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TRADE LIBERALIZATION, EXIT, AND PRODUCTIVITY IMPROVEMENTS: EVIDENCE FROM CHILEAN PLANTS

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ABSTRACT

This paper empirically investigates the effects of trade liberalization on plant productivity in the case of Chile. Chile presents an interesting setting to study this relationship since it underwent a massive trade liberalization that significantly exposed its plants to competition from abroad during the late 1970s and early 1980s. Methodologically, I approach this question in two steps. In the first step, I estimate a production function to obtain a measure of plant productivity. I estimate the production function semiparametrically to correct for the presence of selection and simultaneity biases in the estimates of the input coefficients required to construct a productivity measure. I explicitly incorporate plant exit in the estimation to correct for the selection problem induced by liquidated plants. These methodological aspects are important in obtaining a reliable plant-level productivity measure based on *consistent* estimates of the input coefficients. In the second step, I identify the impact of trade liberalization on plants' productivity in a regression framework allowing variation in productivity over time and across traded- and nontraded-goods sectors. Using plant-level panel data on Chilean manufacturers, I find evidence of within plant productivity improvements that can be attributed to a liberalized trade policy, especially for the plants in the import-competing sector. In many cases, aggregate productivity improvements stem from the reshuffling of resources and output from less to more efficient producers.

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1. Introduction

During the 1980s, many developing countries abandoned their inward-looking development strategies for drastic trade liberalization programs. The supporters of these reforms claimed that the exposure of home producers to additional import competition and easier access of plants to foreign technology would enhance productivity in domestic industries. Despite the high profile of this topic, surprisingly little is known about the actual effects of trade policy changes on plant's productivity.

The theoretical trade literature offers conflicting predictions about the evolution of plant-level productivity following a trade liberalization episode, especially in cases where imperfect competition is present. Rodrik (1988, 1995) provides an excellent survey of the main issues. On one hand, trade liberalization exposes domestic producers to foreign competition, reduces their market power, and might force them to expand output and move down the average cost curve; this might result in the exploitation of the economies of scale. Gains from scale economies are not very likely in developing countries, where the increasing returns to scale are usually associated with the import-competing industries, whose output is likely to contract as a result of intensified foreign competition. In models such as Rodrik (1988), where plants invest in superior technology to reduce their cost, their incentive to cut costs might increase with their market share. If trade liberalization reduces the domestic market shares of unshielded domestic producers without expanding their international sales, their incentives to invest in improved technology will decrease as protection ceases. This effect reduces the benefits of tariff reductions that lower the relative prices of imported capital goods and ease access to foreign technology for domestic plants.

Although trade liberalization facilitates procurement of foreign technology, it is questionable whether domestic plants actually adopt better technology. A recent series of papers by Eaton and

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Kortum (1996, 1997) models how the benefits of innovation are spread from one country to another either through diffusion of technology or through the exchange of goods. They find that the impact of diffusion of knowledge on productivity depends crucially on the proximity of a country to the technology source and the flexibility of the domestic labor force. In light of many models predicting that trade diffuses innovation and knowledge, it is also puzzling that studies of convergence of productivity across countries such as Bernard and Jones (1996) find convergence in service rather than manufacturing sector, which is extensively affected by international trade.

While trade theory has considered intraindustry gains from trade liberalization through expansion of economies of scale, it has so far not explored the implications of plant heterogeneity within an industry as most of the traditional trade models rely strongly on a representative plant assumption. Recent work explaining plant-level data by Olley and Pakes (1996), Roberts and Tybout (1996), and Aw, et. al. (1997), introduces evidence of a significant degree of plant-level heterogeneity within an industry. The presence of plant-level heterogeneity suggests that trade liberalization may yield productivity improvements by reshuffling the resources among plants within the same industry and that plant dynamics such as exit may contribute significantly to this process. In particular, high levels of protection may accommodate the coexistence of producers with different levels of productivity. By reducing protection, trade liberalization lowers domestic prices, potentially forcing high cost producers to exit the market. This would lead to a reallocation of output from less efficient to more efficient producers. These productivity gains emerge only if the irreversibility of investment in capital equipment does not impede the exit of the less productive plants.

Even if trade liberalization enhances plant productivity, such improvements do not occur without costs associated with the exit of plants and large reallocations and displacements of labor and capital. Fear of the initial costs of labor displacement and plant bankruptcies often deters governments from exposing their domestic markets to foreign competition. From a policy perspective, it is therefore important to evaluate the incidence of productivity gains. The goal of this paper is to provide such an evaluation. I approach this topic in two steps. In the first step I estimate a production function to obtain a measure of plant productivity. I estimate the production function semiparametrically to correct for the presence of selection and simultaneity biases in the estimates of input coefficients required to construct a productivity measure. I explicitly incorporate plant exit in the estimation to correct for the selection problem induced by liquidated plants. In the second step I relate productivity changes to trade liberalization exploiting the variation in productivity over time and across traded and nontraded-goods sectors.

I quantify the incidence of productivity gains using a panel of Chilean manufacturing establishments. Chile presents an interesting setting to study the dynamics of plants' adjustment process to trade liberalization. During the 1974 to 1979 period, Chile implemented a large trade liberalization program. The country eliminated most of its non-tariff barriers and reduced the tariff rates, often surpassing 100% in 1974, to a uniform across industries 10% ad valorem tariff in 1979 (Dornbusch, et. al. (1994)). Its commitment to free trade persisted during the 1980s, except for a transitory period of increased tariff protection starting in 1983 in response to the 1982-1983 recession. These temporary measures peaked in 1984, when tariffs increased uniformly to 35%. Yet Chile remained strongly committed to free trade: it introduced no non-tariff barriers and the tariffs declined to a 20% ad-valorem level in mid 1985 (UNCTAD, 1992). Overall, the variation in protection during the early 1980s appears very small relative to the extensive trade liberalization experiment in the late 1970s. These trade developments coincide with massive plant exit, which seems to suggest that plant liquidation played a significant role in the adjustment process. My data is ideal for addressing this issue: it covers 1979-1986, a period of significant adjustment, and includes all Chilean manufacturing plants with ten or more employees. The comprehensive nature of the data enables me to analyze the dynamics of the smaller plants that are often ignored due to data limitations.

Many empirical papers reviewed in the next section of the paper have tackled the relationship between trade protection and productivity, but the questions remain far from settled.[1] This paper improves on previous methodology in three ways: the identification of trade policy effects, the measurement of plant-specific productivity, and the incorporation of plant exit in the estimation procedure. One of the main problems in the empirical literature on trade and productivity has been the identification of the effects of trade liberalization. The identification in studies such as Tybout et. al. (1991) and Harrison (1994) relies on the comparison of plant behavior before and after a trade policy change. As the authors recognize, this approach might attribute productivity variation originating from some other shocks occurring concurrently with trade policy changes, to trade policy reform. Furthermore, these studies presume that plants instantaneously react to the implementation of the policy change. Yet, the uncertainty about the nature and sustainability of government policy, and possible lags in plant adjustment to regime changes prevent us from pinpointing the exact timing of reform outcomes. To identify trade policy effects this paper relies not only on productivity variation over time, but also on variation across sectors. I distinguish between sectors that are affected directly by trade liberalization (import-competing and export-oriented sectors) and the nontraded-goods sector to separate productivity effects stemming from trade liberalization from productivity variation stemming from other sources. It is very difficult to capture trade policy with a single variable. I thus check the robustness of my findings using other measures of exposure to trade such as import to output ratios, tariffs, and exchange rates.

In order to obtain a measure of plant-level productivity I estimate a production function in which plant efficiency is modeled as an unobserved plant specific effect. As discussed in detail in section one of the paper, a plant's private knowledge of its productivity affects its behavior and thus biases the estimates of the coefficients on inputs such as labor and capital in the production function. Since the measure of productivity depends on these estimates, their consistency is crucial for the analysis. Most of the previous studies correct for the biases by relying on simplifying assumptions about the unobserved

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[1] Roberts and Tybout (1996) offer an excellent compilation of studies on this topic.

plant heterogeneity such as time-invariance. I employ semiparametric estimation as in Olley and Pakes (1996) to account for unobserved plant heterogeneity. This approach yields a plant-specific, time-varying productivity measure based on consistent estimates of the production function coefficients; it requires no specific functional form, and is tractable enough to incorporate in the estimation process. A further improvement to previous work is that I explicitly incorporate dynamics like plant exit in the analysis. In particular, I adjust my estimation for the selection bias that is introduced by exiting plants. In the second stage I then investigate whether plant exit contributes to aggregate productivity improvements and whether the effects of exit differ across the plants producing export-oriented, import-competing and nontraded goods.

My research yields several important findings. First, my results show that selection bias induced by plant closings and simultaneity bias induced by plant dynamics significantly affect the magnitude of the capital coefficient in the production function. After I adjust for self selection and simultaneity, the estimate of the capital coefficient increases on average more than doubles relative to the OLS estimate for 5 out of 8 industries where the selection outweighs the simultaneity bias, and decreases on average by 22% relative to the OLS estimates elsewhere. This suggests that semiparametric estimation of a production function provides a useful alternative to techniques used in previous studies. Second, I find support for productivity improvements related to trade liberalization. I show that after trade liberalization, the productivity of plants in the import-competing sectors grew 3 to 10% more than in the nontraded-goods sectors. This finding is robust to several econometric specifications and measures of foreign competition. It suggests that exposure to foreign competition forced plants in sectors that used to be shielded from the outside competition to trim their fat. Third, I find that exiting plants are on average 8% less productive than the plants that continue to produce. Although it is hard to pinpoint the exact mechanism of productivity improvements, this result implies that plant exit also contributes to the reshuffling of resources within the economy. Evidence from the industry-level aggregate productivity indices additionally suggests that the reallocation of market shares and resources from less to more efficient producers is an important channel of productivity improvements.

My findings have important policy implications. Since productivity improvements partially stem from the reshuffling of the resources in the economy, it is important to eliminate barriers to plant turnover. Hurdles such as institutional arrangements that discourage the bankruptcy of less efficient plants, for example, have been blamed to curb economic growth in recent discussions of East Asian economic crisis in popular press (NYT, September 8, 1998). Finally, my empirical evidence indicates that channels other than economies of scale yield intraindustry improvements from trade liberalization. This suggests that incorporating plant heterogeneity in models exploring trade policy effects would be a fruitful area of future research in trade theory.

The next section of the paper provides an overview of the empirical issues, and reviews previous work in this area. Section 3 introduces the model. Section 4 looks at data and descriptive statistics. Section 5 discusses the estimation results. Section 6 contains my conclusions.

2. Empirical Issues and Previous Literature

Most of the literature on trade liberalization and productivity obtains a plant-level productivity measure by estimating a production function. Let us describe plant *i*'s technology at time *t* by a Cobb-Douglas production function:

$$\begin{aligned} y_{it} &= \beta_0 + \beta\, x_{it} + \beta_k k_{it} + e_{it} \\ e_{it} &= \omega_{it} + \mu_{it} \end{aligned} \tag{1}$$

where y_{it} is gross output, x_{it} is a vector of variable intermediate inputs such as labor and materials, and k_{it} is capital used by plant *i* at time *t*. I express all variables in logarithms so that the input coefficients represent input elasticities. Plant specific term e_{it} is composed of a plant-specific efficiency ω_{it} that is known by the plant but not by the econometrician and an unexpected productivity shock μ_{it} that is not known either to the plant or the econometrician. I am interested in the former term. In this framework, any plant-level productivity measure relies on the difference between a plant's actual output and predicted output. It is, then, crucial to obtain consistent estimates of the coefficients in the production function. A plant's private knowledge of its productivity ω_{it} affects its decision about exiting or staying in the market and its choice of hiring labor, purchasing materials and investing into new capital. Yet ω_{it} is unobserved by the econometrician. This information asymmetry introduces two biases in my estimation: simultaneity and selection biases. Although the trade liberalization literature has addressed the first one, it has so far disregarded selection bias stemming from plants' exit.

Let us first focus on the simultaneity bias that arises because a plant's private knowledge of its productivity affects its choice of inputs. If more productive plants are more likely to hire more workers and invest in capital due to higher current and anticipated future profitability, ordinary least squares estimation (OLS) of a production function may lead to estimates of the input coefficients that are higher than their true values. Previous studies have adjusted for this bias in various manners. Comparing pre- and post-trade reform cross-sectional data on the Chilean manufacturing sector, Tybout et. al. (1991) impose normal distribution on the unobserved heterogeneity, assume that the plant-specific efficiency is uncorrelated with the plant's choice of inputs, and use maximum likelihood estimation. Studies such as Harrison (1994) that employ plant-level panel data have corrected for simultaneity bias by assuming that the unobserved plant-specific efficiency is time-invariant. I can then rewrite the production function specified in (1) as:

$$y_{it} = \beta_0 + \beta\ x_{it} + \beta_k k_{it} + \omega_i + \mu_{it}$$

where ω_i is the plant-specific, time-invariant productivity and estimate it using a fixed effects model. Although the fixed effects model partially solves the simultaneity problem, it only removes the effects of the time-invariant plant's productivity component. During times of large structural adjustments such as trade liberalization, the assumption of unchanging productivity seems worrisome, and the fixed effects methodology may lead to biased estimates of the input coefficients. More importantly, I am ultimately interested in how plant efficiency evolves over time in response to a change in a trade policy regime. The assumption that a plant's productivity is constant over time prevents me from tackling this question.

To correct for this shortcoming, Cornwell, et.al. (1990) propose a plant-specific and time-varying efficiency that can be described as a quadratic function of time. This methodology is also used in Liu (1993), and Liu and Tybout (1996) for Chile. Using the notation in (1) their specification of a production function yields:

$$\begin{aligned} y_{it} &= \beta_0 + \beta x_{it} + \beta_k k_{it} + \omega_{it} + \mu_{it} \\ \omega_{it} &= \alpha_{1i} + \alpha_{2i} t + \alpha_{3i} t^2 \end{aligned}$$

They first estimate the production function by fixed effects to obtain the input coefficient vector β. They then calculate the residuals by subtracting the actual from the predicted values of output, and for each plant *i* regress this residual measure on a constant, time, and time squared ($1,t,t^2$). They construct a productivity measure using the estimates of the coefficients from the last regression ($\alpha_{1i},\alpha_{2i},\alpha_{3i}$). Although their approach improves on the fixed effects methodology, it requires a parametric specification of productivity and many degrees of freedom are lost in the estimation process. Moreover, in the presence of simultaneity bias this procedure still uses fixed effects estimation in the first step that provides the residual for the construction of the productivity measure. So although the measure is time-varying, it is still likely to be based on biased coefficients. In the next section I propose a plant-specific, time-varying productivity measure that requires no specific functional form assumption and is based on unbiased input coefficients of the production function.

