Trade Liberalization, Exit, and Productivity Improvements: Evidence from Chilean Plants

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Abstract

This paper empirically investigates the effects of liberalized trade 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 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 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, 1991) 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 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, Chen, and Roberts (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 liberalized trade 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 and Edwards (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 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 unobserved due to data limitations.

Many empirical papers reviewed in the next section of the paper have tackled the relationship between liberalized trade and productivity, but the questions remain far from settled.[1] This paper contributes to the literature in three ways: the identification of trade 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

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

liberalized trade. The identification in studies such as Tybout, de Melo, and Corbo (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. To identify the effects of liberalized trade 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 liberalized trade (import-competing and export-oriented sectors) and the nontraded-goods sector to separate productivity effects stemming from liberalized trade from productivity variation stemming from other sources. Since it is very difficult to measure the exposure to trade with a single variable, I check the robustness of my findings to 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 two 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 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. This suggests that Olley and Pakes (1996) semiparametric methodology provides a useful alternative to techniques used in previous studies. Second, I find support for productivity improvements related to liberalized trade. 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 various measures of foreign competition. It suggests that exposure to foreign competition forced plants in sectors that used to be shielded from the international competition to trim their fat. Third, I find that exiting plants are on average about 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. These results have important policy implications that I discuss in the conclusion of the paper.

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 and empirical implementation. 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, de Melo, and Corbo (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, Schmidt, and Sickles (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.

Alternatively, one could estimate the production function using the GMM estimator proposed in Blundell and Bond (1998). Blundell and Bond (1998) extend the standard first difference GMM estimation as in Arellano and Bond (1991) and use additional moment conditions based on the lagged difference of the explanatory variable as an instrument for the variable in question in the production function expressed in levels. Although their approach is very appealing when time-invariant heterogeneity across plants is correlated with the explanatory variables, their methodology does not account for selection bias stemming from plant exit. It might therefore be more applicable in cases, where plant exit does not play an important role.

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, de Melo, and Corbo (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 the same input prices and market structure, but 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]

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

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:

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

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:

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

[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.

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:

$$i_t = i_t(\omega_t, k_t). \tag{4}$$

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, 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.

Differences in the exposure of plants to international competition might lead to divergence in plant behavior and different evolution of plant 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 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:

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

Substituting (5) into (1) yields

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

where

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

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, Schmidt, and Sickles (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

[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.

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]

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

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 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

$$\begin{aligned} &E[\omega_{t+1} \mid \omega_t, k_{t+1}, X_{t+1} = 1] = E[\omega_{t+1} \mid \omega_t, \omega_{t+1} > \underline{\omega}_{t+1}(k_{t+1})] = \Phi(\omega_t, \underline{\omega}_{t+1}) - \beta_o \\ &\text{where} \qquad (9) \\ &\Phi(\omega_t, \underline{\omega}_{t+1}) \equiv E[\omega_{t+1} \mid \omega_t, \omega_{t+1} > \underline{\omega}_{t+1}(k_{t+1})] + \beta_o. \end{aligned}$$

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

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

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:

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

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 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 reflect the future profitability of a plant.

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.

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. I allow the polynomial to vary over time since the investment rule is indexed by time.[5] This time index accounts for changes in the market structure that firms might adjust to over time. 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. 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

[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). 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.

in $\hat{P}_t$ and $\hat{\omega}_t = (\hat{\lambda}_t - \beta_k k_t)$ to control for *Φ()*:

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

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) 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 data, many observations have zero investment. In order to check whether the use of these observations significantly affects my findings, I also estimate production functions using only the observations with positive investment and compare the estimates to those obtained when all 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 findings on the relationship between trade and productivity discussed in section 5.3, which is the main goal of this paper, do not change 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 (2000) 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 5 is more convoluted.

4. Data and Preliminary Results

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 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 dataset information, variable definitions, and descriptive statistics are provided in Appendix. 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. 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.[6] See Appendix for the sources of trade data and descriptive statistics. This definition of trade orientation could be problematic because of the potential presence of intraindustry trade and because of the potential endogeneity of the definition. In Appendix, I provide some evidence that justifies the use of this trade orientation measure. Nonetheless, given how difficult it is to measure a plant's exposure to trade, I also check the robustness of my analysis to various measures of protection or exposure to trade such as tariffs and import to output ratios. All approaches yield the same conclusions.

The Chilean manufacturing sector experienced significant changes following the trade liberalization period, and plant exit played an important role in the adjustment process.[7] As table 1 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.[8] Evidence presented in the top and middle section of table 1

[6] I have experimented with different cut-off points. The results are robust to definitions based on cut-off points between 10 to 25%.

[7] 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.

[8] Plants could either exit the data because they go bankrupt or their number of workers falls below 10. Table 1 does not count as exit plants that disappear from the data due to low number of employees and then 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.

indicates 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% to 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 part of table 1 depicts the plants of a given trade orientation that are active in 1979 but not in 1986 as a share of the corresponding trade sector in 1979. 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 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 2 presents estimates of the input coefficients from the production function specified in equation (1). I estimate the production function on a two or three digit ISIC industry level for all individual manufacturing industries: food manufacturing (ISIC 311/312), textiles and apparel (ISIC 32), manufacture of wood and wood products (ISIC 33), manufacture of paper and paper products (ISIC 34), chemical industry (ISIC 35), glass (ISIC 36), basic metals (ISIC 37), and manufacture of machinery and equipment (ISIC 38). 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 2 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 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.[9] 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). The coefficient on capital increases in 5 out of 8 industries. In textiles, paper, and machinery the coefficient on capital actually declines, which might indicate that the selection bias is less important than the simultaneity bias. The input coefficients also suggest the existence of increasing returns to scale in all 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 methods used in previous studies.

