Temporary Increases in Tariffs and Investment:
The Chilean Experience

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Abstract

For a small open economy importing its capital goods, a tariff increase may cause the price of investment goods to rise, leading to lower investment and slower productivity growth. This paper develops a structural dynamic programming model of investment and estimates the model using panel data on Chilean manufacturing plants for 1980-1996. The estimates are used to examine the impact of a temporary increase in import tariffs imposed in Chile taking account of endogenous initial conditions and both observed and unobserved heterogeneity across plants. The model replicates the observed investment patterns at both plant and aggregate levels well. The differences across trade-sectors and across plants differing in their use of imported materials are also well captured by the model. A counterfactual experiment suggests that Chile would have recovered from the economic crisis of 1982-1983 at a substantially faster rate had there been no temporary increase in import prices associated with higher tariffs in the mid-1980s.

KEYWORDS: Structural dynamic programming model, productivity, unobserved heterogeneity, initial conditions problem, tariffs, investment.

JEL Classification Numbers: C4, F1, L2.

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1 Introduction

Trade in capital goods is one of the primary channels through which a country adopts new technology (cf., Eaton and Kortum, 2001). This is especially true for developing countries whose productivity crucially depends on its ability to import machines that embody new technology. Hence, an increase in import tariffs which causes the price of imported machines to rise may have a large impact on investment and productivity.

This paper develops a structural dynamic programming model of investment and estimates the model using panel data on Chilean manufacturing plants for 1980-1996. The estimates are used to quantify the impact of a temporary increase in import tariffs on investment and productivity in Chile during the mid-1980s taking account of endogenous initial conditions and both observed and unobserved heterogeneity.

Chile provides an ideal setting for studying the impact of tariffs. In 1983, the Chilean government increased import tariffs (uniformly across industries), partly as a response to a balance of payments crisis. As shown in Figure 1, this led to a significant, although temporary, increase in the price of imported goods measured relative to the wholesale price. Since Chile is a small open economy that imports more than 80 percent of its machines (cf., Banco Central De Chile, 2000), higher tariffs may have discouraged investment by increasing the price of imported machines. A negative relationship between import prices and machine investment rates for the period 1976-1996 is apparent in Figure 1.

The model extends models of machine replacement including Rust (1987), Cooper, Haltiwanger, and Power (1999), and Jovanovic and Rob (1999). Higher import tariffs slow plants' replacement by increasing the machine price. If the high tariff regime is viewed as temporary, the expectation of a future drop in machine prices provides an incentive to delay replacement, thereby magnifying the impact of an increase in machine prices. Reversion from the high tariff regime to the low tariff regime causes a burst of aggregate investment because of synchronized replacement decisions due to lower machine prices.

The estimation method involves the repeated numerical solution of a dynamic optimization problem to maximize a likelihood function that accounts for machine replacement decisions and plant productivity. The empirical specification incorporates other potentially important factors, such as aggregate productivity shocks and the financial crisis of 1982-1983. I also accommodate

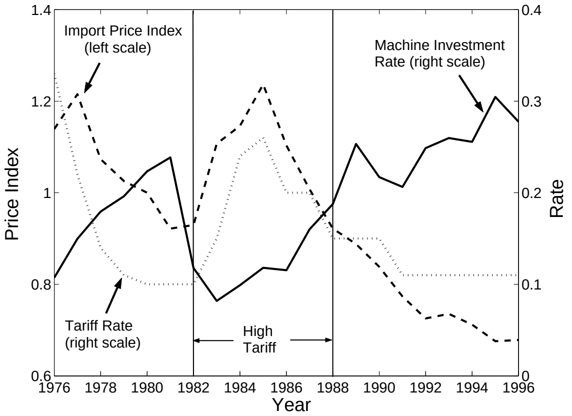

Figure 1: Machine Investment, Import Price, and Tariff Rate

permanent unobserved heterogeneity by assuming that plants differ in their types (cf., Keane and Wolpin, 1997), where each type is characterized by distinct technology parameters. Accounting for unobserved heterogeneity is crucial to correctly infer the decision rule of machine replacement.

The estimated model replicates the observed investment patterns well at both plant and aggregate levels. A counterfactual experiment indicates a substantial negative impact of the temporary increase in import prices in the mid-1980s. Had there been no increase in relative import prices between 1983 and 1987, the aggregate investment rate would have been 6.8 percent higher in 1985 and the output per worker would have been higher by 1.9 percent in 1986. This suggests that Chile would have recovered from the economic crisis of 1982-1983 much more quickly if the government had not imposed higher tariffs in the mid-1980s.

The model's cross-sectional implications are also examined. First, while a tariff increase may not significantly affect output prices in an export-oriented industry, it may lead to higher output prices in an import-competing industry and thus provide greater incentive for plants to hasten replacement. My experiment indicates that, for 1984-1988, the difference in relative import prices can explain more than half of the observed difference between export-oriented industries and import-competing industries in investment rates. Second, a plant that uses imported materials intensively might use imported machines intensively as well, and hence it might have a larger increase in machine price than others during the period of high import prices. I find that import-material-intensive plants experienced substantially larger declines in investment and productivity during the period of high import prices than others.

There are several caveats. First, these results indicate the effects of a temporary increase in relative import prices rather than those in tariffs. Although an increase in tariffs may have been the primary factor that led to higher relative import prices in the mid-1980s, other factors such as the real exchange rate may also have been important determinants. Second, while the model explicitly includes three different observable aggregate state variables, it is still possible that import prices capture spuriously the effect of other omitted aggregate variables. This issue is potentially important because Chile has experienced various political and economic changes during the sample period. Finally, I do not consider a general equilibrium framework. The extent of synchronized investment may be limited in general equilibrium because of the short-run inelastic supply of capital goods (cf., Caballero, 1999), although such a bottleneck might be less important in a small open economy like Chile.

This research complements several branches of empirical literature. First, recent empirical studies find that trade in capital goods plays a significant role for research and development (R&D) spillovers across countries (e.g., Coe, Helpman, and Hoffmaister, 1997; Xu and Wang, 1999). While often motivated by the innovation-driven growth model, the literature does not explicitly specify the mechanism through which trade or R&D affects productivity, nor does it address policy issues, such as the effect of import tariffs on R&D spillovers. Second, the empirical literature investigating the relationship between trade policy and productivity often finds that trade liberalization is associated with productivity improvements.[1] There is little agreement, however, on *why* productivity and trade policy are related.[2] Detailed analyses assessing the importance of a specific mechanism through which trade policy affects productivity are scarce. This paper focuses on the role of imported capital goods, and quantitatively assesses its importance in the context of a temporary tariff change. Finally, this work is related to the literature on the impact of the price of capital goods on investment and productivity.[3] While most empirical work in this literature is based on cross-country data, I closely examine a single country experiencing a large variation over time in the price of capital goods.

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[1] See Tybout, de Melo, and Corbo (1991), Harrison (1994), Tybout and Westbrook (1995), and Pavcnik (2002).

[2] As discussed in Tybout (2000), a number of empirical studies suggest that productivity improvements through trade are *not* due to internal/external scale effects; therefore, intra-plant productivity improvements are a likely source of productivity change. While there are many possible explanations, there is little direct empirical evidence on *how* intra-plant productivity is related to trade liberalization.

[3] See, for example, De Long and Summers (1991), Jones (1994), Greenwood, Hercowitz, and Krusell (1997), and Restuccia and Urrutia (2001).

While its main contribution is empirical, this paper also offers two minor but interesting methodological contributions. First, to my best knowledge, among the existing empirical papers that estimate a structural model of machine replacement (cf., Rust, 1987; Das, 1992; Kennet, 1994; Adda and Cooper, 2000), this is the first paper that incorporates a rich set of permanent unobserved heterogeneity and deals with the initial conditions problem. Second, the presence of unobserved heterogeneity leads to an endogeneity problem in estimating the parameters in the production function. Recent empirical papers that estimate investment models with non-convex adjustment costs (e.g., Bloom, Bond, and Van Reenen, 2007) deal with this issue by applying either the panel GMM method of Arellano and Bond (1991) and Blundell and Bond (1998) or the control function approach of Olley and Pakes (1995). In contrast, given the structure of the model, these approaches are not applicable here. This paper handles the endogeneity issue by estimating the production function parameters jointly with the rest of structural parameters, an approach that also leads to possible efficiency gains.

The paper is organized as follows. Section 2 provides a basic model of machine replacement. Section 3 develops the structural dynamic optimization model of machine replacement. The results are provided in Section 4, and the final section concludes the paper.

2 A Basic Machine Replacement Model with Tariffs

I consider an environment in which producers are risk-neutral and own a single plant with Leontief production technology $Y_t = A_t \min\{L_t, \frac{K_t}{a_k}\}$, where a_k is a parameter; and A_t is the vintage specific technology level. Each producer is assumed to be endowed with one unit of labor.[4] Given the Leontief technology with one unit of labor, the amount of capital a plant employs is $K_t = a_k$. Thus, the production of a plant with technology level A_t is $Y_t = A_t$.

Technology is embodied in the machine. Without replacing its machine, a plant's technology level A_t depreciates over time at the rate of ζ: $A_{t+1} = (1-\zeta)A_t$. The frontier technology level, denoted by A^*, grows at the rate of g: $A^*_{t+1} = (1+g)A^*_t$. In order to adopt new technology, a plant has to scrap the old machine. It is by machine replacement, therefore, that a plant adopts the frontier technology. Upon replacing its old machine by the new machine with technology A^*_t, a plant has to pay $\kappa_t A^*_t$, where κ_t is the efficiency unit price of the new machine. The scrap

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[4] Given the constant returns to scale technology, the scale of production is indeterminate. Thus, it is assumed that each plant can employ at most one unit of labor.

value of old machines is assumed to be zero.[5]

To analyze the effect of tariff rates on the replacement decision, I consider a small open economy that imports capital goods. The domestic machine price, κ_t, is related to the ad-valorem import tariff rate, τ_t, and a constant world price for capital goods, κ, as $\kappa_t = (1+\tau_t)\kappa$. Domestic output price, which is equal to the world price, is normalized to one.

