plants reported all data other than capital stock in 1980 or 1981. They are also excluded from the estimation.

6 The estimation model with balanced data design is based on Schmidt and Sickles (1984). The Cobb-Douglas technology is chosen because it deals better with industrial census data, as indicated by Griliches and Ringstad (1971).

where, y_{it} is the observed output for plant i at time t, expressed in logarithms; x_{it} is a vector of K inputs, also expressed in logarithms; the industry subscript is suppressed; and α and β are unknown parameters to be estimated.

The disturbance is composed of two different types of errors. The first, v_{it}, represents random errors in the production process. The second, u_i, represents technical inefficiency. Its distribution is one sided, reflecting the fact that output must lie on or below the frontier, $\alpha + \beta' x_{it} + v_{it}$.

The random error v_{it} is assumed to be distributed identically and independently across plants and time with identical zero mean and constant variance. It is also assumed to be uncorrelated with factor inputs. This assumption holds if the realized values of v_{it} are unanticipated by managers when they choose factor inputs (Zellner, Kmenta, and Dreze 1966). If data are sorted by plant and year, the error vector $v = (v_{i1}, ..., v_{it}, v_{i2} ...)$ has a covariance matrix $\sigma_v^2 I$, where I is an identity matrix with an order of NTxNT. The other error component, u_i, is assumed to be independently and identically distributed across plants with mean μ and variance σ_u^2.

Equation (1) can easily be modified to fit into the standard variable-intercept model in the panel data literature[7]. We may rewrite the equation as:

$$y_{it} = \alpha_i' + \beta \; x_{it} + v_{it} \qquad (2)$$

where $\alpha_i = \alpha - u_i$.

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7 Schmidt and Sickles (1984) discuss the application of panel data techniques to stochastic frontier models.

1. Fixed-Effect Models

Equation (2) is a fixed-effect model if α_i is treated as fixed, and the least-square dummy variable (LSDV) approach or covariance estimation can be applied. If the α_i are correlated with $\mathbf{x}_{it}$ in an unknown manner, the OLS estimator is BLUE. It is known from the panel data literature[8] that $\hat{\beta}_{cv}$ is unbiased and consistent when either N or T goes to infinity. $\hat{\beta}_{cv}$ is also called the "within estimator" since it is based exclusively on deviations of plant output and factor inputs from their own time series means. The associated plant-specific intercepts, $\hat{\alpha}_{icv}$, are the difference between a plant's actual level of output averaged over time and the predicted level of output given the plant's factor inputs averaged over time. The $\hat{\alpha}_{cv}$ estimators are also BLUE, but consistent only when T goes to infinity.

Differences in the intercepts across plants reveal relative efficiency differences. To derive a measure of technical efficiency relative to the production frontier, we follow Schmidt and Sickles (1984) and define:

$$\hat{a} = \max (\hat{\alpha}_i) \tag{3}$$

$$\hat{u}_i = \hat{a} - \hat{\alpha}_i \tag{4}$$

As N goes to infinity, the efficiency of the most-efficient plant will approach 100%.

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8 See, for example, Hsiao (1986).

2. Random-Effect Models

Alternatively, the technical efficiency indices can be treated as random variables. In that case, equation (2) fits into a random-effect model and can be estimated using the variance components approach. In treating the u_i terms as random variables, all the assumptions about the random vector **v** remain unchanged. In addition, **v** and **u** are assumed to be uncorrelated, and the **u** vector has elements of iid random components with constant variance σ_u^2. But, in contrast to the fixed-effect model, technical efficiency and factor inputs must be uncorrelated to yield consistent estimators.

Some of the well-known results from the panel data literature can be summarized. As either N or T goes to infinity, the GLS estimators of α and β, with known σ_u^2 and σ_v^2, are consistent and more efficient than are the within estimators. For fixed T as N goes to infinity, the efficiency property remains. But as T goes to infinity, the GLS estimator is equivalent to the LSDV estimator. In the more realistic case of unknown variance of **u** and **v**, N approaching infinity is required to obtain a consistent estimator of σ_u^2. Thus the strongest case for GLS is when N is large and T is small, and input and technical efficiency are uncorrelated.

To derive a plant-specific measure of technical efficiency, we can follow Schmidt and Sickles (1984). Define,

$$\hat{\alpha}_i = \frac{1}{T} \sum_{t=1}^{T} \hat{\epsilon}_{it} \qquad (5)$$

where the $\hat{\epsilon}_{it}$ terms are the residuals from GLS estimation.

Given $\hat{\beta}_{GLS}$, $\hat{\alpha}_i$ is consistent as T goes to infinity. Following equations 3.3 and 3.4, $\hat{u}_i$ can be separated, which requires that N go to infinity. Thus the consistent estimator of technical inefficiency requires that both N and T go to infinity.

3. Generalizing to Open Panel

The preceding discussion on estimation techniques is based on balanced data design; it assumes that each cross-sectional unit has T periods of observations. Unbalanced panel data do not create problems for the fixed-effect model since only within-group variations are relevant. But GLS estimation of the random-effect model has to be modified. Hsiao (1986) discusses the case where the total number of observations remains constant for $t=1, ..., T$, with the number of observations dropped equaling the number of observations added in each period. In our analysis of entry-exit, the total number of observations is unlikely to remain constant if the number of entrants does not match the number of exiting plants. The extension of Hsiao is straightforward.

4. Fixed-Effects or Random-Effects

The obvious advantage of the LSDV approach is that it does not require that efficiency and the regressors be uncorrelated. The disadvantages are that the LSDV estimators are less efficient than the GLS ones and that time-invariant plant-specific attributes other than technical efficiency cannot be included as regressors because of the problem of perfect collinearity. Examples of such attributes might be type of ownership and firm location. One way to solve the problem is to regress the estimated plant-specific technical inefficiency on those attributes. This of course assumes that those effects are observable and that they are uncorrelated with technical efficiency. If input choices are not correlated with technical efficiency, the random-effect model will be better since GLS estimators are more efficient.

To see whether the random-effect model can be used, a Hausman test can be used. Hausman (1978) noted that under the null hypothesis that α_i are uncorrelated with $\mathbf{x}_{it}$, the GLS achieves the Cramer-Rao lower bound, but under the alternative hypothesis, GLS is a biased estimator. $\hat{\boldsymbol{\beta}}_{cv}$ is consistent under both the null and the alternative hypothesis. Hence, the Hausman test asks whether $\hat{\boldsymbol{\beta}}_{cv}$ and $\hat{\boldsymbol{\beta}}_{gls}$ are significantly different.