As discussed in section 3.2, semiparametric estimation from Olley and Pakes (1996) technically requires observations with strictly positive investment. Table 2a compares the semiparametric estimates of the production function based on all observations (column 1) and based only on observations with strictly positive investment (column 2). In most cases, the coefficients do not vary significantly.[10] The

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

[10] The estimates based only on observations with positive investment could be biased due to sample selection. If there is selection bias and the selection affects the production function coefficients the same way as the inclusion of zero investment observations, the similarity of the production function coefficients might not be very informative. The selection bias is likely to occur if observations with zero investment are very different in their use of inputs in the production process from the observations with positive investment. Although the comparison of the means of observable characteristics suggests that there are some differences across the two groups (those with zero investment tend to be smaller in absolute terms), these differences don't seem to be large when one compares the means of the ratio of various inputs to output across the two groups.

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, because the estimates of the production function do not vary significantly, the productivity measures and thus my estimates of the relationship between trade and productivity, discussed in section 5.3, do not change much.

5.2 Productivity Measure and Aggregate Industry Productivity Indices

I use the input coefficients based on semiparametric estimation from column 5 in table 2 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, Chen, and Roberts (1997), Caves, Christensen, and Tretheway (1981), and Klette (1996). It insures that the productivity index has the desired properties such as transitivity and insensitivity to the units of measurement.[11] 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 level in 1979) from an individual plant's productivity measure:

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

and 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 log 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

[11] For a review of this literature see Good, Nadiri, and Sickles (1996).

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 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 3 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. 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 seven out of eight industries. In industries such as paper where the covariance grew by 19.5%, basic metals (25.9%), glass (34%), 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 3 reports the productivity 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 with different trade orientations react differently after a trade liberalization episode, I have not formally identified the influence of trade on the evolution of a plant's productivity. Since it is difficult to measure the effects of liberalized trade with a single variable, I approach the relationship in several different ways. First, I utilize the following regression framework:

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

where pr_{it} is the unweighted productivity measure for plant *i* at time *t* defined in section 5.2, *Time* is a vector of year indicators, *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 time (for example, import-competing*year84), and Z_{it} is a vector of plant characteristics such as industry affiliation and whether a plant ceases to produce in a given year. The year indicators capture the omitted macroeconomic variables. The nontraded-goods sector, surviving plants, and the year 1979 are the excluded categories.

Previous studies have identified the effects of liberalized trade on productivity by comparing plant's behavior over time. That approach attributes any variation in productivity originating from other concurrent shocks to trade. My difference in difference framework in equation (12) separates 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 with different trade orientations. The lack of panel plant level data prior to 1979 unfortunately prevents me from extending my analysis to the period preceding trade policy reform. However, plants might not instantaneously react to the implementation of a change in trade policy. Since I do not observe plants' expectations about the nature and sustainability of a change in trade policy, plants 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 liberalized trade might persist during the early 1980s, the period that is included in my data. Moreover, if liberalized trade is interpreted in the broader sense of a plant's exposure to foreign markets and competition, the extension of my analysis past the initial policy changes is valid. I later check the robustness of my results based on equation (12) to other measures of exposure to trade.

Liberalized trade directly affects plants in the import-competing and export-oriented sectors, but not the plants in the nontraded-goods sector. On the other hand, other environment changes, for example, the 1982-1983 recession, that occurred while plants were adjusting to the shifts in trade policy, likely impact all sectors. Here I need to assume that the recession does not interact with domestic sectors differently. My difference in difference estimates of the effects of trade are represented by the coefficient vector α_3 in (12), whose components are the interactions of the indicator of a plant's trade orientation (export-oriented, import-competing) and year indicators. These coefficients indicate the productivity differential for traded goods compared to the nontraded-goods sector attributable to liberalized trade.

I am trying to test whether liberalized trade makes plants more productive. If trade improves plant productivity in the traded-goods sector, the coefficients in α_3 should be positive. Let us first focus on the implications of liberalized trade for plants in the import-competing sectors. If trade lowers the domestic prices of import-competing goods, the domestic plants need to improve their efficiency and trim their fat in order to survive. These are the within plant productivity improvements that I can identify with α_3. Unfortunately, it is harder to pinpoint the impact of trade liberalization on the productivity of plants stemming from better access to foreign technology and intermediate inputs. Since all plants might acquire better technology after trade liberalization, this channel might bias my results against finding any effect. In addition, production inefficiency can be eliminated though the liquidation of less efficient plants. I can directly test the incidence of industry rationalization by including an indicator for exiting plants. If plants that cease to produce are less efficient, the coefficient on the exit indicator should be negative.

Trade theory does not offer many guidelines on how exporting plants react to trade liberalization. Potentially, 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, exporters need to be less productive to compete in the world market, which might imply a reduction in the productivity of the export-oriented sectors. Alternatively, the plants in the export-oriented sector might not change their behavior much over time. Several recent studies (Aw, Chen, and Roberts (1997), Bernard and Jensen (1995)) have found that exporting plants are in general more productive than plants catering solely to the domestic market because only more productive plants enter the export market. None of these studies investigates whether trade liberalization makes exporters more productive relative to other plants.[12]

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

The regression results are presented in table 4. In estimating equation (12), I pool plant productivity indices across industries. The inclusion of the 3-digit ISIC industry indicators controls for the variation of productivity between industries, so that the other regressors capture the effects of within industry variation.[13] I report Huber-White standard errors. I also estimate (12) using plant fixed effects and present the results in columns 4-6. I also repeat the analysis in table 4 using the measure of productivity computed from production function coefficients based on the observations with positive investment (reported in table 2a, column 2) with the entire sample and only with observations with strictly positive investment. These results are presented in tables S.2 and S.3 in the supplement to the paper on the Review's web page. They do not differ much from those in table 4. Moreover, the results in table 4 are robust across various specifications, so I focus my discussion on columns 1-3.