There are two tariff regimes $\{\tau^H, \tau^L\}$ with $\tau^H > \tau^L \geq 0$. The tariff rate follows a first-order Markov process where $Prob(\tau^j_{t+1}|\tau^j_t) = \lambda^j$ for $j = L, H$; accordingly, the transition matrix is given by:

$$\begin{bmatrix} \lambda^H & 1-\lambda^H \\ 1-\lambda^L & \lambda_L \end{bmatrix}. \tag{1}$$

At the beginning of every period, plants observe the realization of tariff τ. Given the state (A, A^*, τ), each plant makes a discrete choice between continuing to use the existing machine or replacing it with a new machine by maximizing the discounted expected sum of profits. The value of a plant at the beginning of period, denoted by $V(A, A^*, \tau)$, is the maximum of the value of the plant if it *does not* replace its technology, $V^N(A, A^*, \tau)$, and the value if it *does* replace, $V^R(A, A^*, \tau)$:

$$V(A, A^*, \tau) = \max\{V^N(A, A^*, \tau), V^R(A, A^*, \tau)\}, \tag{2}$$

with $V^N(A, A^*, \tau) = A + BE[V((1-\zeta)A, (1+g)A^*, \tau')|\tau]$ and $V^R(A, A^*, \tau) = A - (1+\tau)\kappa A^* + BE[V((1+g)A^*, (1+g)A^*, \tau')|\tau]$, where the expectation over τ' is taken using the transition matrix (1); and $B \in (0,1)$ is a discount factor. Define $s \equiv \ln\left(\frac{A}{A^*}\right)$, which we call *technology position* hereafter. Since both the gross profit and the replacement cost are homogeneous of degree one with respect to (A, A^*), the problem may be normalized in terms of the value A^*. Let $v(s, \cdot) \equiv V(exp(s), 1, \cdot)$, $v^N(s, \cdot) \equiv V^N(exp(s), 1, \cdot)$, and $v^R(s, \cdot) \equiv V^R(exp(s), 1, \cdot)$. Then, the Bellman equation (2) become

$$v(s, \tau) = \max\left\{exp(s) + \beta E[v(s-\delta, \tau')|\tau], exp(s) - (1+\tau)\kappa + \beta E[v(0, \tau')|\tau]\right\}, \tag{3}$$

where $\delta \equiv \ln\left(\frac{1+g}{1-\zeta}\right)$ is the rate of technological obsolescence; and $\beta \equiv (1+g)B$ is a discount

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[5] One reason for low resale value of used machines is the "lemons" problem (Akerlof, 1970). Using equipment-level data from aerospace plants, Ramey and Shapiro (2001) find that even barely used capital sells for a substantial discount.

factor adjusted for the rate of technological progress.

The timing of replacement is determined by equating the marginal benefit and the marginal cost of postponing. The benefit of postponing is that a plant can save the replacement cost in terms of present value since a plant discounts the future. On the other hand, a postponement of replacement incurs an opportunity cost: the difference between profit with current technology and the profit that the plant could have had with the new technology. Reflecting an increase in the opportunity cost of using the old machine over time, the policy rule follows an (S,s) policy such that a plant replaces its machine whenever its relative technology position s falls below the threshold value, denoted by $s^*(\tau)$. This threshold value crucially depends on the realization of tariff rates because the marginal benefit of postponing replacement is determined by the tariff-dependent machine price.

To focus on the effect of a *temporary* increase in tariffs, consider the case of $\lambda^L = 1$ and $\lambda^H < 1$. In this case, the high tariff regime is a temporary regime because the economy will revert to the low tariff regime in the "near" future. Then, we may show that the threshold value under the high tariff regime, $s^*(\tau^H)$, decreases in τ^H. The implications are twofold. First, an increase in the tariff rate itself tends to slow replacement by increasing the replacement cost. Second, as τ^H increases, a difference in machine prices between the high tariff regime and the low tariff regime increases; this larger difference increases the benefit of waiting for the tariff to decrease to τ^L, since the plant can incur a lower replacement cost upon reversion of the regime. Here, the temporary nature of the high tariff regime plays an important role since it provides an incentive to delay machine replacement. This is intuitive: if a plant's manager believes that the replacement machine price will drop very soon, he will delay replacement.

Assuming that all plants are the same size, the aggregate investment rate may be defined as the fraction of plants replacing their machines. Denote the cross-sectional density of technology positions at the beginning of period t by $f_t(s)$. Then, the aggregate investment rate is equal to the fraction of plants with technology positions less than the threshold value $s^*(\tau)$ as:

$$\text{Aggregate Investment Rate} = \int_{s \leq s^*(\tau_t)} f_t(s) ds.$$

Holding the cross-sectional density fixed, the aggregate investment rate is nondecreasing in the threshold value $s^*(\tau)$. This provides insight into how an increase in the tariff affects the dynamics of aggregate investment and productivity. Since a temporary increase in the tariff leads to slower replacement (i.e., lower value of $s^*(\tau)$), it may lower temporarily the aggregate investment. Furthermore, the delay in the adoption of frontier technologies embodied in machines results in lower aggregate productivity.

3 Structural Estimation

3.1 Basic Observations

I first examine the model's implications using descriptive statistics. Specifically, I investigate (i) lumpiness in plant-level investment, (ii) the relationship between productivity and machine age, and (iii) the relationship between the timing of investment spikes and machine age.

The data for the analysis are from the Chilean Manufacturing Census collected by Chile's Instituto Nacional de Estadistica (INE). The data set includes all Chilean manufacturing plants employing ten or more workers from 1979 to 1996. The sample includes plants that appeared in the data for the full duration of 1980-1996.[6] See Section 3.4 for other sample selection criteria. The balanced panel data set contains 1441 plants over 17 years.

Lumpiness in investment at the plant level is apparent in the data. Following Cooper et al. (1999), I define episodes of "investment spikes" as occurring if the gross investment rate is greater than 20 percent. In the sample, plants with investment spikes constitute only 22.1 percent, but account for 69.3 percent of aggregate gross investment. On the other hand, 46.8 percent of observations have less than 0.02 percent gross investment rate.[7] A large portion of aggregate investment, therefore, is closely associated with episodes of investment spikes at the plant level. Figure 2 plots the aggregate investment rate with the fraction of plants with investment rates over 20 percent. The correlation between the two series is 0.944. In view of this close connection between aggregate investment and investment spikes, identifying the shocks affecting plants' lumpy investment decisions may be the key to understanding the dynamics of

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[6] Although the link between entry, exit, and productivity growth is an important area of research, I focus attention on those plants continuously staying in the market. Incorporating an exit/entry process into the model requires analyzing industry equilibrium, which is beyond the scope of this paper.

[7] Similar findings on investment spikes are reported for U.S. and Norwegian manufacturing. See Caballero et al. (1995), Caballero and Engel (1999), Cooper et al. (1999), Cooper and Haltiwanger (2000), and Doms and Dunne (1998) for U.S. manufacturing. Nilson and Schiantarelli (1996) provide empirical evidence for Norwegian manufacturing.

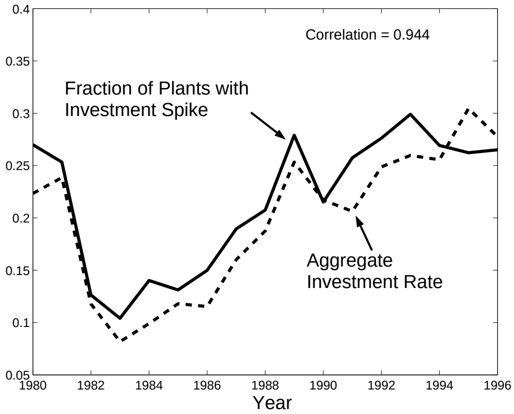

Figure 2: Aggregate Machine Investment and Investment Spike

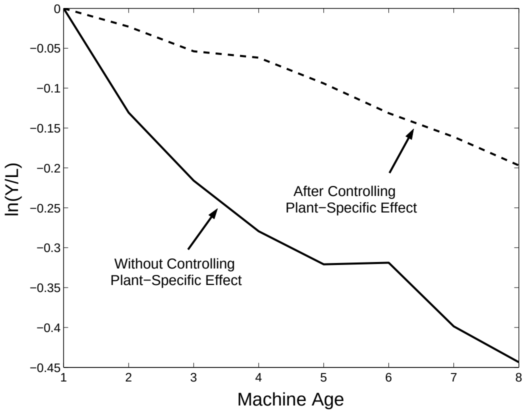

Figure 3: Labor Productivity and Machine Age

aggregate investment.

Motivated by the observed lumpiness in plants' investment, machine replacement is assumed to be identified with episodes of investment spikes. Accordingly, the age of a machine is defined as the number of years passed since the last investment spike. Figures 3 shows the relationship between machine age and the log of plant labor productivity. The solid line plots the relationship without controlling for plant-specific productivity and the dotted line plots the relationship after controlling for plant-specific productivity.[8] While both lines show that plant labor pro-

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[8] Productivity is measured relative to the productivity of machine age 1. The figures are constructed using the plant sample of 1990-1996 for which machine ages are observable at least up to 8 years. The year-specific effect is controlled by subtracting the yearly average labor productivity from plant labor productivity. To control for plant-specific productivity, I subtract the average plant productivity for 1980-1989 from plant productivity and then use the residual as plant productivity.