The trade liberalization literature has so far abstracted from the effects of self-selection induced by plant closings. Unlike previous studies, I explicitly address the selection issue. In my sample, I only observe those plants that continue to produce. A plant decides to stay in business if its expected future profits exceed its liquidation value. A more productive plant is more profitable today, it anticipates higher profits in the future, and is therefore less likely to close down. If a plant's profits are also positively related to the size of its capital stock, given the level of productivity, plants that are endowed with more capital are more likely to continue their operations than are plants with a lower capital stock. The expectation of productivity ω_{it} conditional on the surviving plants is then no longer zero, but a decreasing function of capital, yielding a downward bias on the coefficient on capital. Liu (1993) and Liu and Tybout (1996) are the only studies that examine plant exit; they compare the aggregate productivity indices for exiting and surviving plants in the case of Chile. Yet, the comparison is based on the coefficients that are not adjusted for the selection bias induced by plant exit.

The literature on the links between trade liberalization and productivity presents conflicting evidence. Tybout et. al. (1991) find scant support for productivity improvements in the Chilean manufacturing sector after the trade liberalization. Bernard and Jones (1996) study productivity convergence across countries on a sectoral level. They find that productivity growth does not converge in manufacturing sectors, despite the belief that international trade flows expedite this process. Using plant-level panel data from the Ivory Coast, Harrison (1994) finds a positive correlation between trade reform and productivity growth. Tybout and Westbrook (1995) report productivity improvements related to trade liberalization in Mexico. Furthermore, some of these studies are based on the data sets that oversample large and medium-sized manufacturing plants. Chilean data also includes small establishments, which are anecdotally more likely to quickly respond to the changes in the environment, therefore presenting an opportunity to study an important part of plant dynamics. It is this conflicting evidence in addition to the above mentioned econometric issues that motivates the present study.

3. Empirical Model

3.1 Theoretical Background

I base my econometric analysis upon the theoretical and empirical work on plant profit-maximizing behavior in a dynamic framework presented in Ericson and Pakes (1995) and Olley and Pakes (1996). Although Olley and Pakes (1996) address the uncertainty regarding returns to investment in research and development stemming from the regulatory changes in the U.S. telecommunication industry, they provide a good framework to analyze plant dynamics resulting from trade liberalization. Plants belonging to an industry face same input prices and market structure, but they differ in their levels of efficiency and are subject to plant specific uncertainty about future market conditions and investment.

A plant's goal is to maximize the expected value of its current and future profits (net cash flow). In each period, a plant first decides whether to close down or continue to produce. A plant continues to produce if its expected future net cash flow exceeds its liquidation value. Conditional on staying in the market, the plant then chooses its inputs. This renders the plant's optimal decision regarding exit and input choices as a function of its observable characteristics such as capital and investment. The plant specific uncertainty about the future market conditions affects these plant choices and leads plants to follow different efficiency paths. This set up is consistent with imperfect competition. In each period, firms consider the market structure and the actions of other firms when making their choice about exit and investment. To capture these interactions among firms, a firm's profits (and ultimately the equilibrium exit and investment rule) are indexed by time.

To elaborate, in a given industry *j*, the profits Π_{ijt} of a plant *i* at time *t* are a function of its capital k_{ijt} and unobserved productivity ω_{ijt} (k_{ijt} and ω_{ijt} are plant state variables):[2]

$$\Pi_{ijt} = f_t(k_{ijt}, \omega_{ijt})$$

I assume that each plant can easily adjust its labor force and the use of intermediate materials and treat labor and materials as variable inputs, whereas it takes time to adjust the capital stock. This is not a bad assumption for Chile since it significantly liberated its labor laws and practices in the late 1970s. Overall, the plant's problem can be described by the value function for the dynamic program:

$$V_t(\omega_t, k_t) = \max\left\{L_t, \sup \Pi_t(\omega_t, k_t) - c(i_t) + dE\left[V_{t+1}(\omega_{t+1}, k_{t+1}) \middle| \Omega_{it}\right]\right\}$$

and capital accumulation equation:

$$k_{t+1} = (1-\delta)k_t + i_t \tag{2}$$

where *L* is the value of the plant if it liquidates, *c()* represents the cost associated with investment, *d* is the discount factor, Ω_t is the information at time *t*, and δ is the capital depreciation rate. In order for the model to be econometrically tractable, productivity evolves as a 1st order Markov Process which assures that the plant's state variables in the current period depend on the value of the state variables in the previous period. The market conditions that affect plant's profits, but are the same for all plants in a given time period *t* and industry are captured by the index *t*.

As shown in Ericson and Pakes (1995) the solution to this dynamic program gives rise to a Markov Perfect Equilibrium strategy for plant's choice of exit and investment. The plant continues to produce if its unobserved productivity exceeds some threshold value $\underline{\omega}_t$ that is a function of the plant's capital:

(3) $$\mathrm{X}_t = \begin{cases} 1 & \text{if } \omega_t \geq \underline{\omega}_t(k_t) \\ 0 & \text{otherwise,} \end{cases}$$

where X_t=1 denotes that a plant stays in the market in period *t* and X_t=0 denotes a plant's exit. A plant chooses its investment based on its beliefs about future productivity and profitability. Its decision to invest i_t **,** then depends on its capital stock and productivity:

(4) $$i_t = i_t(\omega_t, k_t)$$

The investment and exit rule can be used in the estimation of a production function to yield a measure of productivity. This framework captures the market structure in which the firms compete with each other. The competitive conditions that plants face in a given industry are depicted by a time index in the profit function, and the time index in the investment function and the cut off productivity in the exit rule. In the estimation, I allow the investment and exit function to vary over time.

Trade liberalization affects a plant's exit and investment decisions and its productivity process. Differences in the exposure of plants to international competition might lead to divergence in their behavior and different evolution of their productivity paths. For example, trade liberalization might force the plants to use their resources more productively and trim their fat. In this framework the industry level productivity improvements induced by trade liberalization could stem from several sources: the exit of

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[2] Each industry is characterized by its own profit function. I omit the industry and plant subscripts in my notation in the rest of the paper.

less efficient plants, the reshuffling of the resources and output from less to more productive plants, or within plant improvements in productivity--i.e. plants becoming leaner by reducing their X-inefficiencies or eliminating some other agency problem, or by acquiring better inputs from abroad.

3.2 Empirical Implementation

I incorporate exit and investment rules into the estimation of a production function to identify the coefficients on capital and variable inputs such as skilled and unskilled labor and materials. The semiparametric procedure that yields consistent estimates of the labor and capital coefficients involves three steps. In this section, I first summarize the estimation procedure and then discuss its implementation in this paper.

Let us first focus on the coefficients on variable inputs, labor, and materials. Within each period a plant can adjust its variable inputs to innovation in its private knowledge about its unobserved productivity ω_t. By inverting the investment rule specified in equation (4), unobserved productivity can be expressed as a function of observable investment and capital:

(5) $$\omega_t = i_t^{-1}(i_t, k_t) = \theta_t(i_t, k_t)$$

Substituting (5) into (1) yields

(6) $$y_t = \beta\, x_t + \lambda_t(k_t, i_t) + \mu_t,$$

where

(7) $$\lambda_t(k_t, i_t) = \beta_0 + \beta_k k_t + \theta_t(k_t, i_t).$$

I can then obtain consistent estimates of the vector of coefficients on variable inputs β by estimating the production function in equation (1) using the partially linear regression model in (6), where the function λ_t is modeled as a polynomial series expansion in capital and investment. Since λ_t controls for unobserved productivity ω_t, the error term in the production function is no longer correlated with a plant's choice of labor hiring and materials, and the coefficient vector β is consistent.[3] This specification of productivity is plant-specific and time-varying, and it does not require productivity to be a function with a specific parametric form as in Cornwell et. al. (1990).

After identifying the vector of variable input coefficients β, I still need to separate the effect of capital on output from its effect on plant's decision to invest. If productivity is serially correlated, current productivity contains information that a plant might incorporate in forming its expectations about its future profitability. If the plant is not myopic, it bases its investment decision at time *t* on its expectation of its future profitability and hence its productivity at time *t*. Since capital at *t+1* includes investment from the previous period i_t by (2), capital and productivity are then correlated at time *t+1*. In particular, capital at *t+1* is correlated with the expectation of productivity, $E(\omega_{it+1}|\omega_{it}, k_{it+1}) = \omega_{it+1} - \xi_{it+1}$ (productivity is here decomposed into expected and unanticipated parts). Expectation of the next period's productivity is a function of productivity in this period. Let us denote this function as $g(\omega_t)$. I can substitute the expression for ω_t from (5) into g() and then the expression for θ_t from (7) to yield:[4]

$$E[\omega_{t+1} \mid \omega_t, k_{t+1}] = g(\omega_t) - \beta_o = g(\theta_t(i_t, k_t)) - \beta_o = g(\lambda_t - \beta_k k_t) - \beta_o \tag{8}$$

Substituting (8) into (1) at *t+1* yields

$$\begin{aligned} y_{t+1} - \beta\, x_{t+1} &= \beta_o + \beta_k k_{t+1} + E[\omega_{t+1} \mid \omega_t, k_{t+1}] + \xi_{t+1} + \mu_{t+1} \\ &= \beta_k k_{t+1} + g(\lambda_t - \beta_k k_t) + \xi_{t+1} + \mu_{t+1} \end{aligned}$$

Thus, I control for the expectation of productivity in (8) with observable variables. If no plant exits the sample, controlling for the expectation of productivity at *t+1* conditional on the information available at time t yields consistent estimates of the coefficient on capital in the estimation of the above production function.

Yet, I still need to consider that in my sample, I only observe those plants that select to stay in the market. A plant continues to produce only if its expectation of future profitability exceeds its

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[3] Andrews (1991) shows that partially linear regression model with the series estimator of the nonlinear part yields consistent and asymptotically normal estimates of coefficients on the linear part of the model, in my case, β.

liquidation value. Otherwise, the plant exits. Using the terminology of the exit rule in (3), a plant stays in the market at time *t+1* only if its productivity at *t*+1 exceeds some threshold value $\underline{\omega}_{t+1}$. This threshold depends on the plant's capital stock. As explained in section 2, this truncation leads to a nonzero expectation of productivity that is correlated with capital, thus biasing the coefficient on capital in the estimation of a production function. Conditional on a plant staying in the market, the expression for its expected productivity at *t+1* becomes

$$E[\omega_{t+1} \mid \omega_t, k_{t+1}, X_{t+1} = 1] = E[\omega_{t+1} \mid \omega_t, \omega_{t+1} > \underline{\omega}_{t+1}(k_{t+1})] = \Phi(\omega_t, \underline{\omega}_{t+1}) - \beta_o \tag{9}$$

where

$$\Phi(\omega_t, \underline{\omega}_{t+1}) \equiv E[\omega_{t+1} \mid \omega_t, \omega_{t+1} > \underline{\omega}_{t+1}(k_{t+1})] + \beta_o$$

The expectation of future productivity is thus a function of productivity in the previous period, ω_t, and the cut-off productivity, $\underline{\omega}_{t+1}$. The effect of the latter attenuates the coefficient on capital in the production function. In view of the substantial plant closings in Chile, the self-selection of plants probably plays a significant role in the adjustment process. I already know how to control for ω_t. Next, I find a way to control for $\underline{\omega}_{t+1}$ in estimating the production function.

I can extract information about the cut-off productivity $\underline{\omega}_{t+1}$ by evaluating the probability that a plant continues to produce at time *t+1*. The probability of a plant staying in the market at time *t+1* can be modeled as a function of its capital and investment:

$$\begin{aligned} \Pr(X_{t+1} = 1) & \\ &= \Pr\{\omega_{t+1} > \underline{\omega}_{t+1}(k_{t+1}) \mid \underline{\omega}_{t+1}(k_{t+1}), \omega_t\} \\ &= p_t(\underline{\omega}_{t+1}(k_{t+1}), \omega_t) \\ &= p_t(\underline{\omega}_{t+1}(k_t, i_t), \omega_t) \\ &= p_t(k_t, i_t) \equiv P_t \end{aligned} \tag{10}$$

where the first line follows from the exit rule (3), the third line follows from the capital accumulation equation (2), and the fourth line from the investment rule (4). The intuition is simple. A plant makes its exit decision based on whether its expected future profits exceed its liquidation value. Since a plant's

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[4] A constant β_0 cannot be identified separately from the polynomial expansion in investment and capital.

productivity depends on its investment and capital, its probability of staying in the market is then also a function of its investment and capital. Any selection correction is more credible if it does not rely solely on distributional or functional form assumptions, but also on exclusion restrictions: variables that affect the probability that a plant exits the market, but do not affect a plant's output. Investment can be viewed as such a variable because it does not affect current output (assuming it takes time for investment to become productive), but it does affect the future profitability of a plant, and therefore its exit decision.

Assuming that function p_t is invertible, the threshold productivity value, $\underline{\omega}_{t+1}$, can be expressed as a function of a plant's survival probability, P_t, and its productivity, ω_t. $\Phi(\omega_t, \underline{\omega}_{t+1})$ from (9) can thus be rewritten as a function of productivity in the previous period, ω_t, and the probability a plant stays in the market, P_t:

$$\Phi(\omega_t, \underline{\omega}_{t+1}) = \Phi\left\{\omega_t, p_t^{-1}(P_t, \omega_t)\right\} = \Phi(\omega_t, P_t).$$

Moreover, as discussed at the beginning of this section, I can express productivity ω_t using (5) and (7), so that $\Phi(\omega_t, P_t)$ becomes $\Phi(\omega_t, P_t) = \Phi(\lambda_t - \beta_k k_t, P_t)$. After these substitutions, we can rewrite the production function in (1) at *t+1* as

$$y_{t+1} - \beta x_{t+1} = \beta_k k_{t+1} + \Phi(\lambda_t - \beta_k k_t, P_t) + \xi_{t+1} + \mu_{t+1} \tag{11}$$

This is the equation I estimate in the final stage of estimation to obtain a consistent coefficient on capital β_k.