First, the coefficient on the exit indicator in column 1 of table 4 suggests that exiting plants are on average 8.1% less productive than surviving plants. My finding supports the idea that the high levels of trade protection in Chile enabled the coexistence of producers with different levels of productivity, while some of those failed to survive in a more competitive setting of the early 1980s. As protection ceased, the less efficient producers exited. Given the increased exposure to foreign competition, this behavior might be most pronounced in the import-competing sectors. Yet, the coefficients on the interaction of the exit indicator and importables (-.007) and the interaction of the exit indicator and exportables (-.021) in column 2 are insignificant. So, although the exit of less efficient plants contributes to productivity improvements, the exit effects do not vary across plants with different trade orientations. Note that the coefficient on the exit indicator in the plant fixed effect regression in column 4 suggests that the exiting plants are on average only 1.9% less productive than surviving plants. This coefficient is based on variation in exit within a plant, so it excludes plants that never cease to produce. These never exiting plants are on average more productive, so the lower estimate is not surprising.

[13] 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

Second, the positive coefficients on the interaction of a plant's import-competing status and the year indicator in column 3 in table 4 suggests that plants in the import-competing sector are on average becoming more productive from 1981 through 1986 relative to the plants in the nontraded goods sector in corresponding years. This difference in productivity increases with time, and the productivity gains for plants in the import-competing sector attributable to liberalized trade range from 3% to 10.4%. These estimates are robust to all of the specifications of equation (12) reported in table 4.[14] These productivity improvements do not stem simply from the liquidation of inefficient plants, which could increase average productivity in the import competing sectors without any within plant improvements. A comparison of the coefficients in column 1 and 3 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 continuing plants improve their productivity as they adjust to a more liberalized trading environment. Possible mechanisms are the elimination of the X-inefficiencies or some other agency problem, or the adoption of better technology from abroad.

Third, the producers of exportable products do not experience productivity improvements attributable to liberalized trade. Column 3 of table 4 shows that although plants in export-oriented sectors are in general 11% more productive than the producers of the nontraded goods, this productivity difference diminishes in 1980 and 1981. The coefficient on the interaction of year and export orientation is insignificant from 1982 onwards. The lack of significant improvements in the productivity of exporters could mean that exporters already had to be very productive to compete successfully in foreign markets, so that trade liberalization was not as significant of a shock to them as to plants in the import-competing sector. Aw et. al (1997), for example, find that exporting plants in Taiwan are more

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.

[14] A potential alternative interpretation of my results is that import-competing sector always has higher productivity growth. Given the lack of panel plant level data prior to 1979, I cannot directly address this concern. However, my plant fixed effects estimates of α_3 for plants in import-competing sectors are partially identified by plants that switch their trade orientation. Also, some anecdotal evidence and evidence based on very aggregate data before my sample period presented in Edwards and Edwards (1987) suggest that this is unlikely to be the case.

productive than nonexporters, because exporters need to face extra transportation costs and tougher market conditions to survive, but the exporters do not appear to become more productive through their exporting activity. Additionally, the productivity decline in export-oriented plants in 1980 and 1981 could be attributed to the real exchange rate appreciation as I discuss in more detail below.

The identification of the impact of liberalized trade on the productivity of plants in the export-oriented and import-competing sectors could be affected by real exchange rate fluctuations. If the real exchange rate impacts traded- and nontraded-goods sectors differentially, its effects are not only captured by the year indicators, but also affect the estimates of α_3 in equation (12). The real exchange rate might impact measured productivity through changes in the composition of demand for nontradables and tradables. In particular, a real exchange rate appreciation might increase demand for nontradables and decrease demand for domestically produced traded goods. If plants do not adjust their inputs instantaneously and have some spare capacity, the demand fluctuations induced by an exchange rate appreciation (depreciation) could lead to an increase (decrease) in measured productivity for plants in the nontraded goods sector and a decrease (increase) in measured productivity for plants in the export-oriented and import-competing sectors. The Chilean real exchange rate appreciated until 1981 and then depreciated in 1982 due to a nominal exchange rate depreciation, so the spare capacity story is consistent with the observed productivity decline in the export oriented sector in 1980 and 1981. However, this explanation might be less consistent with persistent productivity improvements of plants in the import-competing sector. I thus explore the relationship between the exchange rate and productivity further.

First, the above exchange rate mechanism suggests that productivity growth (decline) stems from expansions (contractions) in output without changes in inputs due to spare capacity. Then, plant productivity growth should be strongly positively correlated with output growth. Simple correlation coefficients reported in table 5 suggest that the correlation between plant output growth and productivity growth is very small (ranging from .089 to .226 in various industries). The lack of a strong correlation suggests that the observed productivity improvements could not be explained solely by real exchange shocks. Second, if measured productivity changes occur through plants eliminating (increasing) excess capacity due to demand booms (slowdowns), plant inventories are likely to fluctuate correspondingly. Table 6 reports average inventories of plants with various trade orientations over time. The level of inventories (and the share of inventories in total output) does not fluctuate much over time, and the fluctuations do not seem to correspond to the timing of the real exchange rate fluctuations.