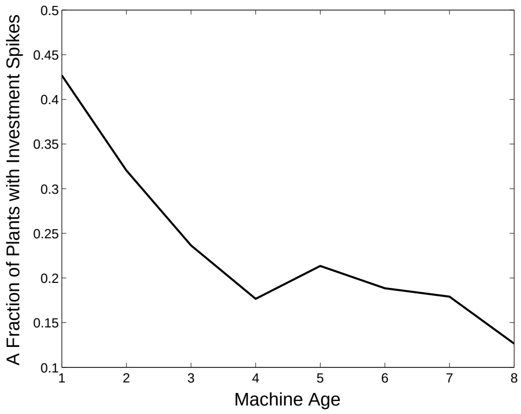

Figure 4: Empirical Hazard

ductivity is negatively related to machine age, the negative relationship is much stronger before controlling for plant-specific productivity (the average slope of -0.063) than after controlling for plant-specific productivity (the average slope of -0.028). This difference in the slopes likely reflects a self-selection among plants with different plant-specific productivity; inherently high productivity plants may replace their machines more frequently than others and may tend to have lower machine ages. This finding motivates the inclusion of unobserved plant-specific productivity in the empirical model.

Figure 4 plots the empirical hazard—the actual fraction of plants experiencing investment spikes against the observed machine age—for the years of 1990-1996. The empirical hazard is downward-sloping, indicating that the probability of replacement declines with machine age. This observation contradicts a simple machine replacement model prediction, namely, that a plant is more likely to replace if its machine is older. However, as is well known in the duration dependence literature, the presence of unobserved heterogeneity may lead to downward-sloping hazard even if individual plants' hazards are increasing in machine ages (cf., Cooper et al., 1999). As I show later, the estimated empirical structural model that incorporates unobserved heterogeneity can predict downward-sloping hazards *even though* any individual plant's hazard is predicted to be upward-sloping. This is because of a composition effect: the newer the machine, the larger the fraction of plants with (unobserved) characteristics that lead to higher replacement probability.

3.2 Empirical Specification

To quantitatively assess the relative importance of the effect of the increase in import prices, I develop a structural dynamic optimization model that incorporates other potentially important factors. The empirical specification includes: (A.1) dependence of machine price on import price, (A.2) aggregate shocks, (A.3) the effect of tax on profits, (A.4) the 1982-83 financial crisis, and (A.5) the possibility of multiyear investment projects. While (A.1) is in keeping with the theoretical model in Section 2, (A.2)-(A.4) capture alternative explanations for the observed Chilean investment dynamics; (A.5) attempts to capture the fact that large investment projects often last more than two years. In (B.1) and (B.2), I discuss different sources of unobserved heterogeneity and idiosyncratic shocks.

(A.1) Dependence of Machine Price on Import Price Given that Chile is a small open economy importing more than 80 percent of its capital goods, a change in the price of imported machines resulting from a change in import prices may affect replacement decisions. The replacement cost, κ_t, depends on the log of the import price index, p_t, as:

$$\kappa_t = \kappa \cdot \exp(\alpha_p p_t), \tag{4}$$

where κ is the replacement cost at the base year and α_p is a parameter that represents the elasticity of machine replacement cost with respect to import price.

(A.2) Aggregate Productivity Shocks As Cooper et al. (1999) emphasizes, a serially correlated aggregate productivity shock could be an important determinant of machine replacement. I incorporate serially correlated aggregate productivity shocks into the production function as

$$Y_{it} = A_{it} exp(\alpha_0 + \alpha_z z_t), \tag{5}$$

where A_{it} represents the vintage-specific productivity of the i^{th} plant at the year t, and z_t is the detrended aggregate productivity shock at year t.

(A.3) Tax on Profits In the sample period, there are two major tax reforms: in 1984-1986 and in 1991-1992.[9] To capture the effect of tax reforms in the model, I let gross profit depend on the tax rate. Furthermore, it is assumed that the tax reforms were unanticipated.[10]

(A.4) The 1982-83 Financial Crisis Due in part to a combination of external shocks including an increase in the world interest rate and the deterioration in its terms of trade, Chile experienced a major economic crisis in 1982-83.[11] I incorporate these events into the model by assuming that the replacement costs in 1982-83 were higher by α_D than in other years, holding other state variables constant. I assume that the 1982-83 increase in replacement costs were unanticipated since the financial crisis of 1982-1983 was, at least partly, caused by unanticipated external shocks.

(A.5) Multiyear Investment Projects In the data, plants that had high investment in the previous year tend to have high investment in the current year. This partly reflects a form of measurement error due to the calender-year nature of the data. As Doms and Dunne (1998) emphasize, large investment projects often last more than two years. To deal with this issue, I assume that the cost of machine replacement is less if a plant conducts lumpy investment in the previous two years; specifically, the replacement cost at t is $\kappa_{it} - \varphi_j$, instead of κ_{it}, if the plant conducts investment spike in year $t - j$ for $j = 1, 2$.

(B.1) Unobserved Heterogeneity As discussed in Section 3.1, it is important to incorporate unobserved heterogeneity into the model. I consider three sources of unobserved heterogeneity: (i) productivity, (ii) replacement cost, and (iii) technological obsolescence rate.

(i) I assume that individual plants differ in their ability to use machines and parameterize the plant-specific productivity by $u_{1,i}$. Explicitly incorporating plant-specific productivity, I may

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[9] In 1984-1986, the effective tax rate on profits fell from 46 percent to 10 percent. The tax rate temporarily reduced to 0 percent in 1991 and increased to 15 percent after 1992.

[10] More specifically, I assume that, before 1983, plant managers believed that the tax rate in the future would be a constant pre-tax-reform tax rate (46 percent). In the beginning of 1984, they came to know the exact tax schedule for the period of 1984-1985 (37 percent in 1984 and 23.5 percent in 1985) and believed that the tax rate would be a constant at 10 percent indefinitely. In 1991, there was an unexpected tax rate change and plants' managers came to know that the tax rate would be a constant 15 percent after 1992. I also estimated the model under the alternative assumption that the 1984-1986 tax reform was fully anticipated but the results were very similar.

[11] After the abandonment of the fixed exchange rate regime in June 1982, the government reintroduced exchange rate controls. The financial system collapsed in the midst of the recession (cf., Barandiaran and Hernandez, 1999).

control for a self-selection, implied in Figure 2, driven by differences in plant-specific productivity.

(ii) Since the machine replacement cost might be systematically different across industries or types of final products, I assume that replacement costs are plant-specific and parameterized by $u_{2,i}$ such that, by modifying equation (4), a plant-time specific replacement cost is given by $\kappa_{it} = \kappa \cdot \exp(\alpha_p p_t + u_{2,i})$. The unobserved heterogeneity in replacement cost controls for plants' unobserved characteristics that are not relevant to labor productivity but are relevant to replacement decisions.

(iii) The rate of technological obsolescence, δ, might not be identical across plants if they face different depreciation rates or different degrees of technological embodiment in machines.[12] The i^{th} plant-specific technological obsolescence rate is denoted by δ_i and I assume that $\delta_i \geq 0$ for all i. The rate of technological obsolescence, δ_i, determines how the plant's vintage-specific productivity, A_{it}, relates to its machine age, which is denoted a_{it}, and the frontier technology level, A_t^*: $A_{it} = A_t^* \exp(-\delta_i a_{it})$.[13]

Letting the vector $u_i \equiv (u_{1,i}, u_{2,i}, \delta_i)$ represent the i^{th} plant-specific unobserved heterogeneity, I assume that plant-specific productivity is normally distributed with mean zero and variance $\sigma_{u_1}^2$ while (u_2, δ) is independent of u_1 and multinomially distributed with the number of support points equal to K, where the k^{th} type is characterized by a vector (u_2^k, δ^k) and the fraction of the k^{th} type in the population is π^k. In practice, I set $K = 4$ and assume that each of u_2^k and δ^k takes either a high value or a low value. The first type has a low replacement cost and a low depreciation rate, with values $u_2 = 0$ and $\delta = 0$.[14] The second type also has a low replacement cost $u_2 = 0$ but a high depreciation rate $\delta = \delta^H > 0$. The third type has a high replacement cost $u_2 = u_2^H > 0$ and a low depreciation rate $\delta = 0$. Finally, the fourth type has

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[12] Note that, assuming that all technological progress is embodied in machines, the technological obsolescence rate of machines is expressed in terms of the rate of technological progress, g, and depreciation, ζ, as $\delta = \ln(\frac{1+g}{1-\zeta})$. Clearly, if the depreciation rates (ζ) are different across plants, so are the technological obsolescence rates. Furthermore, the degree to which technology is embodied in machines also matters for technological obsolescence rates. To see this formally in the context of the model, suppose that the production function takes the form $Y_{it} = A_{it}^{\nu} A_t^{*1-\nu}$ instead of $Y_{it} = A_{it}$, where $\nu \in [0, 1]$ is the degree of technological embodiment; A_t^* is the frontier technology level, and A_{it} is the vintage-specific technology level. In this case, the technological obsolescence rate is $\delta = \ln(\frac{(1+g)^{\nu}}{1-\zeta})$. If $\nu = 1$, all technology is embodied in machines and thus it is the original machine replacement model. If $\nu = 0$, however, then technological progress is totally disembodied such that machine replacement plays no role in adopting the frontier technology. In the empirical specification, differences in ζ and ν are reflected in different values of δ; ζ and ν are not identified separately.

[13] I use machine age, a_{it}, instead of technology position, s_{it}, as the state variable in the empirical specification since the machine age is what I observe in the data. Technology position and machine age are related by the identity $s_{it} \equiv -\delta_i a_{it}$.

[14] I initially estimated a low depreciation rate as a free parameter with a non-negativity constraint and found that it converged to 0.

a high replacement cost and a high depreciation rate. The unobserved heterogeneity (u_2, δ) is, therefore, specified to have the following multinomial distribution: $Pr((u_2, \delta) = (0, 0)) = \pi^1$, $Pr((u_2, \delta) = (0, \delta^H)) = \pi^2$, $Pr((u_2, \delta) = (u_2^H, 0)) = \pi^3$, and $Pr((u_2, \delta) = (u_2^H, \delta^H)) = \pi^4$.