5. Time-Variant Productivity

The models outlined above assume that plant-specific technical efficiency is time-invariant. Relaxing that assumption and allowing productivity to change over time enables one to identify time paths of technical efficiency for various plant cohorts. Cornwell, Schmidt, and Sickles (1990) introduce a parametric function of time into the production function to replace the coefficient of plant-specific technical efficiency. The functional form is.

$$y_{it} = \mathbf{x}_{it}'\boldsymbol{\beta} + \alpha_{it} + v_{it} \qquad (6)$$

where $\alpha_{it} = \mathbf{w}_{it}'\boldsymbol{\theta}_i$

$$\mathbf{w}_{it}' = (1, t, t^2)$$

$$\boldsymbol{\theta}_i = (\theta_{i1}, \theta_{i2}, \theta_{i3})'$$

and other variables are defined as before.

The measurement of productivity growth focuses on temporal variation, and the model allows the rate of productivity growth to vary over plants (cross-sectional variation). Efficiency levels can be derived from the residuals based on either the GLS estimators or the within estimators, as in Cornwell, Schmidt, and Sickles (1990). That is, θ_i is estimated by regressing $(y_{it}-x_{it}'\hat{\beta})$ for plant i on w_{it}, where $\hat{\beta}$ are GLS estimators if factor inputs are assumed to be uncorrelated with plant-specific time-variant effects. However, $\hat{\alpha}_{it}$ is not consistent as T goes to infinity if factor inputs are correlated with firm and time specific effects. Under these conditions, the consistent estimators of α_{it}, as T goes to infinity, can be derived by estimating equation (6) using OLS directly (i.e. the within estimation). The dimensionality problem in this regression can be avoided by proceeding in steps. First, regressing y_{it} and each factor input x_{it} on w_{it}, plant by plant, to get predicted values $\hat{y}_{it}$ and $\hat{x}_{it}$. Second, pooling all the data and regressing $(y_{it} - \hat{y}_{it})$ on $(x_{it} - \hat{x}_{it})$ to get $\hat{\beta}$. Finally, the residuals $(y_{it} - x_{it}'\hat{\beta})$ can be used to derive plant-specific time-variant technical efficiency. To derive technical efficiency relative to the frontier, the analogy (Cornwell, Schmidt, and Sickles, 1990) to equations (3) and (4) is as follows:

The frontier intercept at time t is:

$$\hat{a}_t = \max \ (\hat{\alpha}_{it}) \qquad (7)$$

and the plant-specific technical efficiency of plant i at time t is:

$$\hat{u}_{it} = \hat{a}_t - \hat{\alpha}_{it} \qquad (8)$$

IV. Entry-Exit and Productivity Change: Application to Chilean Industries

This section first provides some background on the liberalization policies implemented in Chile during 1974-79 and summarizes descriptive statistics on the entry-exit pattern and plant adjustment during the post-reform period. It then analyzes the results from fitting the econometric models developed above.

A. Liberalization Policies and Plant Adjustment in Chile

Before 1974, Chile had one of the most protected manufacturing sectors in developing countries. It also had heavily regulated factor and output markets, extensive price controls, widespread black markets, a highly controlled credit market, and a segmented and highly unionized labor market. As a result, there were de facto administrative barriers to entry, and productive inefficiency was rampant.

The Chilean reforms of 1974-79 reform was swift and comprehensive. Micro reforms included removal of protective trade barriers, privatization, and market deregulation. By June 1979, Chile had a uniform 10% tariff rate (except for motor vehicles) and all nontariff barriers were removed (the rapid reduction in trade protection is apparent in table 1). All but one bank and most firms were privatized and almost all prices were decontrolled. By April 1980 both the domestic and external financial markets were liberalized. New labor legislation greatly reduced the power of labor unions and prohibited strikes, --the policy reform most strongly applauded by firm managers (Corbo and Sanchez, 1985).

The contractionary macroeconomic policies aimed at fighting the fiscal deficit and inflation, together with the first oil shocks of 1973, plunged the economy into recession during 1973-76. Industries started to recover in 1976, and the recovery lasted through 1981 as firms dropped redundant labor. At the same time, backward wage indexation was introduced. However, the 1981 debt crisis in Latin America, overvalued exchange rates, and highly leveraged and undiversified financial markets in Chile led to another major recession in 1982-83. Industrial output and employment fell sharply, accompanied by a deepened "deindustrialization" process as import substitution policies were abandoned in the mid-1970s[10]. But industrial output picked up briskly in 1984, stalled temporarily in 1985, and resumed rapid growth in 1986. The structural adjustment program in 1985 aimed at expanding nontraditional export through devaluation of exchange rate, stabilization of copper prices and assistance to export producers; at encouraging public saving and private investment; at strengthening regulations of financial systems; and at reducing external debt. As a result of effective microeconomic policies implemented by the end of 1980 and the structural program in 1985, the period 1986-89 observed rapid growth under a favorable macroeconomic environment: the industrial sector has been a leading sector in growth; employment has expanded; and the industrial trade balance has improved. The Chilean industries are now one of the most efficient in Latin America.[11]

High rates of plant turnover and improvements in efficiency are two of the most important adjustments made by manufacturing firms in response to the changed policy incentives.

10 To help the adjustment reduce unemployment, the fixed exchange rate and wage indexation were abandoned

11 For detailed analysis of the import substitution strategies prior to 1974, liberalization policies implemented during 1974-1979 and post-reform performance of the economy, see Corbo, de Melo and Tybout (1985), Condon, Corbo and de Melo (1989), and Edwards and Edwards (1987).

This result was first casually suggested by a 1982 qualitative survey conducted by Corbo and Sanchez (1985) covering 10 manufacturing firms. Facing increased import competition, the surveyed firms closed their inefficient plants and reduced production lines. They also strived to increase efficiency by expanding investment, improving management and product quality, and, especially, reducing labor force. Compared with 1976, all the firms in the sample had cut employment by 1982-- by 50% in the largest firm and 20% in the smallest one.

More comprehensive descriptive statistics further reflect the importance of entry-exit and the heterogeneity of plant efficiency. Aggregate exit rates were much higher than entry rates during the sample period. The net result was a reduction in the total number of plants (table 2). Compared the end of sample years 1986 with the beginning of the sample year 1979, 25 out of 28 industries had net decline in the total number of plants: at least one third decline in 50% industries. Although the 1982 recession, touched off by the financial market crisis, may largely explain the high exit rates in 1982 and 1983, the equally high exit rates during the period of rapid growth in 1979-81 suggest the importance of turnover effects in industry restructuring in response to the rapidly changed incentives.

