Temporary Increases in Tariffs and Machine Replacement: 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 machines 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 estimation, tariffs, investment, productivity, unobserved heterogeneity, initial conditions problem.

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1 Introduction

Trade in capital goods is one of the primary channels through which a country adopts new technology (c.f., 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 (c.f., 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

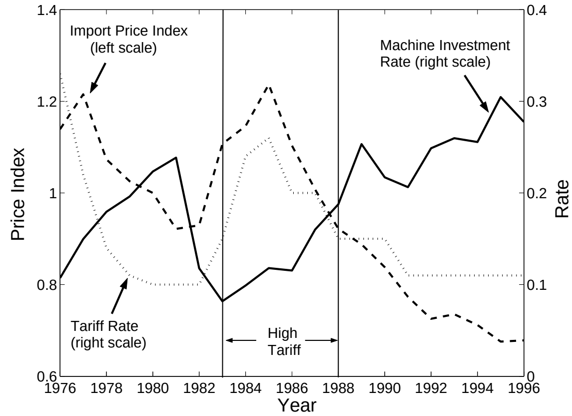

Figure 1: Machine Investment, Import Price, and Tariff Rate

unobserved heterogeneity by assuming that plants differ in their types (c.f., 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 newer the machines, the larger the fraction of plants with unobserved characteristics that lead to higher replacement probability. Without accounting for unobserved heterogeneity, it may appear that replacement probability is decreasing in machine ages even if any individual plant's replacement probability is actually increasing with machine ages. The presence of unobserved heterogeneity also leads to the important issue of how to treat the initial observations which are not independent of the unobserved type (c.f., Heckman, 1981).

The estimation algorithm developed here explicitly deals with the initial conditions problem. Specifically, utilizing the long time-series aggregate data that includes the pre-sample periods of the panel data, I construct a transitory distribution of machine age of the initial year of the panel data by simulating the structural model *conditional on both unobserved heterogeneity and the past realizations of aggregate variables.* The constructed initial distribution is used, in turn, to integrate out the unobserved initial machine age to evaluate the type-specific likelihood.

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. The accumulated loss in output per worker for 1983-1996 is estimated as 11.1

percent of annual output. 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. Such a difference across sectors is well captured by the model; for 1984-1988, the difference in the dynamics of 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 tariffs. I find that import-material-intensive plants experienced substantially larger declines in investment and productivity during the period of high tariffs than others.

This research complements several branches of literature. First, a number of 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 (e.g., Grossman and Helpman, 1991), the existing empirical 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 as the main source of productivity change, and quantitatively assesses its importance in the context of a temporary tariff change. Finally, this work is related to the

[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.

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. Since the findings of cross-country studies are essentially from a limited amount of data (i.e., Summers and Heston), looking at one country using detailed microdata provides additional important evidence concerning the relationships between the price of capital goods, investment, and productivity.

The paper is organized as follows. Section 2 provides theoretical analysis. 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

In this section, I extend the machine replacement model of Cooper et al. (1999) and Jovanovic and Rob (1999) by embedding tariff regime switching in order to analyze the effect of a tariff change on machine replacement timing.

Consider a risk-neutral producer who owns a single plant in discrete time with the following 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. An individual 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. The value of A_t essentially reflects the "vintage" of technology embodied in capital. 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

[3] De Long and Summers (1991), Jones (1994), and Restuccia and Urrutia (2001) indicate that cross-country differences in investment rates and productivity are at least partly driven by differences in the relative price of capital goods in terms of consumption. Greenwood, Hercowitz, and Krusell (1997) argue that the declining relative price of equipment contributes as much as 60 percent of total factor productivity growth through its effect on the introduction of new technology embodied in capital in the United States.

[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.

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

To analyze the effect of tariff rates on the replacement decision, 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.

Assume that 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 $Prob(\tau_{t+1}^j | \tau_t^j) = \lambda^j$ 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, $V^R(A, A^*, \tau)$. Thus, it satisfies the following Bellman equation:

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

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); $B \in (0,1)$ is a discount factor. Since both the gross profit and the replacement cost are homogenous 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 $v^R(s, \cdot) \equiv$

[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.

$V^R(exp(s), 1, \cdot)$, where $s \equiv \ln\left(\frac{A}{A^*}\right)$.[6] 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; $\beta \equiv (1+g)B$ is a discount factor adjusted for the rate of technological progress. Notice that $s \equiv \ln\left(\frac{A}{A^*}\right)$ is the position of the plant's technology relative to the frontier technology—which we call **technology position** hereafter.

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 falls below the threshold value. The threshold value for replacement crucially depends on a realization of tariff rates; this is because the marginal benefit of postponing replacement—the saving in the replacement cost—is essentially determined by the tariff-dependent machine price. Proofs of all propositions are in the appendix.

Proposition 1

There exists a unique $s^*(\tau) \in (-\infty, 0]$ for $\tau \in \{\tau^L, \tau^H\}$ such that a plant replaces its machine whenever its technology position falls below $s^*(\tau)$.

Thus, the timing of replacement is characterized completely by the regime-dependent threshold technology position $s^*(\tau)$. In order to focus on the effect of a *temporary* increase in tariffs, consider the case of $\lambda^L \to 1$ and $\lambda^H < 1$. In this case, the high tariff regime is a temporary regime in the sense that the economy will revert to the low tariff regime in the "near" future and, once the economy goes back to the low tariff regime, τ^L will persist. In the extreme case of

[6] More precisely, it can be proved that $V(\cdot)$ defined by the fixed point of (2) is homogenous of degree one with respect to (A, A^*). It follows that $V(A, A^*, \cdot) = V(A/A^*, 1, \cdot)A^*$. Thus, the number of states may be reduced by considering A/A^* instead of (A, A^*).