(B.2) Idiosyncratic Shocks I allow for a replacement cost shock that is choice dependent, $\epsilon_{it}(d)A_t^*$, for $d = \{0, 1\}$, where $d = 0$ implies that a plant does not replace its machine and $d = 1$ implies that it does. Following Rust (1987), I assume that, conditional on other state variables, $\epsilon_{it}(0)$ and $\epsilon_{it}(1)$ are drawn independently from the Type I extremum distribution. I also allow for a serially uncorrelated idiosyncratic productivity shock, ξ_{it}, so that the production function is given by $Y_{it} = A_{it} exp(\alpha_0 + \alpha_z z_t + u_{1,i} + \xi_{it})$, where ξ_{it} is drawn independently from the normal distribution with mean zero and variance σ_ξ^2. It is assumed that $\epsilon_{it} = (\epsilon_{it}(0), \epsilon_{it}(1))$ and ξ_{it} are known to the plant before the updating decision is made in the beginning of year t.

When a plant replaces its machine in year t, only a fraction $\vartheta \in [0, 1]$ of a new machine is assumed to become productive at year t. Specifically, the production for a plant replacing its machine at year t is assumed to be given by a geometric average of production under the new machine (machine age 0) and production under the old machine (machine age a_{it}) so that $A_{it} = [A_t^*]^\vartheta [A_t^* \exp(-\delta_i a_{it})]^{1-\vartheta} = A_t^* \exp(-(1 - \vartheta)\delta_i a_{it})$ when $d_{it} = 1$. It follows that the plant's value added (per worker) is

$$Y_{it} = A_t^* \exp(\alpha_0 + \alpha_z z_t - (1 - \vartheta d_{it})\delta_i a_{it} + u_{1,i} + \xi_{it}). \tag{6}$$

By incorporating (A.1)-(A.5) and (B.1)-(B.2), the net profit flow normalized by the value of A_t^* with the state $(a_{it}, z_t, p_t, \gamma_t, D_t, u_i, \xi_{it}, \epsilon_{it})$ and the replacement choice $d_{it} \in \{0, 1\}$ is $\Pi(a_{it}, z_t, p_t, \gamma_t, D_t, u_i, \xi_{it}, d_{it}) + \epsilon_{it}(d_{it})$ where

$$\Pi(a_{it}, z_t, p_t, \gamma_t, D_t, u_i, \xi_{it}, d_{it}) = \begin{cases} (1 - \gamma_t) \exp(\alpha_0 + \alpha_z z_t - \delta_i a_{it} + u_{1,i} + \xi_{it}) & \text{for } d_{it} = 0 \\ (1 - \gamma_t) \exp(\alpha_0 + \alpha_z z_t - (1 - \vartheta)\delta_i a_{it} + u_{1,i} + \xi_{it}) & \\ \quad -[\kappa \exp(\alpha_p p_t + u_{2,i}) - \sum_{j=1,2} \varphi_j I[a_{it} = j]] - \alpha_D D_t & \text{for } d_{it} = 1, \end{cases}$$

and where γ_t is the effective tax rate on profit, z_t is the aggregate productivity shock, δ_i is the technological obsolescence rate, a_{it} is the machine age, $u_{1,i}$ and $u_{2,i}$ capture unobserved heterogeneity in productivity and replacement cost, respectively, ϑ is a fraction of a new machine that becomes productive at year t upon replacement, α_p is the elasticity of machine replacement cost with respect to import price, $I[\cdot]$ is an indicator function that is equal to one if its argument is true and zero otherwise, φ_j represents the saving in replacement cost when a plant replaces its machine across two or three years, α_D is the additional replacement cost in 1982-1983, and D_t is a dummy variable for the years of 1982 and 1983, which is equal to one if $t = 1982$ or 1983 and zero otherwise.

The aggregate variables z_t and p_t are assumed to follow a stationary AR(1) process:

$$\begin{aligned} z_t &= c_z + \psi_z z_{t-1} + \eta_{z,t} \\ p_t &= c_p + \psi_p p_{t-1} + \eta_{p,t}, \end{aligned}$$

where $\eta_{z,t}$ and $\eta_{p,t}$ are independent, normally distributed with the variance σ_z^2 and σ_p^2.[15]

A plant manager maximizes the expected present value of total profits which, in terms of the Bellman's equation, can be written as

$$v(a_{it}, z_t, p_t, \gamma_t, D_t, u_i, \xi_{it}, \epsilon_{it}) = \max_{d_{it} \in \{0,1\}} \{v^*(a_{it}, z_t, p_t, \gamma_t, D_t, u_i, \xi_{it}, \epsilon_{it}(d_{it}), d_{it})\}$$

with

$$\begin{aligned} v^*(a_{it}, z_t, p_t, \gamma_t, D_t, u_i, \xi_{it}, \epsilon_{it}(d_{it}), d_{it}) &= \Pi(a_{it}, z_t, p_t, \gamma_t, D_t, u_i, \xi_{it}, d_{it}) + \epsilon_{it}(d_{it}) \\ &+\beta E[v((1 - d_{it})a_{it} + 1, z_{t+1}, p_{t+1}, \gamma_{t+1}, D_{t+1}, u_i, \xi_{i,t+1}, \epsilon_{i,t+1})|z_t, p_t], \end{aligned}$$

where the expectation is taken with respect to $(z_{t+1}, p_{t+1}, \xi_{i,t+1})$ conditional on (z_t, p_t). Denote the expected value function $\bar{v}_\theta(a_{it}, z_t, p_t, \gamma_t, D_t, u_i, \xi_{it}) \equiv E_\epsilon[v(a_{it}, z_t, p_t, \gamma_t, D_t, u_i, \xi_{it}, \epsilon)]$, where the expectation on the right hand side is taken with respect to $\epsilon \equiv (\epsilon(0), \epsilon(1))$. For the purpose of exposition, I assume that γ_t and D_t are constants over time. Given the extreme-value distributional assumption, the functional equation in terms of the expected value function $\bar{v}_\theta(\cdot)$ can

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[15] Note that z_t and p_t are assumed to be orthogonal to each other. I also estimated a joint stationary first-order VAR process $z_t = c_z + \psi_{zz} z_{t-1} + \psi_{zp} p_{t-1} + \eta_{z,t}$ and $p_t = c_p + \psi_{pz} z_{t-1} + \psi_{pp} p_{t-1} + \eta_{p,t}$, where $\eta_{z,t}$ and $\eta_{p,t}$ are normally distributed innovations with the variances σ_z^2 and σ_p^2 and correlation coefficient ρ_{zp}. I found that ψ_{zp}, ψ_{pz}, and ρ_{zp} are not significantly different from zero.

be derived as (cf., Ben-Akiva and Lerman, 1985):

$$\bar{v}_\theta(a,z,p,\gamma,D,u,\xi) = \\ \ln\left[\sum_{d'=0,1} exp\{\Pi(a,z,p,\gamma,u,\xi,d') + \beta E[\bar{v}_\theta((1-d')a+1,z',p',\gamma,D,u,\xi')|z,p]\}\right], \quad (7)$$

while the conditional choice probability is given by the logit formula (cf., McFadden, 1973):

$$P_\theta(d|a,z,p,\gamma,D,u,\xi) = \\ \frac{\exp\{\Pi(a,z,p,\gamma,D,u,\xi,d) + \beta E[\bar{v}_\theta((1-d)a+1,z',p',\gamma,D,u,\xi')|z,p]\}}{\sum_{d'}\exp\{\Pi(a,z,p,\gamma,D,u,\xi,d') + \beta E[\bar{v}_\theta((1-d')a+1,z',p',\gamma,D,u,\xi')|z,p]\}}. \quad (8)$$

Evaluation of (8) requires the solution to (7). Since there is no closed-form solution, I discretize the state space using quadrature grids and solve the approximated decision problem numerically by backward induction.

It is plausible that observed labor productivity is measured with error. By modifying (6), the data generating process of the observed labor productivity in log form, denote by y_{it}, follows

$$y_{it} = \alpha_{y0} + [\ln(1+g)]t + \alpha_z z_t - (1-\vartheta d_{it})\delta_i a_{it} + u_{1,i} + \xi_{it} + \eta_{it}, \quad (9)$$

where η_{it} is an i.i.d. normal random measurement error with variance given by σ^2_η. The first two terms on the right of (9) are derived from (6) using $\ln A^*_t = \ln A^*_0 + [\ln(1+g)]t$ and defining $\alpha_{y0} \equiv \ln A^*_0 + \alpha_0$. The sum of an idiosyncratic productivity shock ξ_{it} and a measurement error η_{it} is denoted by ω_{it} so that $\omega_{it} = \xi_{it} + \eta_{it}$.

In estimating the parameters in the production function (9), there is an important endogeneity problem. Namely, both machine age a_{it} and replacement decision d_{it} on the right hand side of (9) are correlated with the permanent unobserved productivity $u_{1,i}$ as well as the unobserved technological obsolescence rate δ_i. In this context, there are no valid observable instruments to estimate the production function, and the GMM procedures of Arellano and Bond (1991) and Blundell and Bond (1998) are not applicable. Using a control function approach (cf., Olley and Pakes, 1995) is not an option either because the replacement decision is purely discrete. As discussed below, to deal with the endogeneity problem, I estimate the parameters in the production function (9) jointly with the parameters in the replacement decision (8) by full information maximum likelihood method.

3.3 Estimation

3.3.1 Likelihood Function

The likelihood function consists of two parts. The first part represents the likelihood contribution from the time-series of aggregate TFP shocks and the import prices. The second part is the contribution from the firm-level labor productivities and replacement decisions, where a rich set of permanent unobserved heterogeneities are present.

Letting the transition density functions of z and p be denoted by $q_z(z'|z) = \phi\left(\frac{z'-\psi_z z}{\sigma_z}\right)/\sigma_z$ and $q_p(p'|p) = \phi\left(\frac{p'-\psi_p p}{\sigma_p}\right)/\sigma_p$, where $\phi(\cdot)$ is the standard normal density, the partial likelihood function of aggregate TFP shocks and import prices is given by:

$$L_1^p(\theta_1) \equiv q_z^*(z_{70})q_p^*(p_{70}) \prod_{t=71}^{96} q_z(z_t|z_{t-1})q_p(p_t|p_{t-1}) \qquad (10)$$

where $q_z^*(z) = \phi\left(\frac{z'}{\sigma_z/(1-\psi_z)}\right)/[\sigma_z/(1-\psi_z)]$ and $q_p^*(p) = \phi\left(\frac{p'}{\sigma_p/(1-\psi_p)}\right)/[\sigma_p/(1-\psi_p)]$. $\theta_1 = (c_z, c_p, \psi_z, \psi_p, \sigma_z, \sigma_p)$ is a subvector of parameters that appear only in $q(\cdot)$. The aggregate data cover longer periods (1970-1996) than the plant-level panel data (1980-1996). The availability of the aggregate data in pre-sample period of panel data is crucial to deal with the initial conditions problem discussed below.