Before going through the more rigorous econometric analysis of efficiency frontiers and total factor productivity, looking at a simple measure labor productivity may help to reveal some of the most interesting patterns of the heterogeneity of plant efficiency adjustment. Table 3 presents labor productivity across plant cohorts. Efficiency labor units[12] were derived using a weighted average of labor inputs to take into account the heterogeneity of labor productivity. Plants were divided into three cohorts, as discussed in section III.A: surviving plants, exiting plants, and entrants. Four interesting observations emerge from table 3. First, average labor productivity is higher among

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[12] The efficiency labor units is based on Griliches and Ringstad (1971).

surviving plants and entrants than among exiting plants. Second, all cohorts display increasing trends in productivity over the sample period, although three cohorts had various degrees of decline in productivity in the recession and in 1985. Third, the increase in productivity for the exiting plants as a whole reflects both within-group efficiency improvement over time and changes in the sample sizes over time. This is because each cohort of exiting plants improves its productivity over time, and the exiting of the least efficient plants also contributes to efficiency gains. This applies to entrants as well. Fourth, as a result of within-group improvements and the dropping out of the least efficient plants, labor productivity for the whole manufacturing sector increased steadily over the sample period.

Although the results are suggestive, they reflect only single factor productivity. The following section applies the econometric models developed in section III to derive and examine the distributions of cohort-specific technical efficiency.

B. Econometric Analysis of Cohort-Specific Productivity

The variables used in estimation are derived as follows. Plant output was deflated by three-digit industry-specific output price indices. Intermediate material inputs were deflated by their own indices, which was constructed from sectoral output prices using the 1977 Chilean input-output table. Each energy input was deflated by its own deflator, which was constructed from reported physical volumes and values. The perpetual inventory method was applied to derive capital stocks, with each of four capital goods categories deflated by its own deflator.[13] Unfortunately, capital

[13] A complete description of the data preparation is in Appendix II which is available upon request.

stock was reported only in 1980 and 1981, so capital stock variables derived from the perpetual inventory method could not be constructed for entrants after 1981 and exiters in 1979. Those plants are, therefore, excluded from the estimation.[14]

As indicated in section III, the key question in choosing the fixed or the random-effect model is whether input choices are correlated with technical efficiency. The Hausman test is first applied to balanced data in 27 industries. Only surviving plants (accounting for over 50% of plants in all industries) are included in the test because computation of the Hausman statistic is more cumbersome with unbalanced panel. If the null hypothesis is rejected using the balanced data, there is no need to go over the unbalanced data. The test statistic indicates rejection of the null hypothesis for 23 industries with 3 degrees of freedom and a significance level of 0.025. The test was then applied again for the remaining four industries to the unbalanced data which included surviving plants, entrants, and exiters. The null hypothesis was rejected with 3 degrees of freedoms and a significance level of 0.025 for two out of these four industries. To sum up, the null hypothesis that inputs and technical efficiency are uncorrelated is rejected for 25 industries.

Given that the assumptions of the error components framework are not satisfied by our data, we first fit the fixed-effect model to equation (2) where plant-specific technical efficiency is time-invariant and time dummies are added to the equation 2:

$$y_{it} = \alpha_i + \beta' x_{it} + v_{it}$$

14 In addition, industry 314 (tobacco) has only three to four plants in the sample period, so there are not enough degrees of freedom for estimation.

This will give us a general idea of productivity differentials across cohorts, although it will force all plants to exhibit the same rate of productivity change through time. The estimated coefficients are presented in Table 4.

The overall fit reflected by adjusted R^2 looks reasonable. The estimated labor elasticities are positive for all industries, significant at the 0.05 level for 24 of 27 industries and at the 0.10 level for 2 more industries. But the elasticities exhibit considerable variation across industries, from 0.021 to 0.329, with most industries averaging 0.2. The estimated elasticities of intermediate inputs are all statistically significant at the 0.05 level. Although capital elasticities are significant at the 0.05 level for 11 industries and at the 0.10 level for 1, the elasticities appear small, and 5 industries have implausible negative elasticities, suggesting possible measurement errors.[15] The estimated low returns to scale do not support the hypothesis of constant returns to scale when plant fixed effects are controlled for. Experiments with the largest industry (SIC 312) based on cross-sectional estimation indicate increasing returns to scale when individual effects are not controlled for. This finding suggests possible bias in the estimated elasticities due to cross-sectional data, measurement errors, inappropriate functional form, or simultaneity.

The plant-specific intercept $\hat{\alpha}_i$ measures relative technical efficiency among plants. We could follow Schmidt and Sickles (1984) to obtain plant-specific technical efficiency indices measured relative to the frontier (equations 3, 4). However, we would gain little insight from doing so since we are mainly interested in the evolution of cohort-specific technical efficiency. The transformation of relative efficiency only shifts all cohorts by some common unit, leaving relative patterns unchanged.

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15 Using techniques developed by Griliches and Hausman (1986), Westbrook and Tybout (in progress) estimated returns to scale by specifically dealing with measurement errors. Their approach is being adapted to an additional paper.

Table 5 reports average cohort-specific technical efficiency over time, which is the weighted average of relative plant-specific indices ($\hat{\alpha}_i$'s) within each cohort. Since the time trends are already controlled for, the differences in technical efficiency among cohorts reflect their average deviations from the time trend. The most notable result is that technical efficiency is higher on average among surviving plants and entrants than among exiting plants. The distribution of technical efficiency for surviving plants versus entrants does not show any obviously uniform pattern. Entrants have higher technical efficiency than surviving plants in some industries and lower technical efficiency in others.

Since the time dummies force all plants to follow a common productivity growth path, they obscure plant-specific productivity changes over time. To relax this, we apply OLS to equation (6) and derive $\hat{\alpha}_{it}$ which is the predicted value of plant-specific time-variant technical efficiency.

After deriving the $\hat{\alpha}_{it}$ values, we average them over surviving plants, exiting plants, and entrants in the manufacturing sector, respectively for each time period. The average technical efficiency by plant cohorts in the manufacturing sector is plotted in figure 1. (The 1979 exiting plants and 1982-86 entrants are excluded from figure 1 because of missing capital stock data, and the 1980 exiting plants are excluded because of lack of degrees of freedom to estimate α_{it}.) Recall the findings in Table 5 (where plant-specific technical efficiency is assumed to be time-invariant) that technical efficiency is on average higher among surviving plants and entrants than among exiting plants. Figure 1 reinforces this finding by showing that in every time period technical efficiency is on average higher among surviving plants and entrants than among exiting plants. In addition, figure 1 indicates the time path of technical efficiency change. Surviving plants show slightly declining productivity from 1979 to 1985, but with productivity stabilizing from 1985 to 1986. Entrants started with lower technical efficiency than surviving plants and show a slight decline in productivity from 1980 to 1983 similar to that of surviving plants, but their productivity increased faster than that of surviving plants from 1983 to 1986. In contrast to the trends of surviving plants and entrants, exiting plants have declining productivity throughout 1980-85. As a result, the net gaps in technical efficiency between exiters and entrants and between exiters and surviving plants increase over time.