Finally, if measured productivity reflects exchange rate induced demand changes, the correlation between measured productivity and the real exchange rate should be positive for plants in the nontraded-goods sector and negative for plants in the export-oriented and import-competing sector.[15] To check this hypothesis I regress productivity on the real exchange rate, plant trade orientation indicators, a time trend, and the interaction of the time trend with trade orientation indicators. Plants in the nontraded-goods sectors are the excluded category, so that the effect of the exchange rate on their productivity is given by the coefficient on the exchange rate. The coefficient on the interaction of the exchange rate with the export (import) indicator captures any *additional* effect the exchange rate has on the productivity of plants in the export sector (import-competing sector) *relative* to plants in the nontraded goods sector. Results are reported in table 7. The real exchange rate is positively correlated with the productivity of plants in the nontraded-goods sector. The negative coefficient on the interaction of the exchange rate with the export-oriented indicator suggests that *relative* to plants in the nontraded goods sector, the real exchange rate appreciation has a negative impact on export-oriented plants. However, the insignificant coefficient on the interaction of the real exchange rate and the import-competing sector indicator means that we cannot reject the hypothesis that the real exchange rate does not impact the productivity of plants in the import-competing sector differently from plants in the non-traded goods sector. In summary, although some of the evidence indicates that the exchange rate story provides a possible alternative explanation for the productivity decline in the export-oriented sectors in 1980 and

[15]The real exchange rate is measured by the real effective exchange rate reported in the IMF's International Financial Statistics Yearbook. An increase in the exchange rate means appreciation by the IMF's definition.

1981, there is little evidence that the exchange rate affected plants in the import-competing sectors differently than plants in the nontraded goods sectors. The exclusion of the real exchange rate from my initial analysis thus unlikely affects the robustness of my results for the import-competing sector.

An additional concern with the interpretation of my results in table 4 regards the timing of my sample and the impact of a temporary increase in tariffs in 1983 and 1984. Since Chile had uniform tariffs across manufacturing sectors and I use the Census of Manufacturers', the impact of tariffs is captured by year indicators in equation (12), so I do not include a tariff measure in my initial regressions. When I regress plant productivity on tariff levels (columns 1, 2 of table 8), plant productivity is negatively correlated with tariffs.[16] As a final robustness check of the analysis in table 4, I relate plant productivity to exposure to foreign competition measured with imports as a share of domestic output at a four-digit ISIC level. Blundell, Griffith, and Van Reenen (1999) also follow this approach when examining the relationship between innovation and competition for British firms. The regression results suggest that plants in industries with greater import competition are more productive: the coefficient on the import to output ratio is positive (columns 3, 4 of table 8). This additional analysis is consistent with my initial finding that liberalized trade enhances the productivity of plants in the import-competing sector. Tables S.4, S.5, and S.6 in the supplement to the paper on the Review's web page repeat the analysis from tables 5, 7, and 8 using the productivity measure constructed from the estimates of the production function coefficient based only on observations with positive investment. They yield similar conclusions.

6. Conclusion

This paper studies the effects of liberalized trade 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

[16] 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. Tariff data is reported by the Chilean Central Bank.

function coefficients, the identification of the trade effects, and the role of plant exit and the resource reallocations from less to more efficient producers within industries.

These methodological aspects turn out to be important. After I adjust for self selection and simultaneity, the estimate of the capital coefficient on average more than doubles relative to the OLS estimate for 5 out of 8 industries, and decreases on average by 22% relative to the OLS estimates elsewhere. These results reconfirm 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 liberalized trade on plant productivity in a regression framework. I identify the impact of trade 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 liberalized trade from productivity variation stemming from other sources. My results suggest that liberalized trade 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 liberalized trade. This finding suggests that the plants responded to intensified foreign competition by trimming their fat. The positive relationship between liberalized trade and productivity is robust to other measures of exposure to trade such as import to output ratios, tariffs, and exchange rate. The evidence for plants in the export-oriented sectors of the economy is less conclusive and could also be consistent with plant responses to real exchange rate fluctuations.

My finding of within-plant productivity improvements for plants in the import-competing sector are consistent with the study by Blundell, Griffith, and Van Reenen (1999), who examine the relationship between innovation, market share, and competition using a panel of British firms. Blundell et. al. (1999) find that firms innovate more in industries facing more import competition and lower domestic concentration ratios. They also find that within each industry, conditional on the level of competition, the firms with a bigger market share innovate more. These incumbents have a stronger incentive to innovate, because the innovation preempts additional entry or the expansion of smaller incumbents and thus shields their profits.

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 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%. Overall, 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%).

Given the importance of plant heterogeneity within an industry, my findings imply 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, Chen, and Roberts (1997) analyzing the importance of plant turnover in Taiwan, where sunk costs do not present a large barrier. My results also substantiate concerns raised in popular press regarding recent economic turmoil in East Asia. Hurdles such as institutional arrangements that discourage the bankruptcy of less efficient plants have been blamed to curb economic growth in recent discussions of East Asian economic crisis in popular press. When 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 can prove very harmful.

Finally, my empirical evidence indicates that channels other than economies of scale yield intraindustry productivity improvements from trade. The incorporation of within industry plant heterogeneity should be a fruitful area for the future theoretical work on welfare gains from trade.

Appendix

This appendix provides the details of data construction. The original plant-level data set and the variable definitions and construction are described in detail in Liu (1993) and Tybout (1996). 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. Skilled and unskilled labor is measured by the total number of employees in each skill group working in a plant. The data set does not provide the information on hours worked. It also does not provide the information on when a plant was established. Capital, investment, intermediate materials, value added, and output are expressed in constant 1980 pesos. Descriptive statistics for the data are given in tables A.1 and A.2.