Machine age, a_{it}, is defined as the number of years passed since the last investment spike. For each value of machine ages in 1980, the i^{th} plant's machine ages for subsequent years can be constructed based on the law of motions $a_{i,t+1} = (1-d_{it})a_{it} + 1$ using (observable) replacement decisions $\{d_{it}\}_{t=80}^{96}$. Given the initial machine age $a_{i,80}$ and the unobserved type $u_i = (u_{1,i}, u_{2,i}, \delta_i)$, the type-specific likelihood contribution for production function and replacement decision of the plant is

$$L_i(\theta; a_{i,80}, u_i) =$$
$$\prod_{t=80}^{96} \underbrace{\frac{1}{\sigma_\omega}\phi\left(\frac{\tilde{\omega}_{it}(u_i, a_{it}(a_{i,80}))}{\sigma_\omega}\right)}_{\text{production function}} \underbrace{\int P_\theta(d|a_{it}(a_{i,80}), z_t, p_t, \gamma_t, D_t, u_i, \xi')f(\xi'|\tilde{\omega}_{it}(u_i, a_{it}(a_{i,80})))d\xi'}_{\text{replacement decesion}}, \qquad (11)$$

where $\{a_{it}(a_{i,80})\}_{t=80}^{96}$ denotes the sequence of machine ages for the i^{th} plant conditional on $a_{i,80}$ while $\tilde{\omega}_{it}(u_i, a_{it}) \equiv y_{it} - \{\alpha_{y0} + [\ln(1+g)]t + \alpha_z z_t - (1 - \vartheta d_{it})\delta_i a_{it} + u_{1,i}\}$, $\sigma_\omega = \sqrt{\sigma_\xi^2 + \sigma_\eta^2}$, and $f(\xi|\omega) = \frac{1}{\sigma_\xi\sqrt{1-\rho^2}}\phi\left(\frac{\xi_{it}-\rho^2\omega}{\sigma_\xi\sqrt{1-\rho^2}}\right)$ is the density of ξ conditional on ω. Here, $\rho^2 = \frac{\sigma_\xi^2}{\sigma_\omega^2}$ is the fraction of the sum of variances of ξ and η accounted for by idiosyncratic productivity shock. The likelihood for replacement decision is obtained in (11) by integrating out unobserved idiosyncratic productivity shock ξ using its distribution conditional on "observable" variable ω. The endogeneity problem in estimating the parameters of the production function (9) is dealt with here by simultaneously estimating them with the parameters in replacement decision.

It is not possible to directly evaluate the individual likelihood contribution (11) because we do not observe either $a_{i,80}$ or u_i. Then, the partial likelihood function for productivity shocks and replacement decisions is obtained by integrating out $(a_{i,80}, u_i)$ from (11):

$$\begin{aligned} L_2^p(\theta) &\equiv \prod_{i=1}^{N} \int L_i(\theta; a'_{80}, u') dm^*(a'_{80}, u') \\ &= \prod_{i=1}^{N} \left[\sum_{k=1}^{K} \pi^k \int \sum_{a'_{80}} L_i(\theta; a'_{80}, (u'_1, u_2^k, \delta^k)) m_{80}^*(a'_{80}|(u'_1, u_2^k, \delta^k)) \frac{1}{\sigma_{u_1}} \phi\left(\frac{u'_1}{\sigma_{u_1}}\right) du'_1 \right], \quad (12) \end{aligned}$$

where $m_{80}^*(a_{80}, u)$ is the joint distribution of the machine age in 1980 and the unobserved heterogeneity while $m_{80}^*(a_{80}|u)$ is the distribution of the machine age in 1980 conditional on the unobserved heterogeneity. The model has a rich structure in terms of unobserved heterogeneity and, in the second line of (12), the likelihood is evaluated by integrating out the unobserved heterogeneities with respect to their distributions.

The full information likelihood function is the product of the partial likelihood functions (10) and (12):

$$L_f(\theta) = L_1^p(\theta_1) L_2^p(\theta). \quad (13)$$

The parameter θ is estimated by maximizing the log of the full information likelihood (13).

3.3.2 Initial Conditions Problem

The initial year's machine ages, $\{a_{i,80}\}_{i=1}^N$, are not independent of the type u_i (cf., Heckman, 1981) and, furthermore, they are not observable. One way to deal with this initial conditions problem is to assume a type-specific stationary distribution and use it to integrate out the unobserved initial machine ages. Just before the sample period, however, Chile conducted a major trade liberalization and simultaneously experienced a major recession in the mid 1970s (cf., Tybout et al., 1991). These events are likely to have caused substantial deviation from the steady state, and hence the assumption of a stationary distribution in 1980 would be inappropriate. The distribution of the unobserved initial machine ages depends not only on the plant's type but also on the past realizations of aggregate variables.

To deal with this issue, for each candidate parameter θ, I construct a "transitory" distribution of machine ages in the beginning of 1980 conditioned on both the unobserved heterogeneity u and the realization of aggregate variables for 1970-1979. Let the probability distribution of plants with machine age a at year t conditional on the type u be $m^*_{\theta,t}(a|u)$. At the beginning of 1970, $m^*_{\theta,70}(a|u)$ is assumed to be a stationary distribution. I obtain the 1971 distribution $m_{\theta,71}(a|u)$ by updating the 1970 distribution $m^*_{\theta,70}(a|u)$ using the conditional choice probability (8) evaluated at the *realized values* of the aggregate shock and the import price of 1970, (z_{70}, p_{70}). Similarly, the 1971 distribution $m^*_{\theta,71}(a|u)$ is updated to obtain the 1972 distribution $m^*_{\theta,72}(a|u)$. Repeating this process up to 1980, I obtain the transitory machine age distribution in the beginning of 1980, $m^*_{\theta,80}(a|u)$, which is conditioned on $\{(z_t, p_t)\}_{t=70}^{79}$. Using this 1980 distribution to integrate out the unobserved initial machine age, I evaluate the partial likelihood function (12).

The validity of this "model-based" approach requires that the time-series of aggregate productivity shocks and import prices fully capture the aggregate shocks that are relevant for replacement decisions. This could be a strong assumption because there were many policy changes in Chile during the 1970s. To check the robustness, I also estimate the model using a "flexible" initial conditions distribution in the spirit of Heckman (1981). I find that the quantitative implications of counterfactual experiments are similar between the "model-based" approach and the "flexible" approach. Furthermore, the result from the "flexible" approach indicates that the initial conditions distribution may not be well identified if it is modeled flexibly. For these reasons, I focus on the results from the "model-based" initial conditions specification.

3.4 Variable Definitions

Recall the assumption that a plant's replacement decision may be identified with a gross investment rate over 20 percent.[16] That is, $d_{it} = 1$ if the i^{th} plant's gross investment rate at year t

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[16] This definition is the same as that of Cooper et al. (1999).

is more than 0.2 and $d_{it} = 0$ otherwise. Here, the gross investment rate is defined as the gross investment in new capital goods during the current year, divided by capital stock at the end of the previous year.[17] The measure of gross investment here includes machinery and equipment and vehicles but excludes buildings.[18] Furthermore, since the model focuses on the replacement of old machines by new machines embodying the frontier technology, I exclude the purchase and sale of used capital from the measurement of gross investment. The capital stock is constructed from the 1980 book value of capital (the 1981 book value if the 1980 book value is not available) using the perpetual inventory method.[19]

The detrended Solow residuals are used as a proxy for the aggregate productivity shock. A time series of the Solow residuals is first constructed from 1970 to 1996 using growth accounting: $Z_t = \frac{Y_t}{{K_t^{w_k}} L_t^{1-w_k}}$, where w_k represents the share of capital, Y_t, K_t, and L_t are the gross domestic products in 1986 pesos, aggregate capital stock in 1986 pesos, and working age person (15-64) in Chile. A value for w_k is set to 0.3.[20] Then, I regress the log of Z_t on a constant and a time trend and use the residuals, z_t, as the data for the log of aggregate productivity shock.

For relative import prices, p_t, the log of the ratio of import wholesale price indices in the Chilean peso to respective output price indices is used.[21] For plants' labor productivity, y_{it}, I use the log of the ratio of value added, deflated by the respective output price deflators, to the number of workers.[22] Trade orientation is classified into two categories: export-oriented

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[17] The original data contains information on five types of investments: purchases of new capital, purchases of used capital, production of capital for own use, improvements in own capital by third parties, and sales of capital.

[18] Buildings are more likely to be rented rather than owned by plants, since zero values are found frequently for buildings. Furthermore, the replacement timing of buildings is likely to be different from that of machines since, for example, the rates of technological change and depreciation are likely to be different.

[19] Since the reported book values are evaluated at the end of year t, the book values of capital are deflated by the (geometric) average deflater of machinery and equipment for years t and t+1. Depreciation rates are set to 10 % for machinery and equipment and 20% for vehicles. Some plants did not report the book values of capital in either 1980 or 1981. Since it is not possible to construct capital stock without these reports, the plants missing their book values of capital were excluded from the sample. I also excluded from the sample the plants with capital-output ratios less than 1 percent, since I consider the observations mis-coded or mis-reported.

[20] See Bergoeing, Kehoe, Kehoe, and Soto (2001) for the choice of the share of capital in Chile in computing total factor productivity.