Figure 2a shows the time paths of average productivity for each exiting cohort. Three patterns are obvious. First, cohorts with the lowest technical efficiency exited first in every year. (Although we were not able to estimate technical efficiency for the 1979 and 1980 exiting cohorts, table 3 indicates that they have low labor productivity.) Second, productivity improvement occurred only from 1979 to 1980, a high growth period, and only for two exiting cohorts (1982 and 1983). But the two still had much lower efficiency than did surviving plants. Finally, after 1980, all exiting cohorts showed declining productivity. In contrast to entrants, exiting plants were not able to catch up when the economy started to recover in 1984.

Figure 2b plots average technical efficiency levels for entering cohorts. Although the 1980 entrants had declining technical efficiency initially, they were able to bounce back after the recession. The 1981 entrants showed much faster and steadier growth, leading to a steadily increasing trend for entrants as a whole and suggesting that learning processes were taking place.

The time path of each exiting (entering) cohort in Figure 2a (Figure 2b) illustrates that turnover effects and within-group efficiency changes combined to shape the general time path of productivity for exiting (entering) plants as a whole (figure 1). Therefore, the trend of exiting (entering) plants over time in figure 1 reflects both within-group efficiency changes and turnover effects. Take the example of productivity change for exiting plants from 1982 to 1983. The average technical efficiency of all exiting plants in 1983 (figure 1) is the weighted average of efficiency levels of each exiting plant cohort in 1983 (figure 2a). When the 1982 cohort exits, the lowest technical efficiency cohort in 1982 has dropped out, so the market share of the remaining plants (which had higher technical efficiency) increased, causing a positive turnover effect. However, from 1982 to 1983, each remaining exiting cohort (i.e., plants that continued production from 1982 to 1983 but dropped out later) failed to improve its productivity. Their declining productivity outweighs the positive turnover effect, leading to a net decline in total productivity from 1982 to 1983 (figure 1).

As figure 1 shows, overall productivity levels among entering, exiting, and surviving plants do not increase significantly, probably because of the economy-wide recession. Despite this, it is possible that industry-wide productivity improved as the less efficient producers exited and incumbents and entrants increased their market share. This appears to have been the case. Figure 3 plots average technical efficiency in manufacturing over the sample period. Changes in technical efficiency within each cohort, variations across cohorts, and plant turnover have combined to increase the industry-wide average productivity from 1982 to 1986. A significant portion of the efficiency gain is due to distributional effects, i.e., replacing inefficient producers by efficient and/or improving plants. Such results suggest that competitive pressures have been significant and that micro reform policies have been effective in discriminating between inefficient and efficient producers.

Note that the estimated trend in figure 3 may have underestimated the improvement in productivity for two reasons. First, as mentioned before, we excluded the 1979 and the 1980 exiting cohorts. These two cohorts have lower labor productivity (table 3), so their exit would probably have increased average productivity from 1979 to 1981. Second, all entrants after 1981 were excluded, as mentioned earlier. Table 3 shows that average labor productivity among entrants after 1981 increased over time. We might have obtained a different trend for the period of 1983 to 1986 had these entering cohorts been included.

Sustained learning at an industry-wide level should be reflected in the growth of measured technical efficiency not accounted for by measurable factor inputs (Pack, 1990). But capacity utilization may significantly influence the measured residuals, and cyclical demand may also exert an impact on residual changes. This measurement problem is particularly acute in the present study because the data cover periods of growth (1979-80), recession (1982-84), and recovery (1985-86). The change in plant-specific technical efficiency levels will thus reflect both plant-level effects and industrial or macro fluctuations over time.

Two bits of evidence suggest that micro efficiency improvement took place despite fluctuations in capacity utilization. First is the ratio of skilled to unskilled labor by cohorts, a simple yet revealing statistic, suggesting the important impact of education on learning and productivity growth (table 6). The ratios are higher and increasing faster among surviving plants and entering plants, reinforcing the labor productivity findings presented in table 3. The increase in the ratio of skilled to unskilled labor contributed to the rise of labor productivity. Second, even if we make the extreme assumption that the trends presented in figure 1 reflect purely capacity utilization changes (which is unlikely), figure 3 would still reflect efficiency gains from replacing less efficient plants with more efficient ones.

V. Conclusion

The findings support .he hypothesis that the forces of competition discriminate against less efficient producers. Average technical efficiency levels are higher among surviving and entering plants than among exiting plants. The gap in productivity between surviving and exiting plants and between exiting and entering plants has widened over time; while the gap between surviving ano entering plants has narrowed. Moreover, both surviving and entering plants have improved their productivity. The ratio of skilled labor to unskilled labor is higher and increasing more rapidly among surviving plants and entrants than among exiting plants, suggesting that learning is a source of productivity growth. Although the economy-wide recession in 1982-83 affected the productivity of each cohort to different degrees, there were steady increases in productivity over the sample period, reflecting both the replacement of inefficient producers by efficient ones and the improvement of productivity by surviving plants and e· ·nts. This suggests that microeconomic policies that removed all distortions are effective in pushing efficiency improvement in the manufacturing sector.

The study suggests several areas for additional research which is currently in progress. First, the model specifications have assumed away measurement errors which are shown to be empirically important (Westbrook and Tybout, in progress). If returns to scale were underestimated, the estimated technical efficiency based on residuals would also include scale effects. Second, open panel data also bring up the question of selectivity bias. Finally, it would be of great interest to compare the econometric estimation of efficiency frontiers with the mathematical programming method[16]. Efforts are being made to test whether the results are sensitive to different model specifications.

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16 The mathematical programming model is also called data envelopment analysis (DEA). The theoretical motivation can be found in Farrell (1957) and Varian (1984a, 1984b). Banker, Charnes, and Cooper are among the major contributors to empirical models. Recent developments in DEA are summarized by Seiford and Thrall (1990).

Table 1 Effective Protection in Chile, 1961-79

Sector	Effective protection (percent)					
	1961	1967	1974	1976	1978	1979
Foods products	2,884	365	161	48	16	12
Beverages	609	-23	203	47	19	13
Tobacco products	141	-13	114	29	11	11
Textiles	672	492	239	74	28	14
Footwear and clothing	386	16	264	71	27	14
Wood and cork	21	-4	157	45	16	15
Furniture	209	-5	95	28	11	11
Paper and paper products	41	95	184	62	22	17
Printing and publishing	82	-15	140	40	20	12
Leather and leather products	714	18	181	46	21	13
Rubber products	109	304	49	54	26	15
Chemicals products	89	64	80	45	16	13
Petroleum and coal products	45	1,140	265	17	12	13
Nonmetallic mineral products	227	1	128	55	20	14
Basic metals	198	35	127	64	25	17
Metal products	43	92	147	77	27	15
Nonelectrical machinery	85	76	96	58	19	13
Electrical machinery	111	449	96	58	19	13
Transportation equipment	101	271	--	--	--	--
Other manufacturing	164	--	--	--	--	--
Equally weighted arithmetic mean	346.5	176.7	151.4	51.0	19.7	13.61
Standard deviation	618	279.0	60.4	15.70	5.3	1.7
Variability coefficient	1.78	1.57	0.399	0.31	0.27	0.124
Range	2.863	1.163	216	60	17	6