Several estimation issues should be pointed out. First, when I estimate the partially linear regression model in (6), I use a fourth order polynomial expansion in capital and investment to approximate λ_t.[5] I allow the polynomial to vary over time since the investment rule is indexed by time.[6] This time index accounts for changes in the market structure that firms might adjust to over time.

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[5] The coefficients on the variables of interest and the sum of squares did not vary substantively when the reported polynomial or a higher order polynomial was used to estimate (6).

[6] I distinguish between 1979-1981, 1982-1983, and 1984-1986 by including time indicators corresponding to these periods. I also interact time indicators with investment and capital.

This estimation yields an estimate of the coefficient vector β on variable inputs, $\hat{\beta},$ and an estimate of λ_t, $\hat{\lambda}_t$, that are subsequently used to estimate (11). Estimation of (11) also requires an estimate of a plant's probability of staying in the market, P_t. Expression (10) shows that the probability of staying in the market, P_t, is a function of investment and capital. I estimate this probability using a probit with regressors that are terms in the fourth order polynomial expansion of capital and investment.[7] As in the estimation of (6), I allow the polynomial to vary over time since the exit rule is indexed by time to account for changes in the market structure across periods. Finally, the estimates of the polynomial expansion lambda λ_t, $\hat{\lambda}_t$, the coefficients on variable inputs β, $\hat{\beta}$, and the estimate of the survival probability P_t, $\hat{P}_t$, can be used to eliminate the selection and simultaneity bias and obtain a consistent estimate of the coefficient on capital β_k in (11). Since the equation is nonlinear in the coefficient on capital β_k, I utilize the non-linear least squares technique, using a third order polynomial series expansion in $\hat{P}_t$ and $\hat{\omega}_t = (\hat{\lambda}_t - \beta_k k_t)$ to control for *Φ()*:[8]

$$\Phi(\omega_t, P_t) = \sum_{j=0}^{3-m} \sum_{m=0}^{3} \beta_{mj} \hat{\omega}_t^m \hat{P}_t^j = \sum_{j=0}^{3-m} \sum_{m=0}^{3} \beta_{mj} (\hat{\lambda}_t - \beta_k k_t)^m \hat{P}_t^j$$

Second, unlike Olley and Pakes (1996), this paper uses series approximation in all the stages of estimation. While the use of a series approximation for λ_t in (6) yields estimators with known limiting properties (Andrews (1991)), the use of the series approximation to control for *Φ()* in (11) yields an estimator that does not have a well-defined limiting distribution. Pakes and Olley (1995) prove asymptotic results for the case when kernel estimator is used for *Φ()*. No asymptotic results are proven in the case that uses the series estimator for *Φ()*. Nevertheless, the use of the series estimator has several advantages. First, it is easier and faster than the kernel approximation. Second, Pakes and Olley (1995)

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[7] The fit and the predicted survival probabilities do not vary much when either the reported or the higher order polynomials are used.

[8] The coefficients on the variables of interest and the sum of squares did not vary much when the reported polynomial or the higher order polynomial were used to estimate (11).

show that for their particular application, the results based on the series estimator in (11) do not differ much from the results obtained using the kernel estimator, so they argue that the convergence of the series estimator in the last stage of estimation is a technicality that still needs to be proven. I therefore use the series estimator. However, since the limiting distribution has not been worked out, I compute and report bootstrap estimates of the standard errors.

Third, the Olley and Pakes (1996) procedure relies on the observations whose investment is nonzero. In order to be able to express unobserved productivity as a function of investment and capital using the optimal investment rule (4), investment needs to be a strictly monotonic function of unobserved productivity. Pakes (1994) shows that this is achieved as long as the marginal productivity of capital is an increasing function of a firm's unobserved productivity, and investment is strictly positive. In my sample, many plants make no investments. In order to check whether the use of the observations with nonzero investment significantly affects my findings, I also estimate production functions using only the plants with positive investment and compare the estimates to those obtained when all plant observations are used. As discussed in section 5.1 of the paper, the estimates are in most cases relatively close, so the use of zero investment observations does not seem as problematic in practice. More importantly, my estimates of the relationship between trade and productivity discussed in section 5.3, which is the main goal of this paper, do not change at all if I use the measure of productivity constructed from production function estimates based solely on the observations with strictly positive investment.

Finally, as is common in the literature, the estimation of a production function uses the real value of output rather than physical units of output produced by a given plant as a measure of output. The value of output is deflated using a four-digit industry price index. A measure of productivity based on the real value of output might not reflect the ranking of firms in their productivity if plants charge different markups. Differentiating between the true productivity and the plant specific markups across plants within an industry is a big challenge in the productivity literature. Harrison (1994) is one of the few studies that explicitly models plant markups. She assumes that plants are Cournot competitors and allows the markups to vary over time and across industries, but not across plants within an industry. In her setup, this is the same as assuming that all firms within an industry have the same market share.

In order to empirically distinguish the true efficiency from the plant specific markups within an industry, one would need plant level price data. Otherwise, one needs to impose some assumptions on the joint distribution of productivity and markups. Bernard, Eaton, Jensen, and Kortum (1999) provide an example. They set up a model in which they show that, on average, a more efficient plant charges a higher markup. Measured productivity based on the real value of output is then on average higher for plants with higher efficiency. Without detailed price data, one cannot identify if such a relationship holds. This caveat should be considered when interpreting the results in section 5 of the paper. In my estimation of the relationship between measured productivity and trade, I control for plant specific markups with plant fixed effects. If plants change markups over time and a positive relationship between efficiency and markups does not hold, the interpretation of the results in section five is more convoluted.

4. Data and Preliminary Results

4.1 Data

This paper draws on a census of Chilean manufacturing plants employing ten or more workers provided by Chile's National Institute of Statistics. The panel data set of 4379 plants extends from 1979 to 1986. A unit of observation is a plant, not a firm, however, over 90% of the plants are single-plant establishments. The data set and the variable definitions and construction are described in detail in Liu (1993) and Tybout (1996).[9] Capital, investment, intermediate materials, value added, and output are expressed in constant 1980 pesos. Skilled and unskilled labor is measured by the total number of

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[9] I use the information on 4379 plants after eliminating those with incomplete information. The capital variable was initially constructed using a perpetual inventory method by Liu (1993) and is described in detail in Tybout (1996). I have reconstructed the variable so that the capital stock at time t does not contain the investment at time t. Since the balance sheet information was only available for the plants in 1980 and 1981, capital measures are based on the book value of capital in those two periods. In my capital variable, I use figures based on the 1981 book value of capital if both 1980 and 1981 are available. Otherwise, capital measure based on the 1980 book value of capital was used. I experimented with several options and all capital measures are highly correlated.

employees in each skill group working in a plant.[10] Descriptive statistics for the sample are given in Tables 1and 2. I characterize each plant in terms of its trade orientation, as being in the export-oriented, the import-competing, or the nontraded goods sector. The trade orientation of an industry is determined at a four-digit ISIC level, on the basis of Chilean trade balance in that particular industry. The data used to compute the trade balance are exports and imports from the UN Yearbook of International Trade Statistics and Statistics Canada CD-ROM. A more detailed classification in the Statistics Canada enables me to improve on the definitions provided by Tybout (1992) that are only at the three-digit ISIC level. Although I have experimented with different cut-off points, all of the tables reported in this paper use the following definition of trade orientation.[11] Plants that belong to a four-digit ISIC industry that exports more than 15% of its total output are characterized as export-oriented. Plants that belong to a four-digit ISIC industry whose ratio of imports to total domestic output exceeds 15% are characterized as import-competing. The rest of the plants belong to the nontraded-goods sector. Tables 3 and 4 provide import to output and export to output ratios for specific three and four digit ISIC sectors in my data.

Defining trade orientation in this manner raises two concerns: the presence of intra industry trade and the endogeneity of the definition. Neither of these presents a problem in the Chilean data. Intra industry trade was rarely an issue within three or four digit ISIC classifications. The Grubel-Lloyd index of intra industry trade averaged .30 from 1979 to 1986 on a four-digit ISIC level, and .35 on a three-digit ISIC level. The median import-output ratio was .257, the median export-output ratio was .017. As Table 3 and 4 indicate and Figure 1 illustrates, in the sectors that had both imports and exports, one of the categories significantly prevailed over the other so that the trade orientation was easily determined.

The endogeneity of trade orientation could arise from the traditional omitted variable problem: unobserved factors that affect a plant's productivity might also affect a plant's trade orientation during

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[10] The data set does not provide the information on hours worked. It also does not provide the information on when a plant was established.

[11] In most cases, the results are robust to definitions based on any cut-off point between 10 to 25% (20% in textiles).

trade liberalization. Most obviously, trade liberalization could have changed also a plant's trade orientation. One way of solving this problem is to define trade orientation of a sector using information on imports and exports preceding the sample period. Interestingly, trade orientation of the three- and four-digit ISIC industries does not change much over time, which implies that the endogeneity does not seem to be a concern in the case of Chile. In my regression analysis I also use plant fixed effects, so that this specification eliminates the effects of any permanent unobserved plant characteristic that influence trade orientation and plant productivity. Moreover, Chile underwent a comprehensive reform that enhanced the economy as a whole. I could have used a measure such as tariff concessions or changes in protection. Yet, the change in tariffs does not completely depict the change in the trading environment. Some sectors might not experience an increase in imports regardless of the drop in tariffs because of transportation costs or other barriers to trade. Category 3117, manufacturing of bakery products is a good example. Despite low tariffs, it involves a good that is nontraded because it is perishable. Therefore, a definition of a trade orientation of a sector based on trade balance seems more appropriate. In addition, if one considers political economy issues, measures such as tariffs might suffer from the endogeneity issues as well (Trefler 1993), i.e. less productive industries might be more likely to lobby and receive higher tariffs. One is unlikely to worry about this in terms of Chile during the 1980s, however, since all tariff changes were uniform for all manufacturing sectors. Nevertheless, in the estimation I employ other measures of trade and protection such as tariffs and import to output ratios to check the robustness of my results. All measures lead to the same findings.

4.2 Preliminary Analysis

The Chilean manufacturing sector experienced significant changes following the trade liberalization period, and plant exit played an important role in the adjustment process.[12] As Table 5

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[12] Plant entry is also an interesting topic. This paper does not focus on entry because the magnitude of entry was much smaller than the magnitude of exit. It is also unclear how to correct for selection bias from entry because we do not know the population of possible entrants. However, selection bias due to entry might not be that important in this particular application. The average capital level of entering plants is not statistically different from the average capital level of the incumbents.

indicates, 35% of the plants that were active in 1979 ceased their production by 1986. The liquidated plants accounted for 25% of the 1979 total manufacturing labor force, 13% of the 1979 investment, and 16% of the 1979 manufacturing output.[13] Evidence in Table 5 suggests that the incidence of exit varied across plants in the export-oriented, import-competing, and nontraded goods sectors. Out of the 35% of the plants that exited the market, 13% belonged to the export-oriented sectors, 40% belonged to the import-competing sector, and 47% exited from the nontraded-goods sector. Similarly, of the 25% of the workers that were employed in 1979 but lost their job thereafter, 19% are displaced from the export-oriented sector, 43% from the import-competing sectors, and 38% from the nontraded goods sector. Finally, out of 16% of the 1979 output attributable to the exiting plants, 15% belonged to the plants exiting from the export-oriented sectors, 42% to the plants from the import-competing sectors, and 43% to the plants from the nontraded-goods sectors.

The above figures suggest that plants in the import-competing sectors experienced the largest displacements in terms of employment, whereas plant closings did not play as significant of a role for the plants in the export-oriented industries. Yet, these results might be misleading due to the small size of the export-oriented sector. The bottom section of Table 5 depicts the contribution of plants that are active in 1979 but not in 1986 by using the shares of employment and output that these plants had in the corresponding sectors. 42% of the plants in the export-oriented sector that were active in 1979 are no longer active in 1986, these plants accounted for 30% of employment, 17% of investment and 13% of output in the export-oriented sector in 1979. Similarly, 38% of plants in the import competing sector, and 32% of plants in the non-traded sector, accounting for 26% and 22% of the 1979 employment in the corresponding sectors respectively, are active in 1979 but no longer produce in 1986.

Overall, these descriptive statistics suggest that exit seems to play an important role in the adjustment process after the Chilean trade liberalization. Part of these exit patterns potentially stems

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[13] Plants could either exit the data because they go bankrupt or their number of workers falls below 10. In this application, I do not count as exit plants that disappear from the data due to low number of employees and then

from the large recession in 1982 and 1983. Regardless of the causes of the exit, I expect a large attenuation of the capital coefficient in the estimation procedures that ignore self-selection induced by plant closings. This would translate into skewed productivity measures.

5. Estimation Results

5.1 Estimates of the Production Function Coefficients

Table 6 presents estimates of the input coefficients from the production function specified in equation (1). I follow the rest of the literature and estimate the production function on a two or three digit ISIC industry level for all individual manufacturing industries: food manufacturing, textiles and apparel, manufacture of wood and wood products, manufacture of paper and paper products, chemical industry, glass, basic metals and manufacture of machinery and equipment.[14] This implies that plants producing various four digit ISIC goods within a three or two digit ISIC classification use the same factor proportions, but are imperfect substitutes in consumption, which can lead to different trade orientation within an industry. This assumption is in line with the models of intra-industry trade where goods require the same factor input coefficients in their productions, but play different role in a country's trade (some are exported, some are import-competing and some are nontraded). Difference in their exposure to international competition might lead to difference in their behavior and differences in the response of their productivity to international shocks. I include skilled and unskilled labor, materials and capital as factors of production.