[21] When the model is estimated for all manufacturing sectors, domestic-material-intensive plants, and import-material-intensive plants, I use the manufacturing wholesale price index for the output price index. When the model is estimated by trade-sector, I use the trade-sector-specific Laspeyres output price indices constructed by aggregating over 2-digit industry output price indices. Some plants change their trade-sector classifications during the sample period. I did not use these samples for estimating the model by trade-sectors. Data for the import price and the manufacturing wholesale price index are from IFS and Banco Central De Chile (1989) *Indicadores Economicos Y Sociales 1960-1988.* Data for the 2-digit industry output price indices, output, exports, and imports are from the original data set for the years of 1979-1985 and Banco Central De Chile (2000) *Anuario De Cuentas Nacionales* for the years 1986-1996.

[22] I excluded from the sample the plants with negative value added. The labor productivity variables are then

and import-competing. In particular, plants that belong to a two-digit ISIC industry of which export-output ratio is more than 20 percent are classified as export-oriented; plants that belong to a two-digit ISIC industry of which import-output ratio is more than 20 percent are classified as import-competing.[23] To classify plants into domestic-material-intensive and import-material-intensive, I use the plant-level information on the use of imported materials. Specifically, plants are classified as import-material-intensive if they use imported materials more than a half of sample years (i.e., no less than 9 years out of 17 sample years); otherwise, they are classified as domestic-material-intensive.

4 Results

4.1 All Manufacturing Sectors

Table 1 presents the maximum likelihood estimates and their asymptotic standard errors, which are computed using the outer product of gradients estimator, for all manufacturing sectors.[24] The estimates of coefficients ψ_z and ψ_p are both significantly positive, implying persistence in both aggregate shock and import price series. The parameter estimates for the microeconomic model of machine replacement are plausible, and standard errors are generally small. The import price elasticity of replacement cost, α_p, is estimated as 0.819. This estimate is largely consistent with what is expected if the price of machines is determined by the geometric average of the domestic price and the import price since Chile imports the 82.5 percent of machines from abroad, on average, for the period of 1985 to 1996 (see Banco Central De Chile, 2000). The replacement cost during the financial crisis of 1982-1983 is systematically higher than during the other periods as shown by the positive estimate of α_D. A comparison of the point estimates for α_D and $\bar{\kappa}$ implies that, holding constant relative import prices, the replacement cost of 1982-1983 is 37.2(= .693/1.862) percent higher than that of other years.

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trimmed using the sample 1st percentile and the sample 99th percentile.

[23] While the four-digit ISIC industry classification for each plant is available in the panel data, the output price indices for the whole sample period are only available at two-digit ISIC industry-level. Since a comparison of export-oriented and import-competing industries is based on the difference in the dynamics of output prices during the period of high tariffs, I use the two-digit industry classification to identify plant's trade orientation. Plants belong to ISIC 39 (Miscellaneous Industry) are not included in the samples of either export-oriented industry or import-competing industry since both export-output ratio and import-output ratio of ISIC 39 are more than 20 percent.

[24] The discount rate β is not estimated but set to 0.95. The results from counterfactual experiments are robust to changes in the value of β.

Table 1: Maximum Likelihood Estimates by Full MLE: All Manufacturing Sectors

TFP Process			Import Price Process		
c_z	-0.011	(0.019)	c_p	-0.017	(0.033)
ψ_z	0.792	(0.240)	ψ_p	0.842	(0.115)
σ_z	0.069	(0.006)	σ_p	0.095	(0.016)
Production Function			Replacement Cost		
α_0	6.175	(0.014)	α_{y0}	-2.017	(0.837)
g	0.012	(0.000)	κ	1.321	(0.062)
α_z	1.156	(0.022)	α_p	0.819	(0.060)
ϑ	0.486	(0.037)	φ_1	0.677	(0.048)
σ_ω	0.478	(0.001)	φ_2	0.339	(0.051)
ρ	0.072	(0.140)	α_D	0.693	(0.064)
Permanent Unobserved Heterogeneity					
δ^H	0.081	(0.001)	π_1	0.347	(0.030)
u_2^H	0.625	(0.035)	π_2	0.181	(0.023)
σ_{u_1}	0.592	(0.005)	π_3	0.265	(0.028)
$\bar{\kappa}$	1.862				
$\frac{exp(\bar{\alpha}_{y0})}{\bar{\kappa}}$	0.096				
$\ln L^f$	-31830.7				

Notes: Standard errors are in parentheses. $\bar{\kappa} \equiv \sum_{k=1}^{4} \pi^k \kappa \exp(u_2^k)$ is the average replacement cost. $exp(\bar{\alpha}_{y0}) \equiv \exp(\alpha_{y0} + 0.5\sigma_{u_1})$ is the average value added with the frontier technology.

The estimate of ϑ implies that only a fraction 0.486 of a new machine becomes productive at the year of investment, providing evidence for the importance of "time-to-build" in capital investment. The similar evidence of non-convex adjustment cost is reported in previous studies; Caballero and Engel (1999) and Cooper and Haltiwanger (2006) find that plant productivity falls during the adjustment period by 16.5 percent and 20.4 percent, respectively, although we should be cautious of directly comparing these estimates given differences in specifications and data-sets. On the other hand, the estimates for φ_1 and φ_2 imply that a plant saved on replacement cost by 36.4(= .677/1.862) and 18.2(= .339/1.862) percent if it replaced its machine one year or two years prior, respectively. The positive estimates of φ_1 and φ_2 can be interpreted as evidence of some convexity in adjustment costs. Overall, the result is consistent with the finding of Cooper and Haltiwanger (2006) that both non-convex and convex elements in capital adjustment costs are important.

The technological obsolescence rate, δ, differs across plant-types. The estimated fraction of plants with zero technological obsolescence rate in the population is large: $\pi^1 + \pi^3 = 0.612$. This indicates that for a majority of plants, machine replacement is not the way to increase productivity. On the other hand, the technological obsolescence rate for other plants is high:

Table 2: Estimates of Average Technological Obsolescence Rates Across Different Estimators

	Full MLE	OLS	Within-Groups
ϑ	0.486	0.869	0.606
$\bar{\delta}$	0.031	0.049	0.015

Notes: Standard errors are in parentheses. For MLE, the average technological obsolescence rate is computed as $\bar{\delta} \equiv \sum_{k=1}^{4} \pi^k \delta^k$.

8.1 percent. Thus, there exists substantial heterogeneity in technological obsolescence rates across plants.

Table 2 compares the ML estimate of average technological obsolescence rate with the alternative estimates from using OLS and Within-Groups estimators. For OLS, I regress the log of the labor productivity on machine age, an interaction between machine age and discrete investment choice, and year dummies, ζ_t, so that the specification is given by $y_{it} = -\bar{\delta} a_{it} + \vartheta \bar{\delta} a_{it} d_{it} + \zeta_t + e_{it}$, where the error term e_{it} is equal to $-(\delta_i - \bar{\delta}) a_{it} + \vartheta(\delta_i - \bar{\delta}) a_{it} d_{it} + u_{1,i} + \omega_{it}$ from the viewpoint of the model (9).[25] The specification of Within-Groups estimator is similar but plant-specific effects are partly controlled for by within-groups transformation.

The average technological obsolescence rate is estimated by the MLE at 3.1 percent. The OLS estimate is significant at 4.9 percent with standard error of 0.3 percent, which is likely to be biased upward because of the negative correlation between machine ages and unobserved productivities. The Within-Groups estimate is also significant but lower than the ML estimate at 1.5 percent with standard error of 0.2 percent. While there are different sources of biases, the Within-Groups estimator might be biased downward because of measurement errors in machine ages; within-transformation lowers signal to noise ratio and magnifies the bias toward zero induced by measurement errors that are deriven by the classification errors in past replacement decisions.[26]

Figure 5 graphically depicts the fit of the model to the actual fraction of plants with investment spikes as well as the aggregate machine investment rate data.[27] The model appears to

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[25] The panel data from 1990 to 1996 is used for OLS and Within-Groups estimators because, prior to 1990, we may not observe machine age if its value is less than 10 years.

[26] Even without measurement errors, the Within-Groups estimator is not consistent in this context because within-group transformation does not fully solve the endogeneity problem.

[27] The aggregate machine investment rate is defined as $I_{m,t}/K_{m,t-1}$, where $I_{m,t}$ is the aggregate gross investment in machinery and equipment and in transportation equipment at the year t; $K_{m,t-1}$ is the aggregate capital stock in machinery and equipment and in transportation equipment at the end of year $t-1$. I constructed the capital stock series $\{K_{m,t}\}_t$—starting from the year of 1960—from the gross investment series $\{I_{m,t}\}_t$ using the

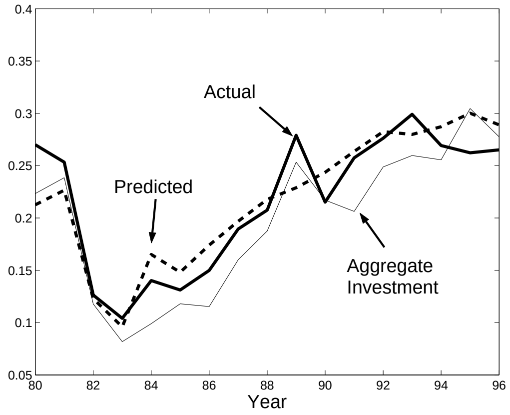

Figure 5: Fraction of Plants with Investment Spike (Predicted vs. Actual)

replicate well the observed aggregate investment patterns. As shown in Figures 6, the model also performs well in replicating the observed machine age distribution.[28] Table 2 compares the actual and predicted proportion of plants with investment spikes by machine ages for the years 1994 to 1996.[29] The model appears to predict the machine replacement probability, conditional on machine ages, reasonably well. In particular, the model correctly predicts a downward empirical hazard even though the replacement probability for any individual plant is predicted to be non-decreasing in machine ages. This is because plants with younger machines are more likely to have unobserved characteristics that lead to more frequent replacement.