Source: Corbo and Sanchez (1985)

Table 2 Net Reduction in the Number of Plants by the Three-Digit Industry

1979-86

ISIC	1979	1980	1981	1982	1983	1984	1985	1986	(1986-1979)/1979
312	1610	1507	1421	1383	1354	1401	1397	1343	-0.166
313	211	188	158	151	148	138	127	111	-0.474
314	3	4	4	4	3	4	4	4	0.333
321	503	445	403	350	327	336	337	331	-0.342
322	442	398	346	305	265	294	275	280	-0.367
323	90	76	68	59	53	51	50	46	-0.489
324	185	156	137	127	127	133	128	137	-0.259
331	524	449	406	358	335	339	342	313	-0.403
332	211	192	171	143	116	117	115	104	-0.507
341	70	67	60	56	52	60	58	57	-0.186
342	242	227	206	196	177	167	164	163	-0.326
351	65	59	59	56	51	58	60	61	-0.062
352	171	166	159	148	145	151	149	153	-0.105
353	10	9	9	9	10	10	2	2	-0.8
354	8	7	9	9	8	9	16	16	1
355	63	67	59	53	52	56	55	48	-0.238
356	170	163	149	142	142	161	161	166	-0.024
361	13	13	10	15	11	12	12	11	-0.154
362	33	28	29	24	20	22	22	18	-0.455
369	135	139	128	110	104	108	115	113	-0.163
371	64	48	42	35	36	32	31	32	-0.5
372	34	31	28	27	21	24	25	25	-0.265
381	459	447	413	365	322	358	351	347	-0.244
382	169	140	145	138	125	133	127	115	-0.32
383	87	72	64	57	55	59	56	59	-0.322
384	150	124	112	94	87	83	86	86	-0.427
385	15	20	14	15	15	14	16	15	0
390	77	66	63	55	44	48	52	49	-0.364

TABLE 3

Labour Productivity in the Manufacturing Sector

	1979	1980	1981	1982	1983	1984	1985	1986
Surviving Plants	1101	1161	1231	1201	1223	1264	1241	1422
Exiters Average	717	765	847	831	784	950	898	
Exiters Decomposition:								
1979	629							
1980	689	718						
1981	667	664	706					
1982	798	826	913	793				
1983	743	778	806	698	638			
1984	999	929	1099	1076	943	836		
1985	767	840	894	897	850	1011	898	
Entrants Average		866	1094	1119	1081	1000	1005	1013
Entrants Decomposition:								
1980		866	926	828	946	955	942	1040
1981			1370	1641	1554	1326	1423	1129
1982				1073	1142	1024	1053	1142
1983					958	1064	1171	1145
1984						931	949	993
1985							827	953
1986								939
Manufacture Average	906	971	1069	1071	1100	1139	1139	1288

Note: Labour is defined as efficiency labour units. Output is the gross value of output.

<u>Table 4 - Fixed-Effect Model</u>

Regression Coefficients Dependent Variable Ln (Y)
(Standard Error in Parentheses. * implies significance at α = 0.05 level, ** implies α = 0.10 level)

Industry	Ln(L)	Ln(K)	Ln(M)	RTS	$\bar{R}^2$	$\hat{\sigma}^2$	F-Stat	N
312	0.142* (0.008)	0.007** (0.005)	0.74* (0.006)	0.89	0.98	0.036	2622.7	8500
313	0.095* (0.026)	0.03* (0.004)	0.58* (0.007)	0.705	0.96	0.093	126.37	693
321	0.200* (0.02)	0.029* (0.009)	0.664* (0.013)	0.89	0.96	0.06	499.39	2383
322	0.244* (0.023)	0.004 (0.011)	0.644* (0.015)	0.89	0.96	0.067	387.7	2019
323	0.292* (0.061)	0.057* (0.027)	0.558* (0.032)	0.91	0.97	0.063	66.95	361
324	0.201* (0.028)	0.031* (0.016)	0.715* (0.021)	0.95	0.98	0.04	249.94	862
331	0.231* (0.022)	0.030* (0.014)	0.652* (0.013)	0.91	0.95	0.082	420.64	1929
332	0.201* (0.04)	0.05* (0.020)	0.678* (0.022)	0.93	0.96	0.064	194.83	860
341	0.058* (0.024)	0.112* (0.033)	0.654* (0.03)	0.82	0.98	0.047	69.326	351
342	0.088* (0.017)	0.081* (0.018)	0.538* (0.018)	0.71	0.97	0.06	235.79	1223
351	0.021 (0.065)	0.004 (0.017)	0.658* (0.047)	0.683	0.95	0.115	39.56	338
352	0.132* (0.02)	0.005 (0.009)	0.603* (0.018)	0.74	0.97	0.05	158.51	1064
353	0.052** (0.04)	0.012* (0.007)	0.683* (0.006)	0.75	0.99	0.026	61.42	64
354	0.24 (0.091)	-0.178 (0.098)	0.81* (0.08)	0.87	0.99	0.02	86.2	48
355	0.181* (0.038)	0.141* (0.036)	0.541* (0.034)	0.86	0.97	0.054	81.229	372
356	0.188* (0.03)	0.007 (0.014)	0.638* (0.019)	0.83	0.96	0.054	216.17	871
361	0.271** (0.21)	0.097* (0.051)	0.378* (0.109)	0.71	0.97	0.075	30.2	51
362	0.329* (0.078)	0.040 (0.062)	0.585* (0.05)	0.95	0.97	0.079	33.21	175
369	0.283* (0.04)	-0.001 (0.014)	0.63* (0.031)	0.91	0.97	0.09	113.11	646
371	0.164* (0.058)	0.053 (0.06)	0.605* (0.042)	0.82	0.97	0.09	39.64	344
372	0.228* (0.06)	-0.028 (0.056)	0.694* (0.042)	0.89	0.99	0.076	42.34	168
381	0.209* (0.018)	0.018* (0.008)	0.631* (0.013)	0.86	0.97	0.065	452.99	2193
382	0.069* (0.025)	0.002 (0.01)	0.638* (0.023)	0.71	0.94	0.087	129.53	691
383	0.216* (0.049)	0.032 (0.03)	0.687* (0.03)	0.94	0.97	0.086	92.3	413
384	0.208* (0.038)	-0.0005 (0.017)	0.682* (0.025)	0.89	0.96	0.094	162	675
385	0.287* (0.109)	0.069 (0.13)	0.462* (0.069)	0.82	0.92	0.063	50.75	87
390	0.291* (0.051)	-0.004 (0.024)	0.615* (0.035)	0.9	0.94	0.076	75.38	366