Table 6 reports the estimates of the coefficients based on the OLS, fixed effects, and semiparametric estimation, first using only plants that never exited the sample (balanced panel) and then the full sample (unbalanced panel). According to the theory the coefficients on variable inputs such as skilled and unskilled labor and materials should be biased upwards in the OLS estimation, whereas the

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appear again later in the data. I also do not count as exit a plant switching its ISIC industry sector. Most of these switches occur on a four digit ISIC level, so they do not affect the estimates of production function.

[14] In an older version of the paper I have also repeated the analysis on a more disaggregated three digit ISIC level and the level of aggregation did not affect my final results. I have also specified and estimated production function in the value added form. Although the coefficients differ, the main findings of the study do not change.

direction of the bias on the capital coefficient is ambiguous. My results confirm this. The estimates of the coefficient on labor, materials, and capital based on semiparametric estimation reported in column 5 significantly differ from the OLS and fixed effects estimates. They move in a direction that points at successful elimination of simultaneity and selection bias.

Let us illustrate this point on the input coefficients obtained for the food processing industry. The skilled labor coefficient from semiparametric estimation (.098) in column 5 is lower than the OLS estimate in column 3 (.131) based on unbalanced panel. The above finding holds for all industries in my sample but paper, as well as for unskilled labor and materials.[15] Moreover, my estimates of the coefficient on capital exhibit the biggest movement in the direction that points at the successful elimination of the selection and simultaneity bias. Semiparametric estimation yields estimates that are from 45% to over 300% higher than those obtained in the OLS estimations in industries where the coefficient increases. For example, my estimate of the coefficient on capital in column 5 in food processing industry is .079 compared to the OLS estimate .052 (column 3) and the fixed effects estimate .014 (column 4). This finding holds in 5 out of 8 industries reported in Table 6 and reconfirms the necessity of adjusting the estimation procedure for the self-selection induced by the exiting plants in a country like Chile during the early 1980s. In three industries (textiles, paper, machinery) the coefficient on capital actually declines, which might indicate that the selection bias is less important than the simultaneity bias. The input coefficients suggest the existence of increasing returns to scale in all of the sectors, with only slight presence in food processing and the highest in wood and glass industry.

Previous literature has often used fixed effects estimation that relies on the temporal variation in plant behavior to pinpoint the input coefficients. The fixed effects coefficients are reported in columns 2 and 4, and they are often much lower than those in the OLS or the semiparametric procedure, especially for capital. This is not surprising since the fixed effect estimation relies on the intertemporal variation within a plant, thus overemphasizing any measurement error. Semiparametric estimation therefore provides a useful alternative for estimation of a production function to techniques used in previous studies.

As discussed in section 3.2, semiparametric estimation from Olley and Pakes (1996) technically requires plants to have strictly positive investment. Table 6a compares the semiparametric estimates of the production function based on all plant observations (column 1) and based only on plants with strictly positive investment. In most cases, the coefficients do not vary significantly. The exceptions are the coefficient on the unskilled labor and the coefficient on capital in paper and machinery. However, these are also the two coefficients with the highest standard errors. More importantly, my estimates of the relationship between trade and productivity, discussed in section 5.3, do not change when I use the measure of productivity constructed from the production function estimates based solely on the observations with strictly positive investment.

5.2 Productivity Measure and Aggregate Industry Productivity Indices

I use the input coefficients based on semiparametric estimation from column 5 in Table 6 to construct a measure of plant productivity. In every industry, the productivity index is obtained by subtracting plant *i's* predicted output from its actual output at time *t* and then comparing it relative to a reference plant *r*. This methodology has been employed in several studies using panel or cross sectional data such as Aw et. al. (1997), Klette (1996) and Caves et. al (1981). It insures that the productivity index has the desired properties such as transitivity and insensitivity to the units of measurement.[16] I obtain such an index by simply subtracting a productivity of a reference plant in a base year (plant with mean output and mean input levels in 1979) from an individual plant's productivity measure:

$$\begin{aligned} & pr_{it} = y_{it} - \hat{\beta}_{ls} l_{it}^{s} - \hat{\beta}_{lu} l_{it}^{u} - \hat{\beta}_{m} m_{it} - \hat{\beta}_{k} k_{it} - (y_r - \hat{y}_r) \\ where\quad & y_r = \bar{y}_{it} \\ and\quad & \hat{y}_r = \hat{\beta}_{ls} \bar{l}_{it}^{s} + \hat{\beta}_{lu} \bar{l}_{it}^{u} + \hat{\beta}_{m} \bar{m}_{it} + \hat{\beta}_{k} \bar{k}_{it} \end{aligned}$$

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[15] The unskilled labor coefficient obtained by OLS is actually lower than the coefficient obtained by semiparametric method in glass and basic metals.

[16] For a review of this literature see Good et. al. (1997).

where the bar over a variable indicates a mean over all plants in a base year. So, y_r is the mean log output of plants in my base year, 1979, and $\hat{y}_r$ is the predicted mean output in 1979. This productivity measure presents a logarithmic deviation of a plant from the mean industry practice in a base year.

To check the importance of productivity gains stemming from the reshuffling of resources from the less to more efficient plants I compute aggregate industry productivity measures for each year. In a given year the aggregate industry productivity measure W_t is a weighted average of the plants' individual unweighted productivities pr_{it} with an individual plant's weight s_{it} corresponding to its output's share in total industry output in a particular year. Further, as in Olley and Pakes (1996) I decompose the weighted aggregate productivity measure W_t into two parts: the unweighted aggregate productivity measure and the total covariance between a plant's share of the industry output and its productivity:

$$W_t = \sum_i s_{it} pr_{it} = \overline{pr}_t + \sum_i (s_{it} - \overline{s}_t)(pr_{it} - \overline{pr}_t)$$

where the bar over a variable denotes a mean over all plants in a given year. The covariance component represents the contribution to the aggregate weighted productivity resulting from the reallocation of market share and resources across plants of different productivity levels. If the covariance is positive, it indicates that more output is produced by the more efficient plants. So, if trade liberalization induces a reallocation of resources within industries from less to more productive plants, the latter measure should be positive, and increasing over time in my sample.

The results of the above decomposition for the industries in my sample are reported in Table 7 in terms of growth relative to 1979. Aggregate productivity, unweighted productivity and covariance growth are reported in columns 1, 2 and 3, respectively. For each industry, the growth figures are normalized, so that they can be interpreted as growth relative to 1979. Note that the figures in column 2 and 3 add to the figures in column 1 as required by the above decomposition.

First, the aggregate productivity column 1 indicates that the aggregate weighted productivity increased from 1979 to 1986 in 6 out of 8 sectors: food processing, textiles, chemicals, glass, basic metals and machinery and equipment; and declined in the wood and paper industry. The aggregate productivity gains over the span of seven years range between 7.6% in the manufacturing of machinery and equipment to around 18% in food, textiles and basic metals, to 33% in glass and 43% in chemicals. Second, as column 2 shows, the growth in aggregate productivity was driven by a substantial growth in unweighted productivity only in food manufacturing and textiles. The unweighted productivity actually declined in wood, paper, and chemical industry. This suggests that most of the improvements in aggregate productivity resulted from the reallocation of the resources and market share from the less to more productive plants over time. Column 3 reports the growth stemming from this process. The figures suggest that, over time, the more productive plants are producing an increasing share of output in six out of eight industries. In many industries such as paper and basic metals, where the covariance grew by 19.5%, to glass (31%) and chemicals (48.8%), this component of aggregate productivity actually counteracts the declining trend or unchanging unweighted mean productivity.

The above evidence indicates that the productivity of plants in Chile has changed after trade liberalization. The bottom section of Table 7 reports the growth for the manufacturing as a whole and for the sectors of various trade orientations. Aggregate productivity has increased by 19% over seven years: 6.6% due to increased productivity within plants, and 12.7% due to the reallocation of resources from the less to more efficient producers. The table furthermore suggests that aggregate productivity, unweighted productivity and covariance between output and productivity grew the most in the import-competing sectors, and the least in the nontraded goods sectors. To further investigate and identify the effects of trade liberalization on plant level productivity, I now proceed with the analysis of productivity evolution in a regression framework.

5.3 Estimation of Variation in Plant-Level Productivity

Although the above evidence suggests that plants belonging to sectors of different trade orientation reacted differently after a trade liberalization episode, I have not formally identified the influence of trade policy on the evolution of a plant's productivity. In order to address this question I utilize the following regression framework:

$$pr_{it} = \alpha_0 + \alpha_1 (Time)_{it} + \alpha_2 (Trade)_{it} + \alpha_3 (Trade*Time)_{it} + \alpha_4 Z_{it} + v_{it} \tag{12}$$

where pr_{it} is the unweighted productivity measure for a plant *i* at time *t*, *Time* is a vector of year dummy variables, *Trade* is a vector of dummy variables indicating trade orientation of a plant (export-oriented, import-competing), *Trade*Time* is a vector of interactions of a trade orientation of a plant and a year (for example, import-competing*year84), and Z_{it} is a vector of plant characteristics such as industry affiliation and whether it ceases to produce in a given year. The omitted macroeconomic variables are captured by the year indicators. The nontraded-goods sector, the surviving plants, and year 1979 are the excluded categories.

This difference in difference framework enables me to separate the variation in productivity due to changes in Chilean trade regime from the variation emanating from other sources by exploiting not only the productivity variation over time, but also across plants of different trade orientation. Previous studies have based the identification of trade policy effects on the comparison of a plant's behavior before and after a trade policy shift. This approach might attribute the variation in productivity originating from some other shocks occurring concurrently with trade policy change such as the 1982-1983 macroeconomic recession, to the trade policy reform. Furthermore, this intertemporal identification presumes that plants instantaneously react to the implementation of a trade policy change. Yet, I do not observe plants' expectations about the nature and sustainability of the trade policy change. They might have responded to the changes in trade regime only after they were convinced of the government's lasting commitment to a liberalized trade regime. Hence, the effects of trade liberalization are likely to persist during the early 1980s, a period that is included in my data.

I therefore also utilize the productivity variation across plants belonging to sectors of different trade orientation. Trade liberalization directly affects plants in the import-competing and export-oriented sectors, but not the plants in the nontraded-goods sector. On the other hand, I expect other environment changes, for example, the 1982-1983 recession, that occurred while plants were adjusting to the shifts in trade regime, to impact all sectors.[17] My difference in difference estimates of the effects of trade policy are represented by the coefficient vector α_3 from equation (12), whose components are the interactions between the indicator of the trade orientation of a plant (export-oriented, import-competing) and the year dummies. The coefficients indicate the productivity differential for traded goods compared to the nontraded-goods sector that can be directly attributed to liberalized trade flows. By including a separate term for each year in my sample, I allow the effects of trade liberalization on productivity to vary across different years. Since I distinguish between the traded-goods and the nontraded-goods sectors, I could also include a measure of the real exchange rate in my specification of equation (12). However, the exchange rate only exhibits variation across years. The real exchange rate therefore does not affect my estimates of the coefficient vector α_3 once year indicators are included in my regression, unless it impacts traded and nontraded-goods sectors differentially. I consider this possibility when I check the robustness of my results.

I am trying to test whether trade liberalization makes plants more productive. If trade liberalization improves plants' productivity in the traded-goods sector, the coefficients in α_3 should be positive. Let us first focus on the implications for the plants in the import-competing sectors. If trade liberalization lowers the domestic prices of import-competing goods, the domestic plants need to become more efficient and trim their fat in order to survive. These are within plant productivity improvements that I can identify with α_3. Liquidation of less efficient plants presents an additional channel of eliminating inefficiencies. I can directly test the incidence of industry rationalization by inclusion of an indicator for the exiting plants. If plants ceasing to produce are less efficient, the coefficient on the exit dummy should be negative.

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[17] Here I need to assume that trade policy does not interact with recession. In other words, I assume that the international recession does not interact with domestic sectors differently.

Unfortunately, it is harder to pinpoint the impact of trade liberalization on productivity of plants stemming from facilitated access to foreign technology and intermediate inputs. This potential channel of productivity improvements affects the plants producing traded and nontraded goods. The presence of within plant productivity improvements in a given industry in general might provide a weak support for this mechanism, as opposed to the elimination of the X-inefficiencies that impacts only the plants in the import-competing markets.

Trade theory does not offer much guidelines about the way exporting plants react to trade liberalization. One possibility would be that only the best plants could export in the past because of the anti-export bias in the import substituting regimes. Once that bias is eliminated, the exporters need to be less productive to compete in the world market, which implies a reduction in productivity of the export-oriented sectors. On the other hand, we might not observe much change in their behavior over time. Several recent studies have found that the exporting plants are in general more productive than the plants catering solely to domestic market (Aw et. al (1997), Clarides et. al (1996), Bernard and Jensen (1995)), Clarides et. al (1996)), but none of these studies investigates whether trade liberalization makes exporters more productive relative to other plants.[18]

In my estimation, I pool productivity indices for plants in different industries while including the industry indicators in the regression. Inclusion of the industry indicators controls for the variation of productivity between industries, so the regressors such as the interaction between trade orientation of a plant and a year indicator are picking up the effects of within industry variation.[19] In addition to accounting for different means of productivities across industries, I also consider a possibility that observations are not identically distributed and might have different variance, which is just a problem of

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[18] These studies actually observe whether a particular plant exports. Chilean data does not provide such detailed information.

[19] Note that the subtraction of the reference plant discussed in section 5.2 is not necessary for my regression analysis with industry indicators. If I include industry indicators, the reference plant gets absorbed in the means for individual industries. This only changes the coefficients on the constant and industry indicators in the reported regression, but does not affect the coefficients on the year and trade orientation interactions.

heteroskedasticity. I account for it by the Huber-White variance correction. Finally, I also use the fixed effects estimation that is based solely on the variation of productivity within a plant.