Figure 7 compares the actual versus predicted average labor productivity for 1980-1996. According to the estimated model, the average machine age decreases from 5.0 to 5.8 between 1981 and 1986. The shift in the machine age distribution caused a 2.4 percent decline in average labor productivity for the same period and thus the delay in the adoption of technology embodied in machines had a non-negligible effect on labor productivity.

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perpetual inventory method with a 13 % depreciation rate, which is roughly equal to the weighted average in the depreciation rates between machinery and equipment (10 percent) and transportation equipment (20 percent) used for constructing the capital stock at the plant level.

[28] Machine Age "10+" includes all machine ages no less than 10.

[29] The χ^2 statistics provided in Table 2 have not been adjusted for the fact that the parameters have been estimated. The goodness of fit statistics are, therefore, intended as an informal summary of the fit of the model.

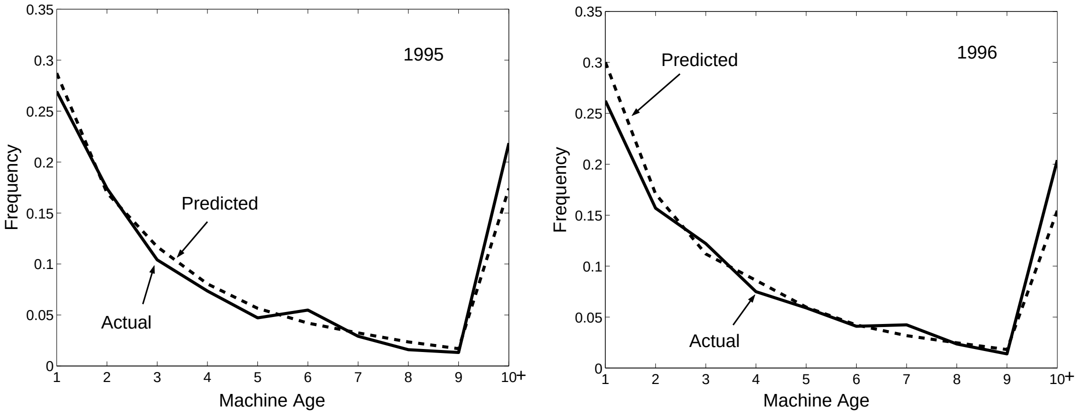

Figure 6: Machine Age Distributions in 1995 and 1996 (Actual vs. Predicted)

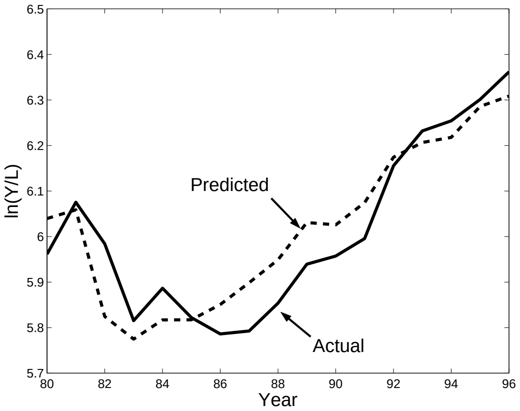

Figure 7: Average Labor Productivity (Actual vs. Predicted)

Table 3: Actual and Predicted Machine Replacement Rate by Years and Machine Ages

	Year					
	1995		1995		1996	
Machine Age	Actual	Predicted	Actual	Predicted	Actual	Predicted
1	0.418	0.399	0.418	0.411	0.447	0.396
	(0.61)		(0.06)		(4.15)*	
2	0.315	0.332	0.299	0.346	0.350	0.332
	(0.29)		(2.49)		(0.33)	
3	0.215	0.256	0.280	0.265	0.216	0.253
	(1.21)		(0.18)		(1.31)	
4	0.209	0.251	0.198	0.259	0.130	0.244
	(0.78)		(2.03)		(7.61)*	
5	0.210	0.244	0.132	0.253	0.282	0.237
	(0.64)		(5.23)*		(0.96)	
6	0.208	0.237	0.228	0.246	0.119	0.231
	(0.26)		(0.14)		(4.20)*	
7	0.258	0.232	0.190	0.239	0.131	0.224
	(0.11)		(0.55)		(3.05)	
8	0.095	0.229	0.130	0.234	0.118	0.217
	(2.13)		(1.38)		(1.98)	
9	0.111	0.227	0.211	0.231	0.000	0.212
	(1.38)		(0.04)		(5.39)*	
10+	0.138	0.175	0.114	0.185	0.133	0.172
	(3.22)		(10.55)*		(3.20)	

Notes: $\chi_1^2 = \sum_{d=0,1}(n_{a,d} - n_{p,d})^2/n_{p,d}$'s are in parentheses, where $n_{a,d}$ and $n_{p,d}$ are the actual and predicted number of plants with the choice d. $*$ implies that the actual and predicted are statistically different at the five percent significance level; $\chi_1^2(0.05) = 3.84$. Machine Age "10+" includes all machine ages no less than 10.

Table 4: MLE: Export-Oriented and Import-Competing

Parameters	Export-Oriented	Import-Competing
α_p	0.909 (0.082)	0.850 (0.098)
$\bar{\delta}$	0.035	0.030
No. of Plants	649	617

Notes: Standard errors are in parentheses. $\bar{\delta} \equiv \sum_{k=1}^{4} \pi^k \delta^k$ is the average technological obsolescence rate.

4.2 Import-Competing vs. Export-Oriented

The impact of a tariff increase on output prices may be different across trade-sectors. In an export-oriented industry, a tariff increase may not significantly affect output prices, while a tariff increase may lead to higher output prices in an import-competing industry. Export-oriented industries, therefore, are likely to experience a larger decline in investment rates during the period of high tariffs. To examine this issue, I re-estimate all the model's parameters using the sub-samples classified by trade-sectors. Table 3 presents the estimates of selected coefficients. The estimate of import price elasticity of replacement cost, α_p, is 0.909 for export-oriented and 0.850 for import-competing industry.

Figures 8 and 9 present the actual and the predicted fractions of plants with investment spikes for export-oriented and import-competing industry. In both figures, the thick and the thin lines show the investment rates for export-oriented and import-competing industries, respectively. The estimated models suitably capture investment patterns as well as their differences between export-oriented and import-competing industries.

I conduct a counterfactual experiment—shown as the dotted line in Figure 9—to test what would happen to the investment rate of import-competing industry if the realization of its relative import prices were identical to that of export-oriented industry for 1980-1996. I find that the gap of investment rates between export-oriented industry and import-competing industry would have been narrower by 60.0 percent on average for the period of 1984-1988 had there been no difference in the realization of relative import prices.

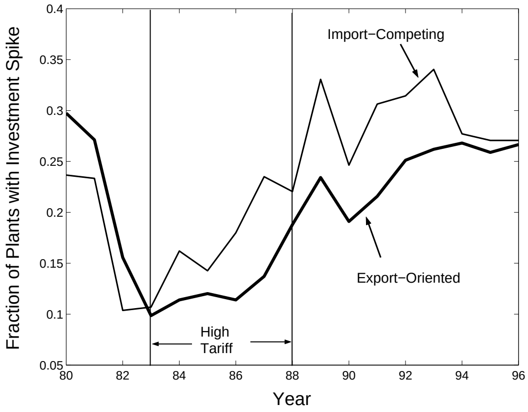

Figure 8: Actual Fraction of Plants with Investment Spike by Trade Sectors

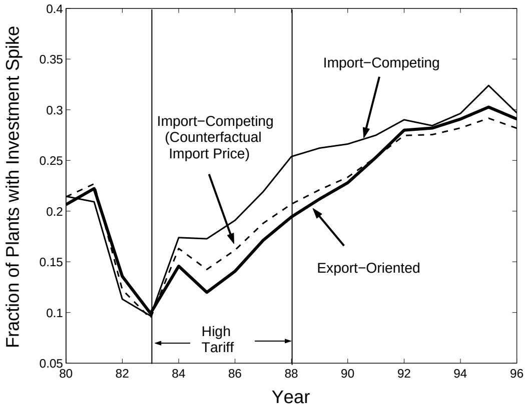

Figure 9: Predicted Fraction of Plants with Investment Spike by Trade Sectors

Table 5: MLE: Import-Material-Intensive vs. Domestic-Material-Intensive

Parameters	Domestic-Material-Intensive	Import-Material-Intensive
α_p	0.628 (0.070)	1.473 (0.144)
$\bar{\delta}$	0.032	0.031
No. of Plants	921	520

Notes: Standard errors are in parentheses. $\bar{\delta} \equiv \sum_{k=1}^{4} \pi^k \delta^k$ is the average technological obsolescence rate.

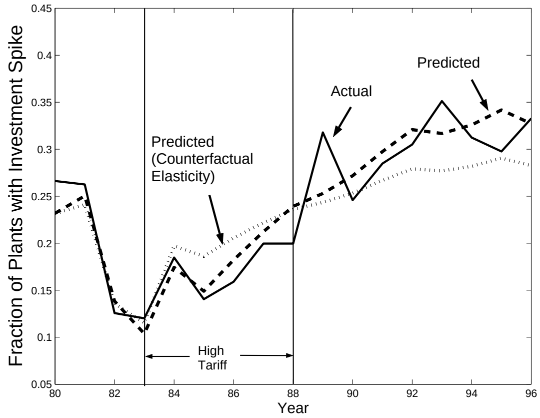

Figure 10: Actual and Predicted Fraction of Plants with Investment Spike for Import-Material-Intensive Plants

4.3 Import-Material-Intensive vs. Domestic-Material-Intensive

Plants that are importing materials may have better access to foreign machines and hence might be more likely to use the imported machines, as opposed to the domestic machines.[30] If so, the machine replacement costs of material-importing plants may be more elastic with respect to import price than those of plants that do not import materials.