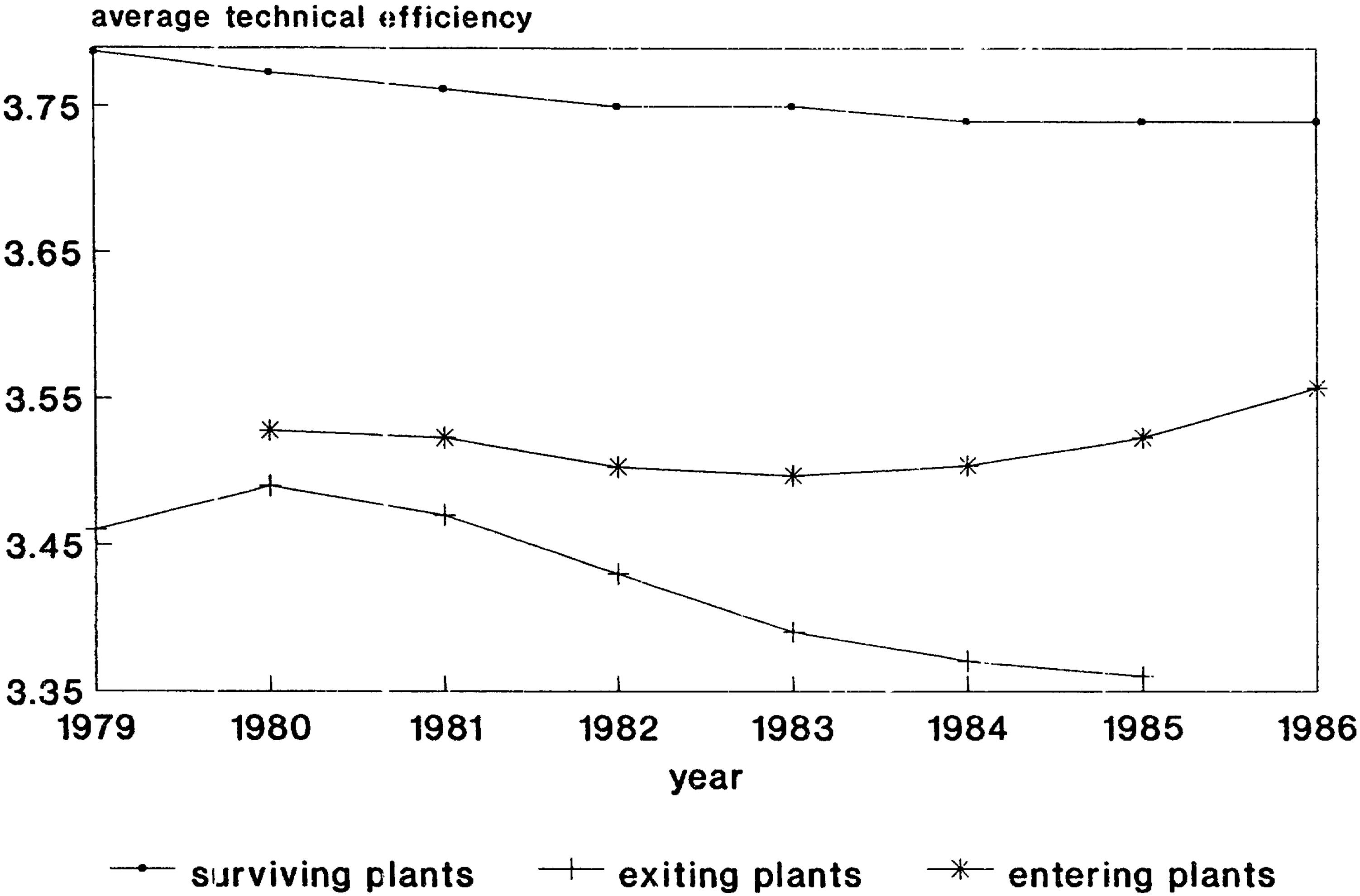
TABLE 5

Average Technical Efficiency by Plant-Cohorts

Industry	Surviving Plants				Exiting Plants				Entrants			
	Mean	SE	STD	N	Mean	SE	STD	N	Mean	SE	STD	N
312	2.384	0.010	0.286	836	2.304	0.017	0.305	310	2.418	0.046	0.321	49
313	4.369	0.068	0.560	67	4.049	0.100	0.546	30	5.308	0.211	0.366	3
321	2.880	0.018	0.274	232	2.731	0.028	0.297	111	2.702	0.063	0.227	13
322	3.048	0.019	0.251	169	2.897	0.022	0.270	152	3.029	0.163	0.399	6
323	3.489	0.049	0.269	30	3.147	0.063	0.328	27	3.120			1
324	2.321	0.025	0.221	78	2.132	0.036	0.241	45	2.218	0.063	0.126	4
331	2.788	0.020	0.261	163	2.638	0.032	0.363	129	2.766	0.110	0.396	13
332	2.456	0.038	0.300	62	2.298	0.033	0.302	84	2.237	0.059	0.117	4
341	2.916	0.077	0.449	34	2.494	0.148	0.592	16	2.906			1
342	4.304	0.040	0.434	115	3.842	0.048	0.380	62	4.015	0.181	0.313	3
351	4.045	0.089	0.536	36	3.633	0.124	0.447	13				
352	4.407	0.046	0.489	115	3.971	0.105	0.546	27	4.067	0.168	0.377	4
353	4.296	0.257	0.726	8								
354	3.143	0.196	0.480	6								
355	3.213	0.047	0.287	38	3.144	0.086	0.320	14	3.053			1
356	3.523	0.028	0.264	91	3.295	0.058	0.303	27	3.365	0.151	0.301	4
361	5.174	0.185	0.414	5	4.707	0.185	0.261	2				
362	3.158	0.078	0.340	19	2.772	0.138	0.338	6				
369	3.337	0.051	0.400	61	2.902	0.062	0.363	34	3.108	0.046	0.065	2
371	3.549	0.059	0.355	36	3.260	0.090	0.348	15				
372	3.275	0.074	0.323	19	3.059	0.100	0.201	4				
381	3.363	0.022	0.321	209	3.084	0.031	0.349	126	3.366	0.224	0.448	4
382	3.893	0.049	0.399	67	3.925	0.075	0.429	33	3.828	0.342	0.484	2
383	2.717	0.043	0.283	44	2.425	0.094	0.363	15				
384	2.983	0.040	0.313	62	2.862	0.054	0.356	43	2.681	0.209	0.295	2
385	4.456	0.076	0.216	8	4.051	0.122	0.211	3	4.092			1
390	3.421	0.045	0.260	34	3.172	0.083	0.373	20	3.782			1
Weighted Avarage	2.998	0.015	0.734	2471	2.806	0.017	0.618	1292	2.821	0.065	0.704	118
Simple Average	3.345	0.157	0.683	19	3.102	0.142	0.620	19	3.266	0.177	0.772	19

Note: N=Number of Observations, SE=Standard Error of Mean, STD=Standard Error.
Simple average: average over industry mean.
Weighted average: average over the entire sample.
Industry 351, 353, 354, 371, 372, and 383 were excluded from mean calculation.