The regression results are presented in tables 8 and 8a. Appendix table 1 and 1a repeat the analysis in table 8 and 8a using the measure of productivity computed from the production function estimates based on the plants with positive investment (reported in table 6a, column 2).[20] The estimates of the relationship between trade and productivity do not change when I use the measure of productivity constructed from the production function estimates based solely on the observations with strictly positive investment. Moreover, the reported results in table 8 and 8a are robust to experimenting with different specifications. Because of the robustness of results across various specifications, let us now focus mostly on the results obtained in the OLS regressions.

First, the coefficients on the exit indicator in column 3 of Table 8a suggest that the exiting plants are on average 8.1% less productive than the surviving plants.[21] My findings support the idea that the high levels of trade protection in Chile during the 1970s enabled the coexistence of producers with different levels of productivity, while some of those failed to survive in a more competitive setting during the early 1980s. As protection ceased, the less efficient producers exited. I presumed that this kind of behavior would be the most pronounced in the import-competing sector, which was sheltered from foreign competition before the trade liberalization. As the relative prices of imports decline, I would expect the most inefficient plants in the import-competing industry to exit. To check this hypothesis I interact the exit indicator variable with an indicator for the trade orientation of the plant. As column 4 of Table 8a indicates, I find no evidence that the exiting plants from the import-competing sector are any less productive than the exiting plants from the export-oriented or the nontraded goods sector. The coefficients on the interaction between exit and importables (-.007) and between exit and exportables

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[20] In addition, appendix tables 2 and 2a repeat the analysis in appendix tables 1 and 1a using only plant observations with strictly positive investment. The main findings do not change.

[21] The fixed effects coefficient in column 1 suggests that the exiting firms are on average only 1.9% less productive than the surviving plants, but since it is based on the variation within a plant it excludes the firms that never ceased to produce between 1979 to 1986. These firms are on average more productive, so the lower estimate is not surprising.

(-.021) are not significantly different from zero. So, although the exit of less efficient plants contributes to productivity improvements, the exit effects do not vary across plants of different trade orientation.

Second, the positive signs of the coefficients on the interaction between the import-competing sector and year dummy variables in column 3 in Table 8 and 8a indicate that plants in the import-competing sectors are on average becoming more productive in 1981, 1982, 1983, 1984, 1985 and 1986 relative to the plants in the nontraded goods sector in the corresponding years. Moreover, this difference in productivity increases with time; this suggests that liberalized trade flows positively influence the productivity of plants in the import-competing sector. The productivity gains attributable to trade policy liberalization range from 3% in 1982 to 10.4% in 1985. As other columns of Tables 8 and 8a indicate, this finding is robust to all specifications of equation (12), and to the inclusion of an exit indicator. This growth in productivity could result from the liquidation of the inefficient plants, which could increase the average productivity in the import competing sectors without any within plant improvements. This, however, is not the case. The results reported in Table 8a control for plant exit and show that the exit of plants only partially explains productivity improvements. The comparison of the coefficients in column 3 in Tables 8 and 8a reveals that the inclusion of the exit indicator in the regression hardly changes the coefficients on the interaction of a plant's import-competing status and year indicators. This suggests that the continuing plants in the import-competing sectors improved their productivity, as they adjusted to a more liberalized trading environment. Possible mechanisms are elimination of the X-inefficiencies or some other agency problem, or adoption of better technology from abroad.

The evidence for producers of exportable products is less robust and suggests slower productivity improvements resulting from trade liberalization.[22] Column 3 of Table 8 shows that although plants in the export-oriented sectors are in general 11% more productive than the producers of the nontraded goods, this productivity difference diminishes at the beginning of the sample in 1980 and 1981. The

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[22] The F-tests indicate that the coefficients on the trade orientation-year interactions are statistically different for the firms in the import-competing and the export-oriented sectors in all years, except for 1984 for all of our specifications of equation (12).

coefficient on the interaction of year and export-orientation becomes either positive or not significantly different from zero in 1982 and onwards. This result is robust to various specifications of equation (12) reported in Tables 8 and 8a. This finding is interesting as well. In an import-substituting regime such as in Chile, the exporters face many discriminatory policies, so probably only the most productive plants export. As trade liberalization diminishes the anti-export bias, the less productive plants can flourish on the export market as well, a finding that would explain the declining productivity of plants in the exporting sectors of the economy from 1980 to 1981. On the other hand, the lack of significant changes in the productivity of exporters could imply that the exporters already needed to be very productive to compete successfully on foreign markets, so that trade liberalization did not represent such a large productivity shock to them as to the plants in the import-competing sectors of the economy. Aw et. al (1997) find that the exporting plants in Taiwan are more productive than nonexporters because they need to face extra transportation costs and tougher market conditions to survive, but not that exporters become more productive through their exporting activity.

The analysis above relies on the identification of trade policy effects by comparing the response of plants in traded goods sectors to plants in nontraded goods sectors, since only the first group could be affected by the increased foreign competition. There are two other variables that could potentially impact my interpretation: the real exchange rate and the temporary increase in tariffs in 1983 and 1984. The Chilean real exchange rate appreciated until 1981 and then depreciated in 1982 due to a nominal exchange rate depreciation.[23] The real exchange rate might affect nontraded and traded sectors differently if it affects the measured productivity through changes in the composition of demand for nontradables and tradables. In particular, a real exchange rate appreciation (an increase in the exchange rate by IMF definition) might increase the demand for nontradables and decrease the demand for domestically produced import-competing goods. For example, in the case of appreciation, if plants do not adjust their inputs instantaneously and plants have some spare capacity these demand fluctuations could lead to an increase in measured productivity for the plants in the nontraded goods sector and a decrease in measured productivity for the domestic plants in the import-competing sectors. Real exchange rate depreciation would do the opposite.

Below I present several independent pieces of evidence that raise doubts that such real exchange rate effects are driving my results. First, I observe persistent productivity improvement in the import-competing sector over relatively long periods of time. These firms would then need to improve their productivity based on spare capacity over six plus years, which is very unlikely. Second, the above exchange rate mechanism suggests that productivity growth (decline) comes from expansions (contractions) in output without changes in inputs due to spare capacity. If that is the case, plant productivity growth should be strongly positively correlated with the output growth. Simple correlation coefficients reported in table 9a suggest that the correlation between plant output growth and productivity growth is very small (ranging from .086 to .224 in various industries). The lack of strong correlation suggests that the measured productivity improvements could not be explained solely by the mechanism through demand real exchange shocks. Third, if measured productivity changes occur through firms eliminating (increasing) excess capacity due to demand booms (slowdowns), inventories are also likely to fluctuate significantly. Firms facing demand booms are likely to reduce their inventories and vice versa. I compare average inventories of plants of various trade orientations during times of the real exchange rate appreciation and depreciations in table 9b. The level of inventories (and the share of inventories in total output) does not fluctuate much and the fluctuations do not seem to correspond to the timing of the real exchange rate fluctuations.

Finally, if Chilean plants have spare capacity and measured productivity reflects demand changes, the correlation between measured productivity and the real exchange rate should be positive for the plants in the nontraded-goods sectors and negative for the plants in the traded goods sectors (since an increase in exchange rate means appreciation by IMF definition). To check this hypothesis I regress my

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[23] The real exchange rate is measured by the real effective exchange rate reported in the IMF's International financial

measure of productivity on the real exchange rate, indicators for trade orientations, a time trend, and the interaction of the time trend with trade orientation. The plants in the nontraded-goods sectors are the excluded category. Results are reported in table 9c and do not support the demand fluctuation story. The real exchange rate is positively correlated with measured productivity of the plants in the nontraded-goods sector (omitted category) and import-competing sectors. Moreover, the real exchange rate does not impact the measured productivity in the two sectors differently. The coefficient on the interaction of the real exchange rate and the import indicator is statistically insignificant. The correlation between measured productivity and the real exchange rate is insignificant for plants in the export-oriented sectors.

Real exchange rate appreciation effectively implies less protection for the domestic sector, while exchange rate depreciation implies more protection. Exchange rate movements could therefore also have productivity effects similar to fluctuations in foreign competition. As the exchange rate increases (appreciates) the plants in the import competing sectors would need to become more productive in order to survive. The positive correlation between productivity in the import-competing sector and the exchange rate in table 9c supports this story.

A second concern with the interpretation of my results regards the timing of my sample and the impact of a temporary increase in tariffs in 1983 and 1984. Since tariffs increased by the same degree for all manufacturing sectors and I use the Census of Manufacturers', year indicators in the estimation of equation (12) in the paper capture their impact on productivity, and I therefore do not include them in my initial regressions. When I do regress tariff levels on plant productivity, the results reported in column 1 and 2 of table 9d indicate that plant productivity is negatively correlated with tariff levels, providing support for my previous results.[24]

So far I have measured the trade orientation of a plant by an indicator variable. It is very difficult to measure the impact of foreign competition and trade liberalization with one variable. In order to

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statistics yearbook.

[24] I cannot control for year indicators and tariff levels at the same time because tariffs only vary by year, and they do not vary at all before 1983.

obtain a more direct relationship between foreign competition facing plants in various industries and plant productivity, I also measure foreign competition with imports as a share of domestic output on a four-digit ISIC level. When I regress productivity on this new measure of foreign competition I find that plants in industries that face a higher share of imports are more productive: the coefficient on the import to output ratio is positive (column 3 of table 9d). The positive correlation persists when I control for the tariff and the real exchange rate (column 4). Appendix tables 3a, 3b, and 3c repeat the above analysis using the productivity measure based on production function coefficient obtained using only plants with positive investment. They yield the same findings and similar coefficient estimates.

Overall, the above analysis suggests that the exclusion of the real exchange rate from my initial analysis is unlikely to affect the robustness of my results, because the exchange rate does affect plants in the import-competing sectors differently than it affects plants in the nontraded goods sectors. The additional findings based on the use of tariffs and import shares as measures of foreign competition show that my initial result, i.e. that increased foreign pressure (trade liberalization) yields productivity improvements, is robust to various measures of foreign competition.

6. Summary and Conclusion

This paper studies the effects of trade liberalization on the evolution of plant productivity. In my analysis I pay particular attention to the methodological hurdles that have haunted the previous empirical studies: construction of a productivity measure that is based on *consistent* estimates of the production function coefficients, the identification of trade policy effects, and the role of plant exit and the transfer of resources from less to more efficient producers within industries.

These methodological aspects turn out to be important. The coefficient on capital is on average about double the OLS estimate after adjusting for self selection induced by plant closings, and declines on average by 22% in sectors with strong simultaneity bias. This finding reconfirms Olley and Pakes's (1996) finding that one cannot ignore selection and simultaneity issues in the estimation of a production function, and that semiparametric estimation of a production function provides a useful alternative to the methods used in previous studies.

I then analyze the effects of trade policy on plant productivity in a regression framework. I identify the impact of trade liberalization on productivity by using both the variation of productivity over time and the variation across traded and nontraded goods sectors. This framework allows me to separate productivity variation resulting from trade policy from productivity variation stemming from other sources. My results suggest that trade liberalization enhances plant productivity. In particular, using unweighted productivity I show that the productivity of the producers of the import-competing goods improved on average 3 to 10% more than the productivity of plants in the nontraded-goods sectors due to a policy change. This finding suggests that the plants responded to intensified foreign competition by trimming their fat. The evidence for the plants in the export-oriented sectors of the economy is less robust and conclusive. The result that foreign competition affects productivity positively is also confirmed when I measure foreign competition with import to output ratios in various industries, tariffs, and exchange rate.

Third, exit in general contributes to productivity gains: exiting plants are on average about 8% less productive than surviving plants. Aggregate industry-level productivity indices in addition suggest that the reshuffling of resources in general from less to more productive producers contributes to aggregate productivity gains, especially for the plants in the export-oriented and import-competing sectors. The aggregate productivity grew by 25.4% and 31.9% in the export-oriented and import-competing sectors over seven years, respectively, whereas the gains in the nontraded goods sectors amounted to 6%. I find that in general, the Chilean manufacturing sector grew at an average annual rate of 2.8% after trade liberalization, mostly due to the reshuffling of the resources within the economy (about 2%).

Although it is hard to pinpoint the exact mechanism behind these productivity improvements, the within industry heterogeneity of plants and the reallocation of market share towards more productive plants seem to play a role in addition to the plants in the import-competing sectors trimming their fat. In terms of policy implications, my finding suggests that the barriers to plant turnover are important determinants of the success of trade liberalization. As such, the study complements the recent empirical work by Aw et. al. (1997) analyzing the importance of plant turnover in Taiwan, where sunk cost do not present a large barrier. My results also substantiate concerns raised in popular press regarding recent economic turmoil in East Asia. When exit of plants and the reallocation of resources within industries play an important role in the economic growth, the institutional arrangements that obstruct plant liquidation as in Japan, or the confinement of such process to smaller businesses as in South Korea (NYT, Sept. 8, 1998) can prove very harmful.

Finally, my findings suggest that incorporation of within industry plant heterogeneity in the analysis of trade liberalization seems to be a fruitful area for the future theoretical work in trade literature.

Bibliography

Andrews, Donald. W. K. (1991). “Asymptotic Normality of Series Estimators for Nonparametric and Semiparametric Regression Models,” *Econometrica* 59, pp. 307-345.

Aw, Bee, Yan, et. al. (1997). “Plant-level Evidence on Productivity Differentials, Turnover, and Exports in Taiwanese Manufacturing,” The Pennsylvania State University, mimeo.

Bernard, Andrew, B. and Charles I. Jones (1996). "Comparing Apples to Oranges: Productivity Convergence and Measurement Across Industries and Countries," *American Economic Review* 86, pp. 1216-38.

Bernard, Andrew, Jonathan Eaton, Brad Jensen, and Sam Kortum (1999). “Plants and Productivity in International Trade: A Ricardian Reconciliation,” mimeo, 1999.

Bosworth, Berry, P. et. al. (1994). *The Chilean Economy: Policy Lessons and Challenges*. Washington D.C.: The Brookings Institution.

Caves, Douglas, W. et. al. (1981). “U.S. Trunk Air Carriers, 1972-1977: A Multilateral Comparison of Total Factor Productivity,” in Cowing, Thomas, et. al. (eds.) *Productivity Measurement in Regulated Industries*. New York: Academic Press.