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. 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. 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. Table A.3 summarizes import to output and export to output ratios for the three-digit ISIC sectors in my data. Table S.1 in the supplement to the paper on the Review’s web page provides this information on a four-digit ISIC level.

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 A.3 indicates and figure A.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 trade liberalization. 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. In my regression analysis I also account for plant specific effects, so that this specification eliminates the impact of any permanent unobserved plant characteristic that influence trade orientation and plant productivity.

Moreover, I could measure a plant's exposure to trade with 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 be endogenous (Trefler (1993)), i.e. less productive industries might be more likely to lobby and receive higher tariffs. However, this is unlikely in Chile during the 1980s, since all tariffs and tariff changes were uniform across all manufacturing sectors.

Bibliography

ANDREWS, D. (1991), “Asymptotic Normality of Series Estimators for Nonparametric and Semiparametric Regression Models”, *Econometrica*, **59**, 307-345.

ARELLANO, M. and BOND, S. (1991), "Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations", *Review of Economic Studies,* **58**, 277-297.

AW, B., CHEN, X. and ROBERTS, M. (1997), “Plant-level Evidence on Productivity Differentials, Turnover, and Exports in Taiwanese Manufacturing” (Mimeo, Pennsylvania State University).

BERNARD, A. and JONES, C. (1996), "Comparing Apples to Oranges: Productivity Convergence and Measurement Across Industries and Countries", *American Economic Review,* **86**, 1216-38.

BERNARD, A., EATON, J., JENSEN, B. and KORTUM, S. (2000), “Plants and Productivity in International Trade: A Ricardian Reconciliation” (NBER Working Paper, No. 7688).

BLUNDELL, R. and BOND, S. (1998), "Initial conditions and moment restrictions in dynamic panel data models", *Journal of Econometrics*, **87**, 115-143.

BLUNDELL, R., GRIFFITH, R. and VAN REENEN, J. (1999), "Market Share, Market Value, and Innovation in a Panel of British Manufacturing Firms", *Review of Economic Studies,* **66**, 529-554.

CAVES, D., CHRISTENSEN, L. and TRETHEWAY, M. (1981), “U.S. Trunk Air Carriers, 1972-1977: A Multilateral Comparison of Total Factor Productivity”, in T. Cowing and R. Stevenson (eds.) *Productivity Measurement in Regulated Industries* (New York: Academic Press).

CORNWELL, C., SCHMIDT, P. and SICKLES. R. (1990), “Production Frontiers with Cross-Sectional and Time-Series Variation in Efficiency Levels”, *Journal of Econometrics,* **46**, 185-200.

DORNBUSCH, R. and EDWARDS, S. (1994), “Exchange Rate Policy and Trade Strategy”, in B. Bosworth, R. Dornbusch, and R. Laban (eds.) *The Chilean Economy: Policy Lessons and Challenges* (Washington D.C.: The Brookings Institution).

EATON, J. and KORTUM, S. (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, No. 6253).

EDWARDS, S. and EDWARDS, A. (1987) *Monetarism and Liberalization. The Chilean Experiment*. (Cambridge, MA: Ballinger).

ERICSON, R. and PAKES, A. (1995), “Markov-Perfect Industry Dynamics: A Framework for Empirical Work”, *Review of Economic Studies,* **62**, 53-82.

GATT (1991) *Trade Policy Review: Chile* (Geneva: GATT).

GOOD, D., NADIRI, I. and SICKLES, R. (1996), "Index Number and Factor Demand Approaches to the Estimation of Productivity" (NBER Working Paper, No. 5790).

HARRISON, A. (1994), "Productivity, imperfect competition and trade reform", *Journal of International Economics,* **36**, 53-73.

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

LEVINSOHN, J. (1996), "Plant Heterogeneity, Jobs, and International Trade: Evidence from Chile", (NBER Working Paper, No. 5808).

LEVINSOHN, J. and PETRIN, A. (1999), "When Industries Become More Productive, Do Plants? Productivity Dynamics in an Open Economy" (Mimeo, University of Michigan).

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

LIU, L. and TYBOUT, J. (1996), "Productivity Growth in Chile and Colombia: The Role of Entry, Exit and Learning" in M. Roberts and J. Tybout (eds.) *Industrial Evolution in Developing Countries* (Oxford: Oxford University Press).

OLLEY, S. and PAKES, A. (1996), "The Dynamics of Productivity in the Telecommunications Equipment Industry", *Econometrica*, **64**, 1263-1297.

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

PAKES, A. and OLLEY, S. (1995), "A Limit Theorem for a Smooth Class of Semiparametric Estimators", *Journal of Econometrics*, **65**, 295-332.

ROBERTS, M. and TYBOUT, J. (1996) *Industrial Evolution in Developing Countries* (Oxford: Oxford University Press).

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

__________ (1991), "Closing the Technology Gap: Does Trade Liberalization Really Help?", in G. Helleiner (ed.) *Trade Policy, Industrialization and Development: A Reconsideration* (Oxford England: Clarendon Press).

SCHMIDT, P. (1985), "Frontier Production Functions", *Econometric Reviews*, **4**, 289-328.

SCHMIDT, P. and SICKLES, R. (1984), "Production Frontiers and Panel Data", *Journal of Business and Economic Statistics,* **2**, 367-374.

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

TYBOUT, J. (1992), "Linking Trade and Productivity: New Research Directions", *World Bank Economics Review,* **6**, 189-211.

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

TYBOUT, J., DE MELO, J. and CORBO, V. (1991), “The effects of trade reforms on scale and technical efficiency: New Evidence from Chile”, *Journal of International Economics,* **31**, 231-250.