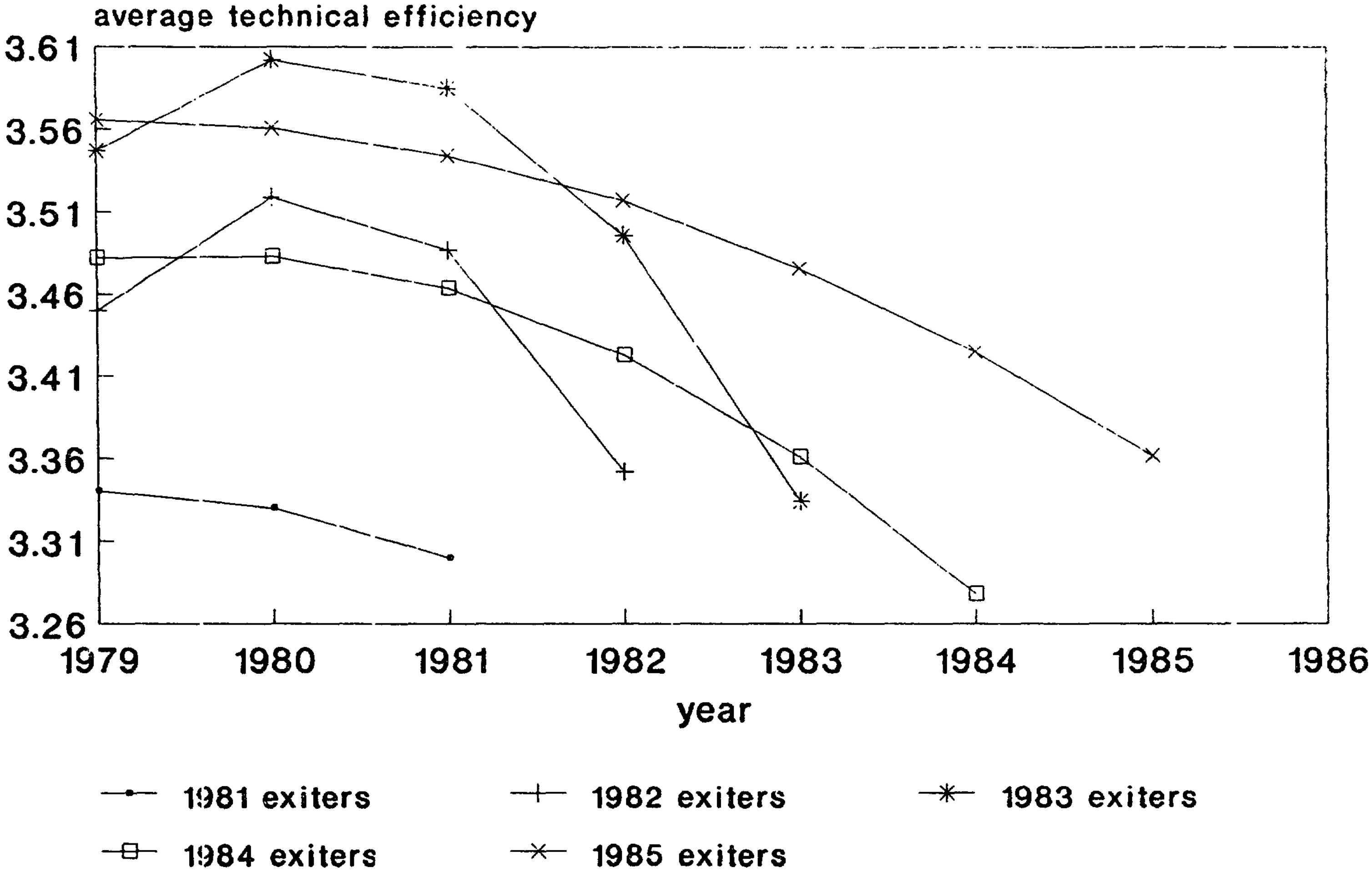
Figure 1: Technical Efficiency Change
By Three Cohorts