Cornwell, Christopher, et. al. (1990). “Production Frontiers with Cross-Sectional and Time-Series Variation in Efficiency Levels,” *Journal of Econometrics* 46, pp. 185-200.

Dornbusch, Rudiger, et. al. (1994). “Exchange Rate Policy and Trade Strategy,” in Bosworth, Berry, et.al. (eds.) *The Chilean Economy: Policy Lessons and Challenges*. Washington D.C.: The Brookings Institution.

Eaton Jonathan, and Samuel Kortum (1996). "Trade in Ideas: Productivity and Patenting in the OECD," *Journal of International Economics* 40, 251-278.

_______________________________(1997). "Technology and Bilateral Trade," *NBER Working Paper* 6253.

Edwards, Sebastian, and Alejadra C. Edwards (1987). *Monetarism and Liberalization. The Chilean Experiment*. Ballinger. Cambridge, MA.

Ericson, Richard, and Ariel Pakes (1995). “Markov-Perfect Industry Dynamics: A Framework for Empirical Work,” *Review of Economic Studies* 62, pp. 53-82.

GATT (1991). *Trade Policy Review: Chile*. Volume 1,2. Geneva: GATT.

Good, David, H., et. al. (1996). “Index Number and Factor Demand Approaches to the Estimation of Productivity," *NBER Working Paper* 5790.

Haddad, Mona and Ann Harrison (1993). “Are there positive spillovers from direct foreign investment? Evidence from panel data for Morocco,” *Journal of Development Economics* 42, pp. 51-74.

Harrison, Ann E. (1994). "Productivity, imperfect competition and trade reform," *Journal of International Economics* 36, pp. 53-73.

Inter-American Development Bank (1992). *Economic Reforms in Chile*. Munoz, Oscar (ed.). Occasional Papers 7. Washington D.C.: IDB.

Klette, Tor Jakob (1996). "R&D, scope economies, and plant performance," *RAND Journal of Economics*, 27, 502-522.

Levinsohn, James (1996). "Plant Heterogeneity, Jobs, and International Trade: Evidence from Chile," *NBER Working Paper* 5808.

Levinsohn, James and Amil Petrin (1999). "When Industries Become More Productive, Do plants? Productivity Dynamics in an Open Economy," mimeo, University of Michigan.

Liu, Lili (1993). "Entry-exit, learning and productivity change: Evidence from Chile," *Journal of Development Economics* 42, 217-242.

Liu, Lili and James Tybout (1996). "Productivity Growth in Chile and Colombia: The Role of Entry, Exit and Learning," in Roberts, Mark J. and James R. Tybout (eds.) *Industrial Evolution in Developing Countries*. Oxford: Oxford University Press.

The New York Times, September 8, 1998.

Olley, Steven G. and Ariel Pakes (1996). "The Dynamics of Productivity in the Telecommunications Equipment Industry," *Econometrica* 64, pp. 1263-1297.

Pakes, Ariel (1994). "Dynamic Structural Models, Problems and Prospects: Mixed Continuous Discrete Controls and Market Interactions," in Sims C. (ed.) *Advances in Econometrics*. Cambridge: Cambridge University Press.

Pakes, Ariel and Steven Olley (1995). "A Limit Theorem for a Smooth Class of Semiparametric Estimators," *Journal of Econometrics* 65, pp. 295-332.

Roberts, Mark J. and James R. Tybout (eds.) (1996). *Industrial Evolution in Developing Countries*. Oxford: Oxford University Press.

Rodrik, Dani (1988). "Closing the Technology Gap: Does Trade Liberalization Really Help?" *NBER Working Paper* 2654.

__________ (1988a). "Imperfect Competition, Scale Economies, and Trade Policy in Developing Countries," in Baldwin, Robert E. (ed.) *Trade Policy Issues and Empirical Analysis*. Chicago: The University of Chicago Press.

Schmidt, Peter (1985). "Frontier Production Functions," *Econometric Reviews* 4, pp. 289-328.

Schmidt, Peter and R. Sickles (1984). "Production Frontiers and Panel Data," *Journal of Business and Economic Statistics* 2, pp. 367-374.

Trefler, Daniel (1993). “Trade Liberalization and the Theory of Endogenous Protection: An Econometric study of U.S. Import Policy,” *Journal of Political Economy* 101, pp. 138-160.

Tybout, James R. (1992). "Linking Trade and Productivity: New Research Directions" *World Bank Economics Review* 6, pp. 189-211.

_______________ (1996). “Chile, 1979-1986: Trade Liberalization and Its Aftermath,” in Roberts, Mark J. and James R. Tybout (eds.) *Industrial Evolution in Developing Countries*. Oxford: Oxford University Press.

______________ (1996a). “Heterogeneity and Productivity Growth: Assessing the Evidence,” in Roberts, Mark J. and James R. Tybout (eds.) *Industrial Evolution in Developing Countries*. Oxford: Oxford University Press.

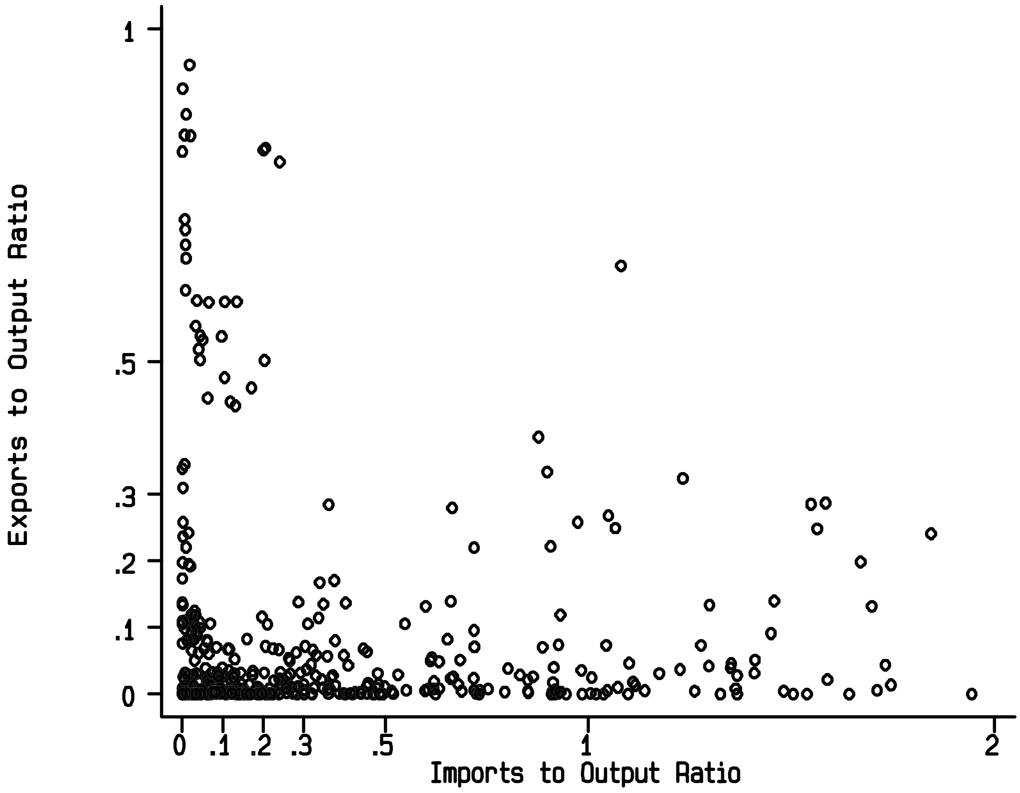
Tybout, James et.al. (1991). “The effects of trade reforms on scale and technical efficiency: New Evidence from Chile,” *Journal of International Economics* 31, pp. 231-250.

Tybout, James, R. and M. Daniel Westbrook (1995). “Trade Liberalization and the Dimensions of Efficiency Change in Mexican Manufacturing Industries,” *Journal of International Economics* 39, pp. 53-78.

UNCTAD (1989). *Handbook of Trade Control Measures of Developing Countries: Supplement*. New York: UN.

________ (1992). *Trade Liberalization in Chile: Experiences and Prospects*. Trade Policy Series No.1. New York: United Nations.

Figure 1
Export-Output vs. Import-Output Ratio
(1980-1986, 4-digit ISIC Industries)



Source: Statistics Canada.

Table 1
Descriptive Statistics

Variable	Mean	S.D.	Median
Output	132,165	985,792	17,922
Value Added	50,386	325,322	6,276
Labor	56	121	23
Skilled Labor	15	41	5
Unskilled Labor	41	87	18
Capital	53,066	360,274	3,682
Investment	3,861	41,624	0
Materials	73,337	700,712	9,643

Note: Quantities in thousands of 1980 pesos. Labor is is number of employees.

Table 2
Panel Information

Year	N	Years in Panel	N*	N**
1979	3,470	8	2,352	1,536
1980	3,704	7	341	716
1981	3,654	6	178	406
1982	3,396	5	209	400
1983	3,034	4	289	441
1984	2,928	3	203	385
1985	2,797	2	185	341
1986	2,508	1	34	154
Total	25,491	Number of distinct plant observations	4,379	4,379

Note: The left hand side of the table indicates the number of plant observations in a given year. The right side of the table indicates how long plants stay in the panel. *These numbers reflect the length of stay in data, but do not distinguish between missing observations (due to missing variables) and exit. **These numbers reflect the actual plant exit. The definiton of exit in this paper is based on the second set of numbers.

Table 3--3-digit ISIC Industry Trade Orientation

(Average 1980-1986)

Industry	Export-Output Ratio	Import-Output Ratio	Import Penetration
312	.174	.078	.072
313	.046	.045	.043
321	.006	.271	.211
322	.004	.174	.145
323	.008	.135	.117
324	.004	.097	.085
331	.254	.019	.019
332	.016	.089	.081
341	.418	.096	.087
342	.023	.062	.059
351	.824	1.326	.567
352	.002	.113	.101
353	.029	.114	.099
354	.019	.262	.170
355	.040	.296	.227
356	.002	.102	.092
361	.092	.716	.320
362	.017	.318	.240
369	.003	.078	.072
371	.063	.112	.100
372	.733	.012	.011
381	.097	.255	.203
382	.053	2.141	.676
383	.036	1.649	.621
384	.210	2.010	.666
385	.089	7.381	.876

Source: Canada Statistics 1980-1986 CD-ROM.

Table 4--4-digit ISIC Industry Trade Orientation

(Averages 1980-1986)

Sector	Export-Output Ratio	Import-Output Ratio	Import Penetration
3111	.087	.038	.036
3112	.006	.075	.069
3113	.135	.026	.025
3114	1.030	.030	.028
3115	.522	.104	.094
3116	.039	.025	.024
3117	.000	.005	.004
3118	.083	.595	.266
3119	.003	.042	.039
3121	.061	.271	.212
3122	.070	.025	.025
3211	.007	.211	.173
3212	.002	.635	.376
3213	.004	.133	.116
3214	.003	.535	.341
3215	.005	3.728	.762
3219	.054	19.532	.887
3220	.004	.174	.145
3231	.008	.061	.056
3232	.020	1.606	.497
3233	.008	.694	.405
3240	.004	.097	.085
3311	.252	.006	.006
3312	.011	.159	.133
3319	.631	.261	.205
3320	.016	.089	.081
3411	.526	.049	.047
3412	.011	.145	.125
3419	.058	.777	.413
3420	.023	.062	.059
3511	1.300	1.001	.493
3512	5.391	16.947	.930
3513	.162	2.035	.649
3514	.824	1.326	.567
3521	.005	.097	.088
3522	.004	.122	.109
3523	.002	.064	.060
3529	.001	.188	.158
3530	.029	.114	.099
3540	.019	.262	.170
3551	.060	.333	.247
3559	.015	.260	.204
3560	.002	.102	.092
3610	.092	.716	.320
3620	.017	.318	.240
3691	.003	.335	.247
3692	.003	.015	.014
3693	.003	.078	.072
3695	.003	.078	.072
3696	.003	.078	.072
3699	.021	.669	.399
3710	.063	.112	.100
3720	.733	.012	.011
3811	.009	.920	.477
3812	.005	.175	.148
3813	.019	.363	.260
3814	.097	.255	.203
3815	.097	.255	.203
3819	.451	.654	.395
3822	.146	2.704	.689
3823	.175	4.256	.803
3824	.359	25.264	.958
3825	.417	62.603	.931
3829	.034	.971	.486
3831	.051	1.460	.582
3832	.028	3.836	.787
3833	.039	1.831	.631
3839	.031	.907	.467
3841	1.198	4.761	.810
3842	.013	1.275	.492
3843	.152	1.761	.635
3844	.008	.616	.374
3849	.210	2.010	.666
3851	.129	7.220	.866
3852	.015	5.230	.834

Source: Statistics Canada 1980-1986.

Table 5--Firms active in 1979 but not in 1986

Trade Orientation	N	Labor	Capital	Investment	Value Added	Output
Total	.352	.252	.078	.135	.155	.156
as a share of total exiting firms						
Export-oriented	.129	.194	.117	.289	.149	.148
Import-competing	.401	.429	.369	.350	.436	.419
Nontraded	.470	.377	.513	.361	.415	.432
as a share of all firms active in 1979						
Export-oriented	.045	.049	.009	.039	.023	.023
Import-competing	.141	.108	.029	.047	.068	.065
Nontraded	.165	.095	.040	.049	.064	.067
as a share of all firms active in 1979 in the corresponding sector						
Export-oriented	.416	.298	.030	.172	.121	.128
Import-competing	.383	.263	.093	.149	.183	.211
Nontraded	.316	.224	.104	.107	.147	.132

Note: This figure also includes plants that exited after the end of 1979, but before the end of 1980 and were excluded in the estimation because of missing capital variable.