TYBOUT, J. and WESTBROOK, M. (1995), “Trade Liberalization and the Dimensions of Efficiency Change in Mexican Manufacturing Industries”, *Journal of International Economics,* **39**, 53-78.

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

Table 1--Plants active in 1979 but not in 1986

Trade Orientation	Share of Plants	Share of Labor	Share of Capital	Share of Investment	Share of Value Added	Share of Output
Exiting plants of a given trade orientation as a share of all plants active in 1979						
All trade orientations	.352	.252	.078	.135	.155	.156
Export-oriented	.045	.049	.009	.039	.023	.023
Import-competing	.141	.108	.029	.047	.068	.065
Nontraded	.165	.095	.040	.049	.064	.067
Exiting plants of a given trade orientation as a share of all exiting plants						
Export-oriented	.129	.194	.117	.289	.149	.148
Import-competing	.401	.429	.369	.350	.436	.419
Nontraded	.470	.377	.513	.361	.415	.432
Exiting plants of a given trade orientation as a share of all plants active in 1979 in the corresponding trade 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 2--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	
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 much. All standard errors in column 5 are bootstraped using 1,000 replications.

Table 2a

Comparision of the Semiparametric Estimates of Production Functions

		(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	
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: All standard errors are bootstraped using 1,000 replications.

Table 3--Decomposition of Aggregate Productivity Growth

Industry	Year	Aggregate Productivity	Unweighted Productivity	Covariance	Industry	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**	79	.000	.000	.000
	80	-.052	-.030	-.022	**Metals**	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
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**	79	.000	.000	.000
	80	-.010	.018	-.027	**Competing**	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	79	.000	.000	.000	**Nontraded**	79	.000	.000	.000
Oriented	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

Note: The reported growth figures are relative to 1979.

Table 4--Estimates of Equation 12

	(1) Coef.	S.E.	(2) Coef.	S.E.	(3) Coef.	S.E.	(4) Coef.	S.E.	(5) Coef.	S.E.	(6) Coef.	S.E.
Export-oriented	.106	.030 **	.106	.030 **	.112	.031 **	.098	.048 **	.095	.048 **	.100	.046 **
Import-competing	.105	.021 **	.105	.021 **	.103	.021 **	-.024	.040	-.025	.040	-.007	.039
ex_80	-.054	.025 **	-.053	.025 **	-.055	.025 **	-.071	.026 **	-.068	.026 **	-.071	.026 **
ex_81	-.099	.028 **	-.097	.028 **	-.100	.028 **	-.117	.027 **	-.110	.027 **	-.119	.027 **
ex_82	.005	.032	.007	.032	.003	.032	-.054	.028 *	-.042	.028	-.055	.028 *
ex_83	.021	.032	.023	.032	.021	.032	-.036	.029	-.025	.030	-.038	.029
ex_84	.050	.031	.051	.031	.050	.031	.007	.028	.017	.028	.007	.028
ex_85	.030	.030	.032	.031	.028	.030	-.001	.029	.013	.030	-.003	.029
ex_86					.043	.036					-.008	.034
im_80	.011	.014	.011	.014	.010	.014	.013	.014	.013	.014	.013	.014
im_81	.047	.015 **	.047	.015 **	.046	.015 **	.044	.014 **	.044	.014 **	.044	.014 **
im_82	.033	.016 **	.034	.017 **	.030	.016 *	.024	.015 *	.024	.015 *	.025	.015 *
im_83	.042	.017 **	.043	.017 **	.043	.017 **	.040	.015 **	.041	.015 **	.042	.015 **
im_84	.062	.017 **	.062	.017 **	.063	.017 **	.059	.015 **	.059	.015 **	.061	.015 **
im_85	.103	.017 **	.104	.017 **	.104	.017 **	.101	.015 **	.102	.016 **	.101	.015 **
im_86					.071	.019 **					.073	.017 **
Exit Indicator	-.081	.011 **	-.076	.014 **			-.019	.010 **	-.010	.013		
Exit_Export Indicator			-.021	.036					-.069	.035 *		
Exit_Import Indicator			-.007	.023					-.005	.021		
Industry Indicators	yes		yes		yes		yes		yes		yes	
Plant Indicators	no		no		no		yes		yes		yes	
Year Indicators	yes		yes		yes		yes		yes		yes	
R^2 (adjusted)	.057		.058		.062		.498		.498		.488	
N	22983		22983		25491		22983		22983		25491	

Note: ** and * indicate significance at a 5% and 10% level, respectively. Standard errors are corrected for heteroscedasticity. Standard errors in columns 1-3 are also adjusted for repeated observations on the same plant. Columns 1, 2, 4, and 5 do not include observations in 1986 because one cannot define exit for the last year of a panel.

Table 5--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

Table 6--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)
Overall	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 7--Relationship between productivity and the real exchange rate

real exchange rate	0.0006 **
	(.0001)
real exchange rate*export indicator	-0.0011 **
	(.0003)
real exchange rate*import indicator	0.0001
	(.0001)
Plant Indicators	yes
R^2 (adjusted)	.48