To examine this issue, I re-estimate all the model's parameters while identifying the use of imported materials at the plant level. Plants are classified as import-material-intensive if they use imported materials more than a half of the sample period. The estimates of selected coefficients are presented in Table 4. The point estimate suggests that plants using imported material intensively experience a higher elasticity of replacement cost by 0.845(=1.473-0.628) points as compared to plants using domestic material intensively.[31]

Figure 10 reports the result of a counterfactual experiment to test what would happen to the investment rates of import-material-intensive plants if the import price elasticity of replacement cost is the same as that of domestic-material-intensive plants. While the dashed line shows the predicted investment rates of import-material-intensive plants given the actual elasticity

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[30] The data for the use of imported *machines* is not available either at the plant-level or at the industry-level and thus I use the intensity of imported materials as a proxy for the intensity of imported machines.

[31] I have tried the following two alternative classifications for import-material-intensive plants and also found that plants using imported material intensively experienced a substantially higher elasticity of replacement cost as compared to plants using domestic material intensively. In the first alternative, a plant is classified as import-material-intensive if the 4-digit industry which the plant belongs to uses more than 15 percent of imported materials in total materials on average over the sample period. Second, a plant that uses more than 15 percent of imported materials in total materials on average over the sample period is classified as import-material-intensive.

($\alpha_p = 1.473$), the dotted line shows the model's prediction of what would happen to investment rates of import-material-intensive plants given the counterfactual elasticity ($\alpha_p = 0.628$). The investment rate of import-material-intensive plants would have been higher by 2.6 percentage points on average for the period of 1984-1988 if the elasticity of replacement cost for import-material-intensive plants had been the same as that for domestic-material-intensive plants.

4.4 Experiment: The Effect of a Temporary Increase in Import Prices

To quantitatively examine the effect of a temporary increase in import prices, I conduct an experiment to determine what would have happened to investment and productivity of Chilean manufacturing if import prices had remained constant at the 1982 level over the period of spanning 1983 to 1987.

Figure 11 presents the simulated fractions of plants with investment spikes for all manufacturing sectors under the counterfactual (dotted line) and the fraction of plants with investment spikes for the actual import prices (dashed line). The impact of the high import prices is substantial; for instance, in 1985—when the tariff rate was the highest—the aggregate investment rate would have been 21.6 % instead of 14.8 % had there been no temporary increase in import prices from 1983-1987. The figure suggests that Chile would have recovered from the economic crisis of 1982-1983 much more quickly had there been no temporary increase in import prices associated with higher tariffs in the mid-1980s.

Figure 12 shows what would have happened to average output per worker for all manufacturing sectors if the import prices of 1983-1987 were the same as that of 1982. To highlight the impact of the delayed technology adoption on productivity, the time trend and the aggregate shocks are eliminated from the graph. According to the experiment, the output per worker would have been higher by 1.9 percent in 1986 if the import prices of 1983-1987 had remained at the 1982 level. The estimated accumulated output loss from 1983 to 1996 associated with the high import prices of 1983-1987 is also substantial at 11.1 percent of annual output.

The results of similar experiments for the export-oriented industry and the import-competing industry are presented in Figures 13(a)-(d). Reflecting the larger increase in relative import prices for the export-oriented industry, the negative impact of temporarily high import prices on investment and productivity was substantially larger for the export-oriented industry than for the import-competing industry. Finally, the results of similar experiments for import-material-

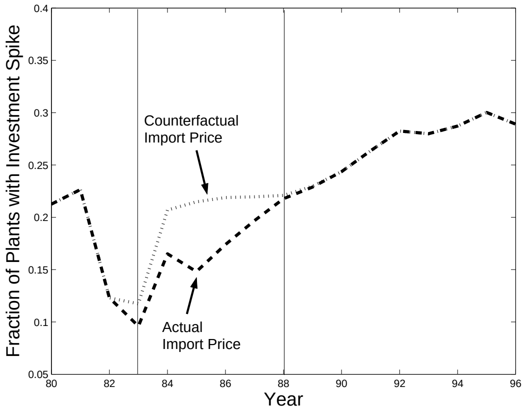

Figure 11: Experiment: Investment — All Manufacturing Sector

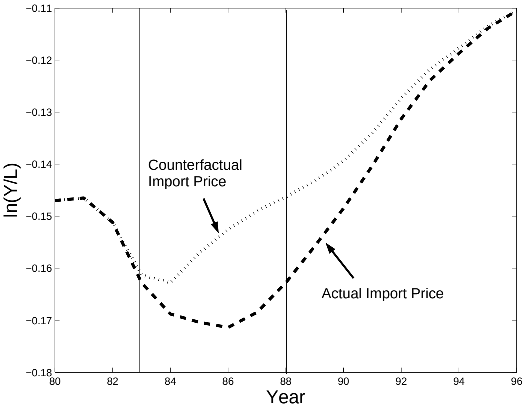

Figure 12: Experiment: Productivity — All Manufacturing Sector

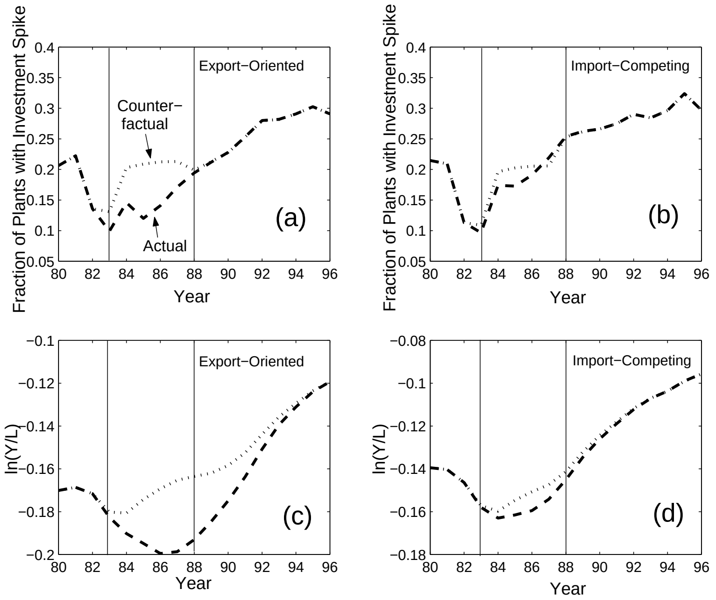

Figure 13: Experiment: Export-Oriented vs. Import-Competing

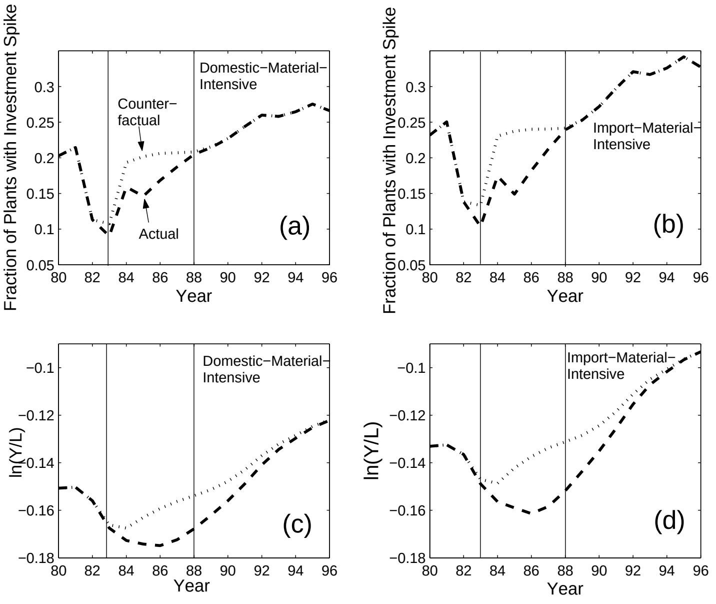

Figure 14: Experiment: Domestic-Material-Intensive vs. Import-Material-Intensive

intensive plants and domestic-material-intensive plants are presented in Figures 14(a)-(d). While the 1985 investment rate of domestic-material-intensive plants would have been higher by 5.3 percent without any temporary increase in import prices from 1983 to 1987, the investment rate of import-material-intensive would have been higher as much as by 10.2 percent. The negative impact of temporarily high import prices on the output per worker of domestic-material-intensive plants in 1986 is 1.5 percent, which is substantially lower than the impact on the output per worker of import-material-intensive plants, 2.3 percent.

5 Conclusion

This paper empirically examines the impact of a rise in the price of capital goods induced by an increase in import tariffs on investment and productivity. A structural dynamic optimization model of machine replacement is developed and estimated using the Chilean manufacturing plant-level data for a period characterized by substantial changes in tariff rates. Using the estimated model, I provide counterfactual experiments to quantify the impact of temporarily high import price on aggregate investment and productivity. I also examine the model's implications across trade-sectors and across plants differing in their use of imported materials regarding the links among relative import prices, investment and productivity.

The results of counterfactual experiments provide important quantitative implications regarding Chile's tariff policy. To the extent that a temporary increase in tariffs affected relative import prices, a change in trade policy may have had a substantial impact on aggregate investment dynamics in the mid-1980s. The counterfactual experiments also indicate that the impact of temporary increases in tariffs may be substantially different across trade-sectors as well as across plants differing in their use of imported materials. During the high tariff period, the export-oriented industry suffered larger negative effects than did the import-competing industry due to the increase in relative import prices. The negative effects of import price increases are particularly large among import-material-intensive plants.

There are at least three directions in which this model may be extended. First, while this paper focuses on analyzing intra-plant productivity change associated with machine replacement, others (cf., Pavcnik, 2002; Melitz, 2003) emphasize the resource reallocation through the process of entry and exit as an important source of aggregate productivity changes. Developing a structural model with entry and exit and estimating it using rich microeconomic data to quantify the role of resource reallocation in explaining the dynamics of aggregate productivity would be a fruitful exercise. Second, the model developed here abstracts from both capital-labor ratio choice and worker flows. The incorporation of technology choice and employment movement into the model is likely to prove useful for analyzing the links between technology choice, worker flows, and investment. Finally, technology adoption through machine replacement might induce a plant to start exporting. Incorporating export decisions into the model in view of recent findings of exporter facts (cf., Bernard, Eaton, Jensen, and Kortum, 2003) and examining how machine replacement is related to export decisions at the plant level, remains an important topic for future research.

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