Table 6
Estimates of Production Functions

		Balanced Panel				Full Sample					
		OLS		FIXED EFFECTS		OLS		FIXED EFFECTS		SERIES	
		(1)		(2)		(3)		(4)		(5)	
		Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Food Processing	Unskilled labor	.152	.007	.185	.012	.178	.006	.210	.010	.153	.007
	Skilled labor	.127	.006	.027	.008	.131	.006	.029	.007	.098	.009
	Materials	.790	.004	.668	.008	.763	.004	.646	.007	.735	.008
	Capital	.046	.003	.011	.007	.052	.003	.014	.006	.079	.034
	N	6342				8464				7085	
Textiles	Unskilled labor	.187	.011	.240	.017	.229	.009	.245	.015	.215	.012
	Skilled labor	.184	.010	.088	.014	.183	.009	.088	.012	.177	.011
	Materials	.667	.007	.564	.011	.638	.006	.558	.009	.637	.097
	Capital	.056	.005	.015	.012	.059	.004	.019	.011	.052	.034
	N	3689				5191				4265	
Wood	Unskilled labor	.233	.016	.268	.026	.247	.013	.273	.022	.195	.015
	Skilled labor	.121	.015	.040	.021	.146	.012	.047	.018	.130	.014
	Materials	.685	.010	.522	.014	.689	.008	.554	.011	.679	.010
	Capital	.055	.007	.023	.018	.050	.006	-.002	.016	.101	.051
	N	1649				2705				2154	
Paper	Unskilled labor	.218	.024	.258	.033	.246	.021	.262	.029	.193	.024
	Skilled labor	.190	.018	.022	.027	.180	.016	.050	.023	.203	.018
	Materials	.624	.013	.515	.025	.597	.011	.514	.021	.601	.014
	Capital	.074	.010	.031	.025	.085	.009	.031	.023	.068	.018
	N	1039				1398				1145	

Note: This table continues on the next page. Under full sample, the number of observations is lower in the series than in the OLS column because the series estimation requires lagged variables. I have also estimated OLS and fixed effects regressions excluding these observations. The coefficients do not change. All standard errors in column 5 are bootstraped using 1,000 replications.

Table 6 continued
Estimates of Production Functions

		Balanced Panel				Full Sample					
		OLS		FIXED EFFECTS		OLS		FIXED EFFECTS		SERIES	
		(1)		(2)		(3)		(4)		(5)	
		Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Chemicals	Unskilled labor	.033	.014	.239	.022	.067	.013	.246	.020	.031	.014
	Skilled labor	.211	.013	.079	.018	.213	.012	.090	.017	.194	.016
	Materials	.691	.009	.483	.013	.698	.008	.473	.013	.673	.012
	Capital	.108	.008	.032	.014	.089	.007	.036	.013	.129	.052
	N	2145				2540				2087	
Glass	Unskilled labor	.353	.032	.405	.045	.406	.030	.435	.043	.426	.035
	Skilled labor	.285	.035	.068	.042	.226	.031	.056	.038	.183	.036
	Materials	.523	.022	.360	.026	.544	.019	.403	.024	.522	.024
	Capital	.092	.014	-.015	.036	.093	.011	-.013	.030	.142	.053
	N	623				816				666	
Basic Metals	Unskilled labor	.080	.037	.137	.070	.105	.037	.174	.072	.121	.041
	Skilled labor	.158	.034	.008	.070	.156	.034	.006	.072	.117	.043
	Materials	.789	.017	.572	.040	.771	.016	.567	.039	.727	.032
	Capital	.030	.014	.033	.030	.025	.013	.034	.032	.110	.051
	N	306				362				255	
Machinery	Unskilled labor	.186	.013	.225	.018	.199	.012	.238	.016	.178	.015
	Skilled labor	.238	.011	.130	.016	.222	.010	.112	.014	.202	.012
	Materials	.611	.008	.530	.012	.619	.007	.548	.010	.617	.009
	Capital	.078	.006	.057	.013	.078	.005	.047	.013	.051	.013
	N	3025				4015				3268	

Note: Under full sample, the number of observations is lower in the series than in the OLS column because the series estimation requires lagged variables. I have also estimated OLS and fixed effects regressions excluding these observations. The coefficients do not change. All standard errors in column 5 are bootstraped using 1,000 replications.

Table 6a
Comparision of the Semiparametric Estimates of Production Functions

		ALL PLANTS		PLANTS WITH NONZERO INVESTMENT	
		(1)		(2)	
		Coef.	S.E.	Coef.	S.E.
Food Processing	Unskilled labor	.153	.007	.081	.012
	Skilled labor	.098	.009	.119	.011
	Materials	.735	.008	.723	.011
	Capital	.079	.034	.070	.030
	N	7085		2806	
Textiles	Unskilled labor	.215	.012	.183	.020
	Skilled labor	.177	.011	.166	.015
	Materials	.637	.097	.626	.014
	Capital	.052	.034	.056	.032
	N	4265		1591	
Wood	Unskilled labor	.195	.015	.149	.023
	Skilled labor	.130	.014	.134	.023
	Materials	.679	.010	.654	.019
	Capital	.101	.051	.107	.020
	N	2154		692	
Paper	Unskilled labor	.193	.024	.120	.032
	Skilled labor	.203	.018	.224	.025
	Materials	.601	.014	.594	.023
	Capital	.068	.018	.138	.046
	N	1145		494	

Note: This table continues on the next page. Column one reports the estimates of production function based on observations with strictly positive and zero investment (same as column 5 in table 6). Column 2 reports the estimates of production function based on observations with strictly positive investment. All standard errors are bootstraped using 1,000 replications.

Table 6a continued
Comparision of the Semiparametric Estimates of Production Functions

		ALL PLANTS		PLANTS WITH NONZERO INVESTMENT	
		(1)		(2)	
		Coef.	S.E.	Coef.	S.E.
Chemicals	Unskilled labor	.031	.014	.018	.017
	Skilled labor	.194	.016	.188	.019
	Materials	.673	.012	.666	.018
	Capital	.129	.052	.138	.021
	N	2087		1247	
Glass	Unskilled labor	.426	.035	.400	.049
	Skilled labor	.183	.036	.132	.059
	Materials	.522	.024	.489	.038
	Capital	.142	.053	.113	.040
	N	666		294	
Basic Metals	Unskilled labor	.121	.041	.117	.063
	Skilled labor	.117	.043	.116	.074
	Materials	.727	.032	.753	.037
	Capital	.110	.051	.079	.029
	N	255		158	
Machinery	Unskilled labor	.178	.015	.089	.021
	Skilled labor	.202	.012	.231	.016
	Materials	.617	.009	.626	.013
	Capital	.051	.013	.119	.057
	N	3268		1520	

Note: Column one reports the estimates of production function based on observations with strictly positive and zero investment (same as column 5 in table 6). Column 2 reports the estimates of production function based on observations with strictly positive investment. All standard errors are bootstraped using 1,000 replications.

Table 7--Decomposition of Aggregate Productivity Growth

(relative to 1979)

Sector	Year	Aggregate Productivity	Unweighted Productivity	Covariance	Sector	Year	Aggregate Productivity	Unweighted Productivity	Covariance
Food	79	.000	.000	.000	**Chemicals**	79	.000	.000	.000
	80	.005	.008	-.003		80	.014	.046	-.032
	81	.008	.058	-.049		81	.126	.076	.050
	82	.209	.099	.110		82	.312	.039	.274
	83	.144	.049	.095		83	.238	-.050	.288
	84	.116	.044	.072		84	.156	-.040	.196
	85	.092	.014	.078		85	.229	-.033	.262
	86	.179	.129	.050		86	.432	-.056	.488
Textiles	79	.000	.000	.000	**Glass**	79	.000	.000	.000
	80	.064	.063	.001		80	.137	-.036	.174
	81	.148	.119	.029		81	.109	-.073	.182
	82	.147	.090	.057		82	.155	-.044	.200
	83	.075	.063	.012		83	.231	-.052	.283
	84	.130	.082	.048		84	.257	-.071	.328
	85	.136	.095	.041		85	.193	-.095	.287
	86	.184	.171	.013		86	.329	-.011	.340
Wood	79	.000	.000	.000	**Basic Metals**	79	.000	.000	.000
	80	-.052	-.030	-.022		80	-.136	-.022	-.114
	81	-.125	-.071	-.054		81	-.002	.050	-.052
	82	.070	-.076	.145		82	.711	.215	.496
	83	.148	-.051	.198		83	.343	.030	.312
	84	.169	.038	.131		84	.153	-.037	.190
	85	.019	-.038	.058		85	.228	-.153	.380
	86	-.035	.045	-.081		86	.183	-.076	.259

Note: This table continues on the next page.

Table 7 continued--Decomposition of Aggregate Productivity Growth

(relative to 1979)

Sector	Year	Aggregate Productivity	Unweighted Productivity	Covariance	Sector	Year	Aggregate Productivity	Unweighted Productivity	Covariance
Paper	79	.000	.000	.000	**Machinery**	79	.000	.000	.000
	80	-.111	-.035	-.076		80	.031	.025	.005
	81	-.127	.038	-.165		81	.125	.070	.055
	82	-.127	-.079	-.048		82	.131	.027	.105
	83	-.084	-.221	.137		83	.077	.025	.053
	84	-.073	-.266	.192		84	.137	.072	.064
	85	-.252	-.362	.110		85	.083	.032	.051
	86	-.131	-.326	.195		86	.076	.040	.036
All	79	.000	.000	.000	**Import Competing**	79	.000	.000	.000
	80	-.010	.018	-.027		80	-.063	.027	-.090
	81	.051	.054	-.003		81	.032	.092	-.061
	82	.329	.048	.281		82	.088	.066	.022
	83	.174	.010	.164		83	.077	.034	.043
	84	.117	.025	.092		84	.089	.059	.030
	85	.120	-.003	.123		85	.095	.061	.034
	86	.193	.066	.127		86	.319	.107	.213
Export Oriented	79	.000	.000	.000	**Nontraded**	79	.000	.000	.000
	80	-.059	-.038	-.021		80	.044	.021	.024
	81	-.048	-.054	.006		81	.101	.047	.054
	82	.591	.040	.551		82	.228	.038	.190
	83	.326	.015	.311		83	.127	-.004	.131
	84	.178	.049	.129		84	.114	.000	.114
	85	.203	-.011	.214		85	.101	-.040	.142
	86	.254	.087	.166		86	.062	.038	.024

Table 8--Estimates of Equation 12 for total manufacturing sample

(dependent variable is productivity measure)

	FIXED EFFECTS				**OLS**			
	(1)		**(2)**		**(3)**		**(4)**	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Export-oriented	.100	.046 **	.077	.037 *	.112	.031 **	.074	.026 **
Import-competing	-.007	.039	.043	.027	.103	.021 **	.088	.016 **
ex_80	-.071	.026 **	-.071	.026 **	-.055	.025 **	-.056	.025 **
ex_81	-.119	.027 **	-.118	.027 **	-.100	.028 **	-.100	.028 **
ex_82	-.055	.028	-.054	.028	.003	.032	.003	.032
ex_83	-.038	.029	-.037	.029	.021	.032	.021	.032
ex_84	.007	.028	.008	.028	.050	.031	.052	.031
ex_85	-.003	.029	-.001	.029	.028	.030	.031	.030
ex_86	-.008	.034	-.007	.034	.043	.036	.048	.037
im_80	.013	.014	.014	.014	.010	.014	.009	.014
im_81	.044	.014 **	.046	.014 **	.046	.015 **	.048	.015 **
im_82	.025	.015 *	.028	.015 *	.030	.016 *	.034	.016 **
im_83	.042	.015 **	.042	.015 **	.043	.017 **	.045	.017 **
im_84	.061	.015 **	.061	.015 **	.063	.017 **	.067	.017 **
im_85	.101	.015 **	.102	.015 **	.104	.017 **	.109	.017 **
im_86	.073	.017 **	.073	.017 **	.071	.019 **	.077	.019 **
ISIC 2 Indicators			yes				yes	
ISIC 3 Indicators	yes				yes			
Year Indicators	yes		yes		yes		yes	
R^2 (adjusted)	.488		.487		.062		.042	
N	25491		25491		25491		25491	

Note: ** and * indicate significance at a 5% and 10% level, respectively. Standard errors are corrected for heteroscedasticity and repeated observations on the same plant.

Table 8a--Estimates of equation 12 for total manufacturing sample

(dependent variable is productivity measure)

	FIXED EFFECTS				OLS			
	(1)		(2)		(3)		(4)	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Export-oriented	.098	.048 **	.095	.048 **	.106	.030 **	.106	.030 **
Import-competing	-.024	.040	-.025	.040	.105	.021 **	.105	.021 **
ex_80	-.071	.026 **	-.068	.026 **	-.054	.025 **	-.053	.025 **
ex_81	-.117	.027 **	-.110	.027 **	-.099	.028 **	-.097	.028 **
ex_82	-.054	.028 *	-.042	.028	.005	.032	.007	.032
ex_83	-.036	.029	-.025	.030	.021	.032	.023	.032
ex_84	.007	.028	.017	.028	.050	.031	.051	.031
ex_85	-.001	.029	.013	.030	.030	.030	.032	.031
im_80	.013	.014	.013	.014	.011	.014	.011	.014
im_81	.044	.014 **	.044	.014 **	.047	.015 **	.047	.015 **
im_82	.024	.015 *	.024	.015 *	.033	.016 **	.034	.017 **
im_83	.040	.015 **	.041	.015 **	.042	.017 **	.043	.017 **
im_84	.059	.015 **	.059	.015 **	.062	.017 **	.062	.017 **
im_85	.101	.015 **	.102	.016 **	.103	.017 **	.104	.017 **
Exit Indicator	-.019	.010 **	-.010	.013	-.081	.011 **	-.076	.014 **
Exit_Export Indicator			-.069	.035 *			-.021	.036
Exit_Import Indicator			-.005	.021			-.007	.023
ISIC 3 Indicators	yes		yes		yes		yes	
Year Indicators	yes		yes		yes		yes	
R^2 (adjusted)	.498		.498		.057		.058	
N	22983		22983		22983		22983	

Note: ** and * indicate significance at a 5% and 10% level, respectively. Standard errors are corrected for heteroscedasticity and repeated observations on the same plant. This table does not include observations in 1986 becaue one cannot define exit for the last year of a panel.