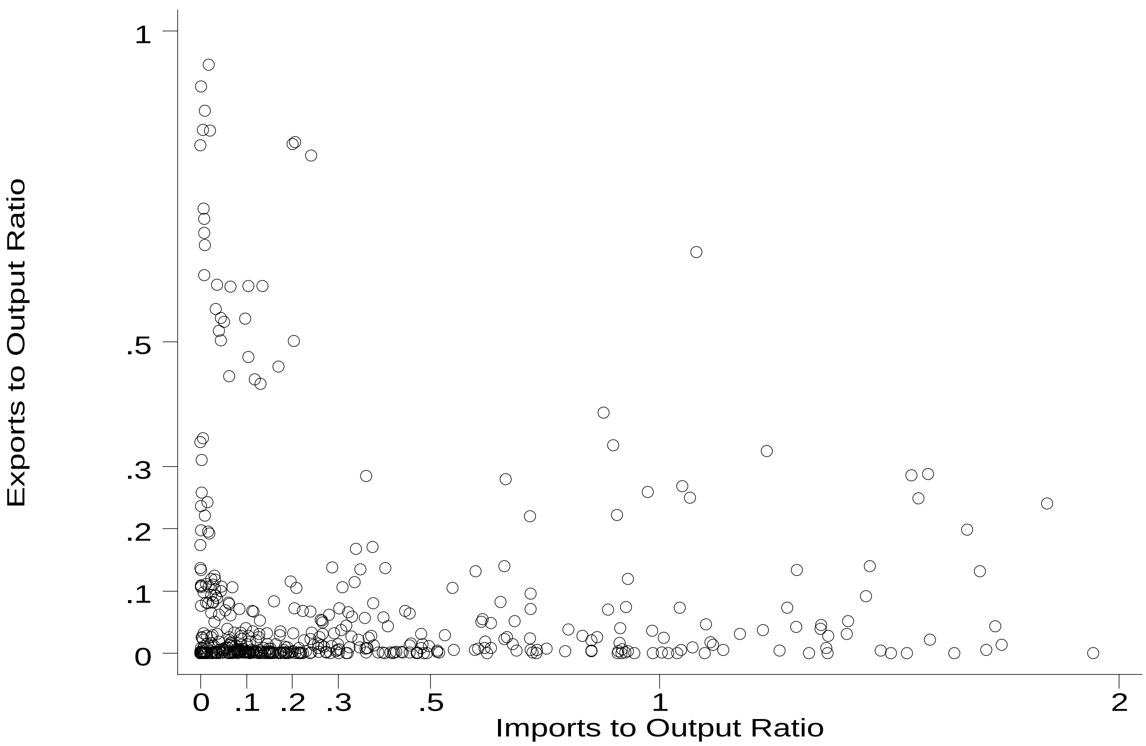
Note: ** and * indicate significance at a 5% and 10% level, respectively. Standard errors are corrected for heteroskedasticity. The regression also includes a time trend, export and import indicators, and the interactions of the time trend with export and import indicators as regressors. N is 25,491.

Table 8--Relationship between productivity
and tariffs, real exchange rate, and import competition

	(1)	(2)	(3)	(4)
real exchange rate		0.0005 **		0.0005 **
		(.0001)		(.0001)
tariff	-0.2790 **	-0.2377 **		-0.2376 **
	(.0280)	(.0286)		(.0285)
imports/output			0.0023 **	0.0023 **
			(.0006)	(.0006)
Plant Indicators	yes	yes	yes	yes
R^2 (adjusted)	.48	.48	.48	.48

Note: ** and * indicate significance at a 5% and 10% level, respectively. Standard errors are corrected for heteroskedasticity. All regressions also include a time trend. N is 25,491.

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



Source: Statistics Canada.

Table A.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 measured by the number of employees.

Table A.2--Panel Information

Year	Number of plants	Years in the panel	Number of plants
1979	3,470	8	1,536
1980	3,704	7	716
1981	3,654	6	406
1982	3,396	5	400
1983	3,034	4	441
1984	2,928	3	385
1985	2,797	2	341
1986	2,508	1	154
Total number of plant-years	25,491	Total number of plants	4,379

Note: The left hand side of the table indicates the number of plants in a given year. The right hand side of the table indicates the number of plants that stay in the panel for a total of 8, 7,... years.

Table A.3--3-digit ISIC Industry Trade Orientation

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

Note: All reported figures are averages over 1980-1986.

Table S.1--4-digit ISIC Industry Trade Orientation

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

Note: All reported figures are averages over 1980-1986.

Sector	Export-Output Ratio	Import-Output Ratio	Import Penetration
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

Table S.2--Estimates of Equation 12 with Alternative Productivity Measure

	(1) Coef.	S.E.	(2) Coef.	S.E.	(3) Coef.	S.E.	(4) Coef.	S.E.	(5) Coef.	S.E.	(6) Coef.	S.E.
Export-oriented	.170	.032 **	.169	.032 **	.175	.032 **	.089	.048 *	.085	.048 *	.095	.046 *
Import-competing	.113	.022 **	.113	.022 **	.112	.022 **	-.025	.040	-.025	.040	-.009	.039
ex_80	-.049	.025 **	-.048	.025 **	-.051	.025 **	-.067	.026 **	-.063	.026 **	-.067	.026 **
ex_81	-.099	.028 **	-.098	.028 **	-.101	.028 **	-.117	.027 **	-.109	.027 **	-.119	.027 **
ex_82	-.006	.032	-.004	.032	-.008	.032	-.064	.027 *	-.051	.028	-.065	.027 *
ex_83	.018	.032	.019	.032	.017	.032	-.037	.029	-.025	.029	-.038	.029
ex_84	.056	.031 *	.057	.032 *	.056	.031 *	.009	.028	.021	.028	.010	.027
ex_85	.039	.031	.041	.031	.036	.031	.005	.029	.021	.030	.004	.028
ex_86					.055	.036					-.003	.034
im_80	.015	.014	.013	.014	.014	.014	.015	.014	.015	.014	.015	.014
im_81	.048	.015 **	.047	.015 **	.048	.015 **	.044	.014 **	.045	.014 **	.044	.014 **
im_82	.032	.017 *	.030	.017 *	.029	.017 *	.020	.015	.020	.015	.020	.015
im_83	.041	.017 **	.039	.018 **	.042	.017 **	.036	.015 **	.036	.015 **	.037	.015 **
im_84	.060	.017 **	.060	.017 **	.061	.017 **	.058	.015 **	.058	.015 **	.060	.015 **
im_85	.103	.017 **	.102	.018 **	.104	.017 **	.102	.015 **	.102	.016 **	.102	.015 **
im_86					.070	.019 **					.074	.017 **
Exit Indicator	-.102	.011 **	-.107	.014 **			-.027	.010 **	-.018	.013		
Exit_Export Indicator			-.017	.037					-.078	.035 *		
Exit_Import Indicator			.019	.024					-.003	.021		
Industry Indicators	yes		yes		yes		yes		yes		yes	
Plant Indicators	no		no		no		yes		yes		yes	
Year Indicators	yes		yes		yes		yes		yes		yes	
R^2 (adjusted)	.060		.060		.065		.519		.612		.510	
N	22983		22983		25491		22983		22983		25491	