27 Industries

Figure 2a: Technical Efficiency Change

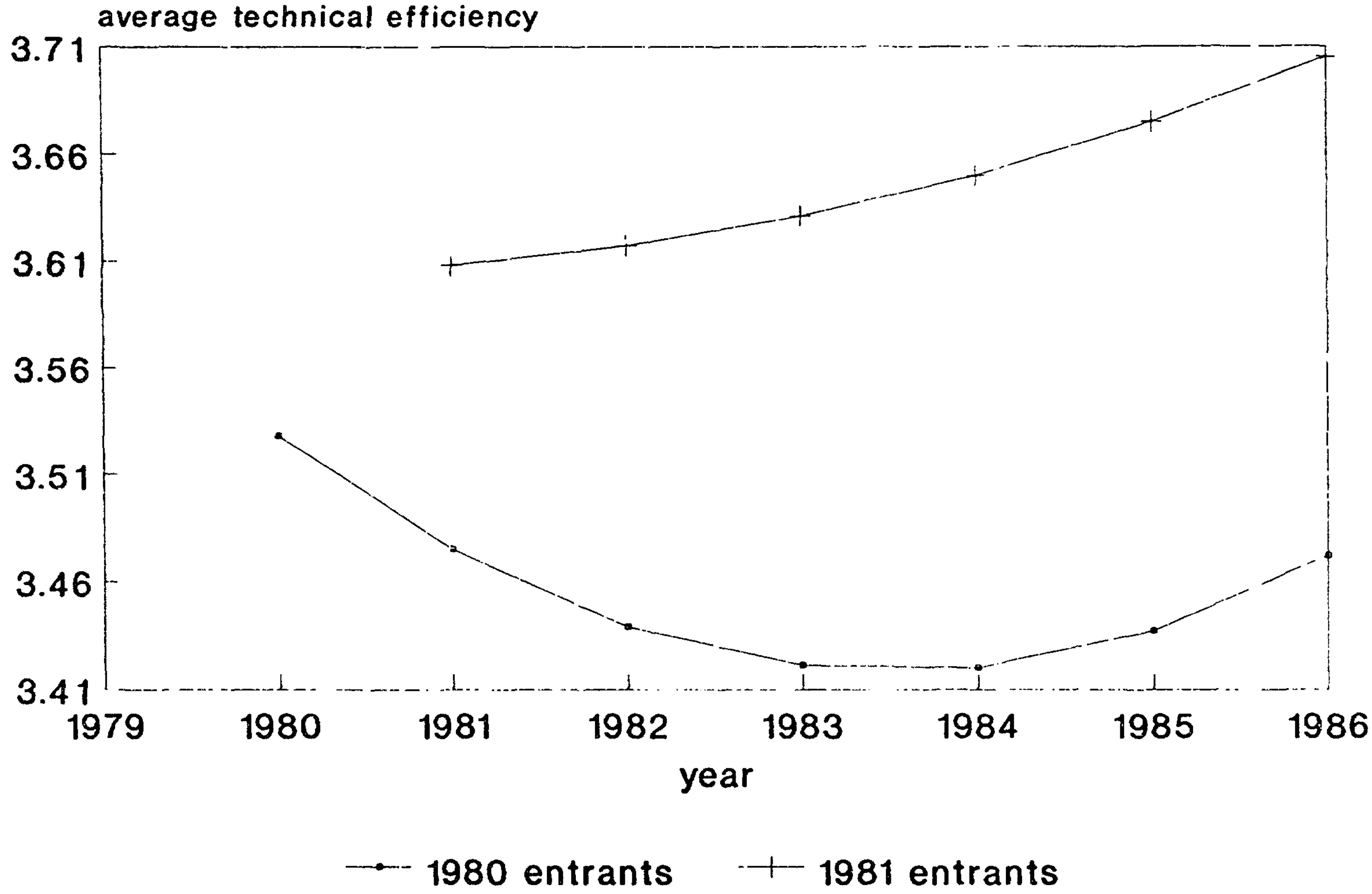
Exiting Cohorts



27 industries

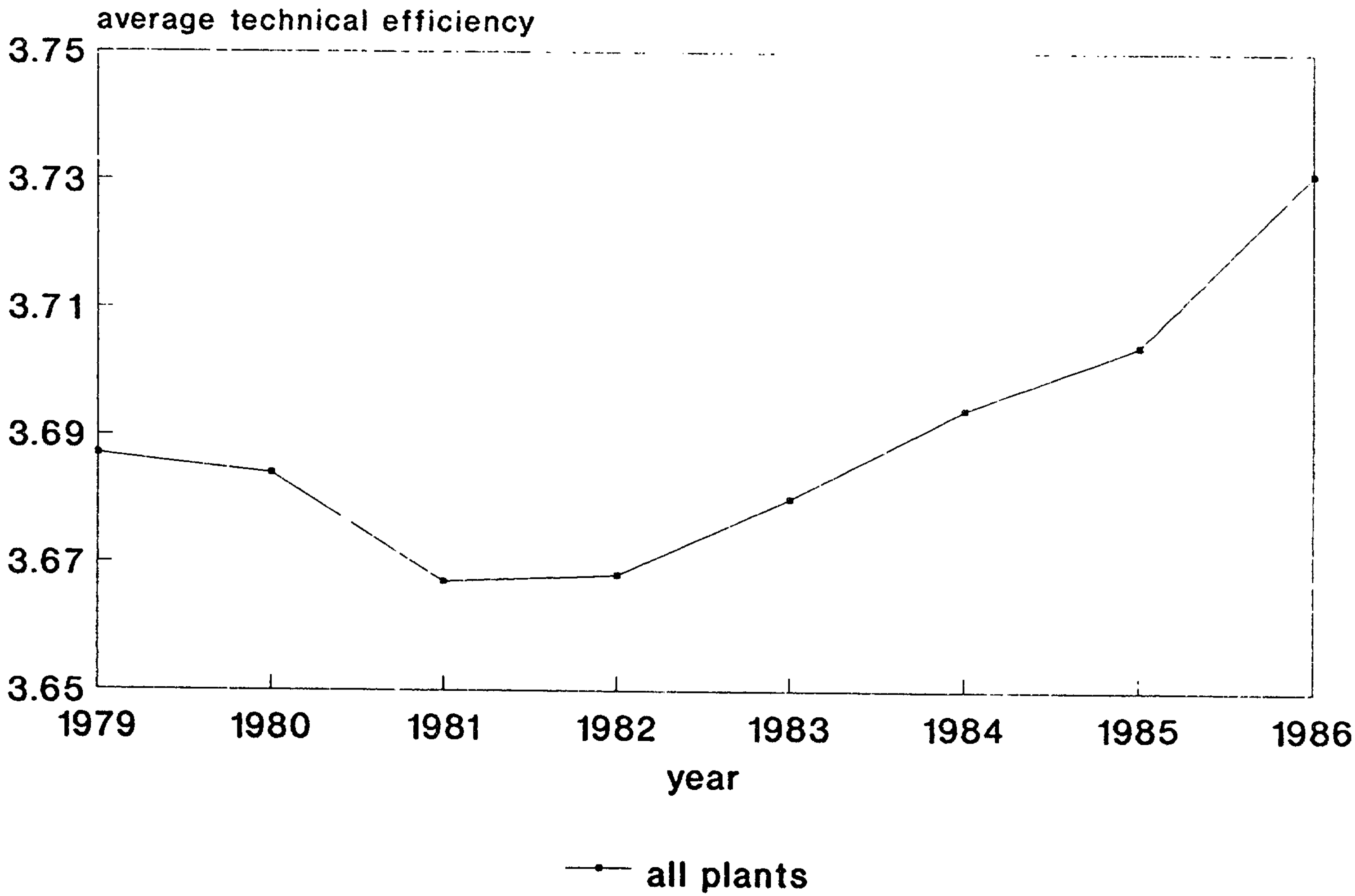
Figure 2b: Technical Efficiency Change

Entering Cohorts



27 industries

Figure 3: Technical Efficiency Change
Manufacturing Average



27 industries

TABLE 6

The Ratio of Skilled over Unskilled Labour: Manufacture Sector

Weighted Average over the Entire Sample

	1979	1980	1981	1982	1983	1984	1985	1986
Surviving Plants	0.277	0.285	0.285	0.298	0.345	0.337	0.330	0.419
Exiters Average	0.2[illegible]2	0.248	0.241	0.268	0.262	0.266	0.268	
Exiters Decomposition:								
1979	0.262							
1980	0.238	0.240						
1981	0.224	0.229	0.234					
1982	0.248	0.247	0.251	0.265				
1983	0.242	0.315	0.242	0.273	0.258			
1984	0.231	C.237	0.221	0.264	0.257	0.268		
1985	0.226	0.235	0.249	0.270	0.270	0.265	0.268	
Entrants Average		0.239	0.234	0.261	0.256	0.269	0.268	0.339
Entrants Decomposition:								
1980		0.239	0.215	0.243	0.240	0.244	0.243	0.561
1981			0.266	0.289	0.282	0.291	0.300	0.358
1982				0.264	0.263	0.279	0.331	0.431
1983					0.252	0.244	0.246	0.294
1984						0.281	0.283	0.326
1985							0.225	0.275
1986								0.315
Manufacture Average	0.261	0.270	0.278	0.291	0.324	0.319	0.314	0.398

Note: Labour is defined as efficiency labour units. Output is the gross value of output.

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