Table 9a--Correlation between productivity growth and output growth

Industry	Correlation
Food Processing	0.154
Textiles	0.226
Wood	0.089
Paper	0.156
Chemicals	0.150
Glass	0.106
Basic Metals	0.109
Machinery	0.119

The correlation coefficients report correlation between plant productivity growth and plant output growth in a respective industry.

Table 9b--Average Plant Inventories

Year	Inventories in Levels			Inventories as a share of output		
	Export-Oriented Plants	Import-Competing Plants	Nontraded Goods Plants	Export-Oriented Plants	Import-Competing Plants	Nontraded Goods Plants
79	18,749	7,847	5,878	0.103	0.089	0.051
	(140,638)	(32,790)	(56,941)	(.160)	(.122)	(.095)
80	21,210	6,252	5,266	0.093	0.085	0.052
	(143,646)	(19,889)	(50,525)	(.151)	(.133)	(.108)
81	24,536	8,379	5,453	0.104	0.098	0.055
	(171,304)	(34,008)	(50,860)	(.183)	(.217)	(.117)
82	39,259	7,716	6,053	0.109	0.117	0.053
	(253,373)	(23,937)	(57,764)	(.228)	(.196)	(.123)
83	37,803	8,222	7,160	0.081	0.115	0.048
	(265,596)	(24,260)	(78,149)	(.149)	(.226)	(.114)
84	44,123	10,536	7,931	0.079	0.114	0.045
	(228,173)	(34,205)	(81,188)	(.141)	(.252)	(.101)
85	27,690	11,331	8,882	0.079	0.103	0.046
	(84,335)	(37,299)	(94,107)	(.185)	(.201)	(.098)
86	24,530	11,612	7,626	0.062	0.077	0.038
	(77,253)	(37,453)	(61,588)	(.120)	(.110)	(.080)
Average	29,531	8,763	6,655	0.091	0.099	0.049
	(186,633)	(30,697)	(66,903)	(.170)	(.188)	(.106)

Note: Inventories are measured as the end of the year plant-level inventories in thousands of 1980 pesos. The reported numbers are means in a given category in a given year. Standard deviations are reported in parenthesis.

Table 9c--Relationship between productivity and the real exchange rate

(dependent variable is productivity)

real exchange rate	0.0006 **
	(.0001)
real exchange rate*export indicator	-0.0011 **
	(.0003)
real exchange rate*import indicator	0.0001
	(.0002)
P-value for F-test for export-oriented plants	0.1366
P-value for F-test for import-competing plants	0.0000
Plant Indicator	yes
N	25491
R^2 (adjusted)	.48

Note: ** and * indicate significance at a 5% and 10% level, respectively. Standard errors are corrected for heteroskedasticity and repeated observations on the same plant. The regression also includes a time trend, export indicator, import indicator, and interactions of the time trend with export and import indicators as regressors. The nontraded goods plants are the excluded category. The reported p values are for the F-test of the hypothesis that the total effect of real exchange rate on productivity of export oriented plants is zero (similarly for imports).

Table 9d--Relationship between productivity and tariffs, real exchange rate, import competition

(dependent variable is productivity)

	(1)	(2)	(3)	(4)
real exchange rate		0.0005 **		0.0005 **
		(.0001)		(.0001)
tariff	-0.2790 **	-0.2377 **		-0.2376 **
	(.0299)	(.0297)		(.0297)
imports/output			0.0023 **	0.0023 **
			(.0005)	(.0005)
Plant Indicator	yes	yes	yes	yes
N	25491	25491	25491	25491
R^2 (adjusted)	.48	.48	.48	.48

Note: ** and * indicate significance at a 5% and 10% level, respectively. Standard errors are corrected for heteroskedasticity and repeated observations on the same plant. All regressions also include a time trend.

Appendix Table 1--Estimates of Equation 12

(dependent variable is productivity measure based on estimates of production function using only observations with positive investment)

	FIXED EFFECTS				**OLS**			
	(1)		**(2)**		**(3)**		**(4)**	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Export-oriented	.095	.055 *	.092	.042 **	.175	.032 **	.115	.026 **
Import-competing	-.009	.052	.046	.035	.112	.022 **	.088	.017 **
ex_80	-.067	.027 **	-.066	.027 **	-.051	.025 **	-.051	.025 **
ex_81	-.119	.031 **	-.117	.031 **	-.101	.028 **	-.099	.028 **
ex_82	-.065	.032	-.064	.032 **	-.008	.032	-.008	.032
ex_83	-.038	.033	-.038	.033	.017	.032	.020	.032
ex_84	.010	.032	.011	.032	.056	.031	.060	.031
ex_85	.004	.031	.005	.031	.036	.031	.044	.031
ex_86	-.003	.037	-.003	.037	.055	.036	.065	.037
im_80	.015	.014	.016	.014	.014	.014	.013	.014
im_81	.044	.015 **	.046	.015 **	.048	.015 **	.050	.015 **
im_82	.020	.017	.023	.017	.029	.017 *	.032	.017 *
im_83	.037	.017 **	.038	.017 **	.042	.017 **	.044	.017 **
im_84	.060	.017 **	.061	.017 **	.061	.017 **	.066	.017 **
im_85	.102	.018 **	.103	.018 **	.104	.017 **	.109	.017 **
im_86	.074	.019 **	.074	.020 **	.070	.019 **	.077	.019 **
ISIC 2 Indicators			yes				yes	
ISIC 3 Indicators	yes				yes			
Year Indicators	yes		yes		yes		yes	
R^2 (adjusted)	.510		.510		.065		.045	
N	25491		25491		25491		25491	

Note: Productivity measure is based on the production function coefficients reported in column 2 of table 6a. ** and * indicate significance at a 5% and 10% level, respectively. Standard errors are corrected for heteroscedasticity and repeated observations on the same plant.

Appendix Table 1a--Estimates of equation 12

(dependent variable is productivity measure based on the production function estimates using only observations with positive investment)

	FIXED EFFECTS				OLS			
	(1)		(2)		(3)		(4)	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Export-oriented	.089	.058 *	.085	.048 *	.170	.032 **	.169	.032 **
Import-competing	-.025	.053	-.025	.040	.113	.022 **	.113	.022 **
ex_80	-.067	.027 **	-.063	.026 **	-.049	.025 **	-.048	.025 **
ex_81	-.117	.031 **	-.109	.027 **	-.099	.028 **	-.098	.028 **
ex_82	-.064	.032 *	-.051	.028	-.006	.032	-.004	.032
ex_83	-.037	.033	-.025	.029	.018	.032	.019	.032
ex_84	.009	.032	.021	.028	.056	.031	.057	.032
ex_85	.005	.032	.021	.030	.039	.031	.041	.031
im_80	.015	.014	.015	.014	.015	.014	.013	.014
im_81	.044	.015 **	.045	.014 **	.048	.015 **	.047	.015 **
im_82	.020	.017	.020	.015	.032	.017 *	.030	.017 *
im_83	.036	.017 **	.036	.015 **	.041	.017 **	.039	.018 **
im_84	.058	.017 **	.058	.015 **	.060	.017 **	.060	.017 **
im_85	.102	.018 **	.102	.016 **	.103	.017 **	.102	.018 **
Exit Indicator	-.027	.012 **	-.018	.013	-.102	.011 **	-.107	.014 **
Exit_Export Indicator			-.078	.035 *			-.017	.037
Exit_Import Indicator			-.003	.021			.019	.024
ISIC 3 Indicators	yes		yes		yes		yes	
Year Indicators	yes		yes		yes		yes	
R^2 (adjusted)	.519		.612		.060		.060	
N	22983		22983		22983		22983	

Note: Productivity measure is based on the production function coefficients reported in column 2 of table 6a. ** and * indicate significance at a 5% and 10% level, respectively. Standard errors are corrected for heteroscedasticity and repeated observations on the same plant. This table does not include observations in 1986 becaue one cannot define exit for the last year of a panel.

Appendix Table 2--Estimates of Equation 12 for plants with positive investment

(dependent variable is productivity measure based on observations with positive investment)

	FIXED EFFECTS				OLS			
	(1)		(2)		(3)		(4)	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Export-oriented	.096	.063	.078	.051	.180	.040 **	.097	.035 **
Import-competing	.073	.054	.085	.041	.104	.028 **	.085	.022 **
ex_80	-.083	.039 **	-.082	.039 **	-.021	.037	-.022	.036
ex_81	-.169	.041 **	-.167	.041 **	-.092	.039 **	-.090	.039 **
ex_82	-.055	.043	-.054	.042	.022	.047	.027	.048
ex_83	-.004	.043	-.002	.043	.059	.047	.071	.047
ex_84	-.041	.042	-.039	.042	.023	.041	.036	.041
ex_85	.015	.046	.016	.046	.104	.045	.122	.045
ex_86	.017	.050	.019	.050	.096	.053	.118	.053
im_80	.016	.020	.017	.020	.007	.020	.006	.020
im_81	.036	.021 *	.037	.021 *	.041	.021 *	.040	.021 *
im_82	.028	.022	.030	.022	.043	.024 *	.045	.025 *
im_83	.064	.022 **	.065	.022 **	.049	.025 *	.049	.026 *
im_84	.079	.022 **	.081	.022 **	.048	.024 **	.050	.024 **
im_85	.118	.022 **	.120	.022 **	.107	.024 **	.114	.024 **
im_86	.119	.024 **	.122	.024 **	.085	.025 **	.095	.026 **
ISIC 2 Indicators			yes				yes	
ISIC 3 Indicators	yes				yes			
Year Indicators	yes		yes		yes		yes	
R^2 (adjusted)	.550		.550		.082		.049	
N	12290		12290		12290		12290	

Note: Productivity measure is based on the production function coefficients reported in column 2 of table 6a. The estimates in this table are based on plants with strictly positive investment in a given period. ** and * indicate significance at a 5% and 10% level, respectively. Standard errors are corrected for heteroscedasticity and repeated observations on the same plant.

Appendix Table 2a--Estimates of equation 12 for plants with positive investment

(dependent variable is productivity measure based on observations with positive investment)

	FIXED EFFECTS				OLS			
	(1)		(2)		(3)		(4)	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Export-oriented	.083	.069 *	.081	.069	.173	.041 **	.172	.041 **
Import-competing	.054	.057	.056	.057	.108	.028 **	.108	.028 **
ex_80	-.081	.039 **	-.072	.039 *	-.021	.037	-.014	.037
ex_81	-.155	.041 **	-.148	.041 **	-.092	.039 **	-.088	.038 **
ex_82	-.051	.043 *	-.042	.043	.024	.047	.027	.047
ex_83	.000	.044	.012	.044	.061	.047	.066	.047
ex_84	-.042	.043	-.033	.043	.025	.041	.026	.041
ex_85	.006	.047	.023	.048	.108	.045	.113	.045
im_80	.012	.020	.012	.020	.006	.020	.004	.020
im_81	.032	.021 **	.032	.021 *	.041	.021 *	.038	.021 *
im_82	.023	.022	.023	.022	.042	.024 *	.039	.025 *
im_83	.058	.023 **	.059	.023 **	.046	.026 *	.045	.026 *
im_84	.076	.022 **	.076	.022 **	.048	.024 **	.047	.024 **
im_85	.118	.023 **	.119	.023 **	.106	.024 **	.104	.024 **
Exit Indicator	-.024	.025	-.003	.036	-.074	.022 **	-.082	.029 **
Exit_Export Indicator			-.190	.079 *			-.087	.078
Exit_Import Indicator			-.006	.052			.046	.048
ISIC 3 Indicators	yes		yes		yes		yes	
Year Indicators	yes		yes		yes		yes	
R^2 (adjusted)	.559		.600		.073		.073	
N	10966		10966		10966		10966	

Note: Productivity measure is based on the production function coefficients reported in column 2 of table 6a. The estimates in this table are based on plants with strictly positive investment in a given period. ** and * indicate significance at a 5% and 10% level, respectively. Standard errors are corrected for heteroscedasticity and repeated observations on the same plant. This table does not include observations in 1986 becaue one cannot define exit for the last year of a panel.

Appendix Table 3a--Correlation between productivity growth and output growth

Industry	Correlation
Food Processing	0.166
Textiles	0.238
Wood	0.106
Paper	0.155
Chemicals	0.152
Glass	0.126
Basic Metals	0.115
Machinery	0.123

The correlation coefficients report the correlation between plant productivity growth and plant output growth in a respective industry. Productivity growth is based on the production function coefficients obtained by using the observations with positive investment (column 2, table 6a).

Appendix Table 3b--Relationship between productivity and the real exchange rate

real exchange rate	0.0006 **
	(.0001)
real exchange rate*export indicator	-0.0012 **
	(.0003)
real exchange rate*import indicator	0.0001
	(.0002)
P-value for F-test for export-oriented plants	0.0671
P-value for F-test for import-competing plants	0.0000
Plant Indicator	yes
N	25491
R^2 (adjusted)	.50

Note: ** and * indicate significance at a 5% and 10% level, respectively. Standard errors are corrected for heteroskedasticity and repeated observations on the same plant. The regression also includes a time trend, export indicator, import indicator, and interactions of time trend with export and import indicators as regressors. The nontraded goods plants are the excluded category. The reported p values are for the F-test of the hypothesis that the total effect of real exchange rate on productivity of export oriented plants is zero (similarly for imports). Productivity measure is based on the production function coefficients obtained by using the observations with positive investment (column 2, table 6a).

Appendix Table 3c--Relationship between productivity and tariffs, real exchange rate, import competition

(dependent variable is productivity)

	(1)	(2)	(3)	(4)
real exchange rate		0.0004 **		0.0004 **
		(.0001)		(.0001)
tariff	-0.2834 **	-0.2458 **		-0.2456 **
	(.0298)	(.0295)		(.0295)
imports/output			0.0025 **	0.0025 **
			(.0006)	(.0006)
Plant Indicator	yes	yes	yes	yes
N	25491	25491	25491	25491
R^2 (adjusted)	.50	.50	.50	.50

Note: ** and * indicate significance at a 5% and 10% level, respectively. Standard errors are corrected for heteroskedasticity and repeated observations on the same plant. All regressions also include a time trend. Productivity measure is based on the production function coefficients obtained by using the observations with positive investment (column 2, table 6a).