Note: Productivity measure is based on production function coefficients reported in column 2 of table 2a. ** and * indicate significance at a 5% and 10% level, respectively. Standard errors are corrected for heteroscedasticity. Standard errors in columns 1-3 are also adjusted for repeated observations on the same plant. Columns 1, 2, 4, and 5 do not include observations in 1986 because one cannot define exit for the last year of a panel.

Table S.3--Additional Estimates of Equation 12 with Alternative Productivity Measure

	(1)		(2)		(3)		(4)		(5)		(6)	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Export-oriented	.173	.041 **	.172	.041 **	.180	.040 **	.083	.069 *	.081	.069	.096	.063
Import-competing	.108	.028 **	.108	.028 **	.104	.028 **	.054	.057	.056	.057	.073	.054
ex_80	-.021	.037	-.014	.037	-.021	.037	-.081	.039 **	-.072	.039 *	-.083	.039 **
ex_81	-.092	.039 **	-.088	.038 **	-.092	.039 **	-.155	.041 **	-.148	.041 **	-.169	.041 **
ex_82	.024	.047	.027	.047	.022	.047	-.051	.043	-.042	.043	-.055	.043
ex_83	.061	.047	.066	.047	.059	.047	.000	.044	.012	.044	-.004	.043
ex_84	.025	.041	.026	.041	.023	.041	-.042	.043	-.033	.043	-.041	.042
ex_85	.108	.045 **	.113	.045 **	.104	.045 **	.006	.047	.023	.048	.015	.046
ex_86					.096	.053 *					.017	.050
im_80	.006	.020	.004	.020	.007	.020	.012	.020	.012	.020	.016	.020
im_81	.041	.021 *	.038	.021 *	.041	.021 *	.032	.021 **	.032	.021	.036	.021 *
im_82	.042	.024 *	.039	.025	.043	.024 *	.023	.022	.023	.022	.028	.022
im_83	.046	.026 *	.045	.026 *	.049	.025 *	.058	.023 **	.059	.023 **	.064	.022 **
im_84	.048	.024 **	.047	.024 **	.048	.024 **	.076	.022 **	.076	.022 **	.079	.022 **
im_85	.106	.024 **	.104	.024 **	.107	.024 **	.118	.023 **	.119	.023 **	.118	.022 **
im_86					.085	.025 **					.119	.024 **
Exit Indicator	-.074	.022 **	-.082	.029 **			-.024	.025	-.003	.036		
Exit_Export Indicator			-.087	.078					-.190	.079 *		
Exit_Import Indicator			.046	.048					-.006	.052		
Industry Indicators	yes		yes		yes		yes		yes		yes	
Plant Indicators	no		no		no		yes		yes		yes	
Year Indicators	yes		yes		yes		yes		yes		yes	
R^2 (adjusted)	.073		.073		.082		.559		.600		.550	
N	10966		10966		12290		10966		10966		12290	

Note: Productivity measure is based on production function coefficients reported in column 2 of table 2a. The estimates in this table are based only on observations with strictly positive investment. ** and * indicate significance at a 5% and 10% level, respectively. Standard errors are corrected for heteroscedasticity. Standard errors in columns 1-3 are also adjusted for repeated observations on the same plant. Columns 1, 2, 4, and 5 do not include observations in 1986 because one cannot define exit for the last year of a panel.

Table S.4--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

Note: Productivity growth is based on production function coefficients reported in column 2 of table 2a.

Table S.5--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
	(.0001)
Plant Indicators	yes
R^2 (adjusted)	.50

Note: Productivity measure is based on production function coefficients reported in column 2 of table 2a. ** and * indicate significance at a 5% and 10% level, respectively. Standard errors are corrected for heteroskedasticity. The regression also includes a time trend, export and import indicators, and interactions of time trend with export and import indicators as regressors. N is 25,491.

Table S.6--Relationship between productivity and tariffs, real exchange rate, and import competition

	(1)	(2)	(3)	(4)
real exchange rate		0.0004 **		0.0004 **
		(.0001)		(.0001)
tariff	-0.2834 **	-0.2458 **		-0.2456 **
	(.0280)	(.0285)		(.0285)
imports/output			0.0025 **	0.0025 **
			(.0006)	(.0006)
Plant Indicators	yes	yes	yes	yes
R^2 (adjusted)	.50	.50	.50	.50

Note: Productivity measure is based on production function coefficients reported in column 2 of table 2a. ** and * indicate significance at a 5% and 10% level, respectively. Standard errors are corrected for heteroskedasticity. All regressions also include a time trend and a plant indicator. N is 25,491.