$\lambda^L = 1$, the low tariff regime is an absorbing state. The value of $1 - \lambda^H$ represents the extent to which the high tariff regime is temporary; in particular, the mean time for the economy to stay in the high tariff regime is $1/(1-\lambda^H)$. The next proposition states that a temporary increase in the tariff slows machine replacement.

Proposition 2

Suppose that $\lambda^L \to 1$ and $\lambda^H < 1$. Then,

(a) $s^*(\tau^H)$ is strictly decreasing in τ^H, and

(b) $s^*(\tau^H) < s^*(\tau^L)$.

The implications of Proposition 2.(a) 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 temporariness 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. Let the state of the aggregate economy be the cross-sectional density of technology positions at the beginning of period t, denoted by $f_t(s)$, and the realized tariff rate, τ. The aggregate investment rate, $I(\tau, f)$, is determined by the cross-sectional density of technology positions and the current tariff regime as follows:

$$I(\tau_t, f_t) = \int_{s \le s^*(\tau_t)} f_t(s) ds. \tag{4}$$

That is, the aggregate investment rate $I(\tau, f)$ is equal to the fraction of plants with technology positions less than the tariff-dependent threshold value, $s^*(\tau)$. Note that, holding the cross-sectional density fixed, the aggregate investment rate is nondecreasing in the threshold value $s^*(\tau)$. Thus, in view of Proposition 2, a high tariff tends to lower the aggregate investment rate. To understand how the tariff rate is related to aggregate investment and the productivity distribution, consider the extreme case of a constant tariff, i.e., $\tau^H = \tau^L = \tau$ and focus on the steady state at which technology positions are uniformly distributed.

Proposition 3[7]

Suppose that the tariff rate is a constant over time. Then, in the steady state,

(a) The higher the tariff, the lower the aggregate investment rate.

(b) The higher the tariff, the lower the average technology position but the higher the standard deviation.

While it presumes a steady state, Proposition 3, together with Proposition 2, provides insight as to how an increase in the tariff affects the dynamics of aggregate investment and productivity. In particular, since a temporary increase in the tariff leads to slower replacement, it may lower temporarily the aggregate investment. The delay in the adoption of frontier technologies embodied in machines results in lower aggregate productivity and higher productivity dispersion across plants.

3 Structural Estimation

In this section, an empirical dynamic optimization model of machine replacement is developed and estimated using plant-level Chilean manufacturing data for 1980-1996. Using the estimated model, I provide various counterfactual experiments to quantify the impact of a temporary increase in import prices on investment and productivity as well as to examine the differential responses across trade sectors and across plants differing in their use of imported materials.

3.1 Basic Observations

Before providing the empirical specification, it is helpful to examine the key implications of the machine replacement model using simple descriptive statistics. More 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 (Encuesta Nacional Industrial Anual) collected by Chile's Instituto Nacional de Estadistica (INE). The data set

[7]Part (b) of this proposition is essentially from Proposition 3 of Jovanovic and Rob (1999).

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.[8] After cleaning, 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.[9] A large portion of aggregate investment, therefore, is closely associated with episodes of investment spikes at the plant level. The observation of investment spikes is consistent with a view of machine replacement in which plants make *discrete* replacement decisions. Furthermore, the time-series fluctuation of the aggregate investment is closely associated with episodes of investment spikes at the plant level; this can be seen from Figure 2 which 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 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

[8]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.

[9]Similar findings on investment spikes are reported for U.S. and Norwegian manufacturing. Caballero et al. (1995), Caballero and Engel (1999) and Cooper and Haltiwanger (2000) emphasize the lumpiness of investment at the plant level and its association with aggregate investment dynamics. Empirical evidence for lumpy investment at the plant level and its connection with aggregate investment are presented by Doms and Dunne (1998) among others. By using the Longitudinal Research Database in the U.S. manufacturing sector for the period 1972-1988, Doms and Dunne found that plants concentrate about 50 percent of their cumulative 17 year investment in the three years surrounding the year with the largest investment. Cooper et al. (1999) confirms their basic findings and also reports that about 13 percent of their observations have less than 0.02 percent gross investment rate. Based on Norwegian microdata, Nilson and Schiantarelli (1996) found zero equipment investment in 21 percent of their observation for production units.

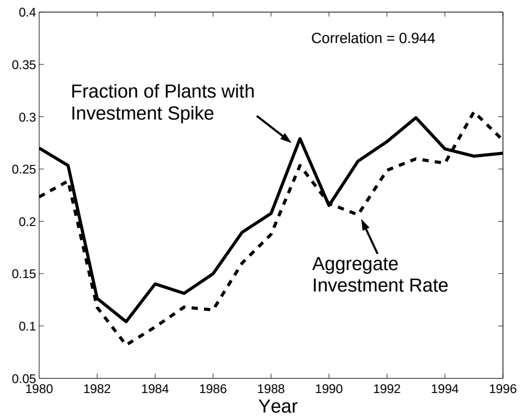

Figure 2: Aggregate Machine Investment and Investment Spike

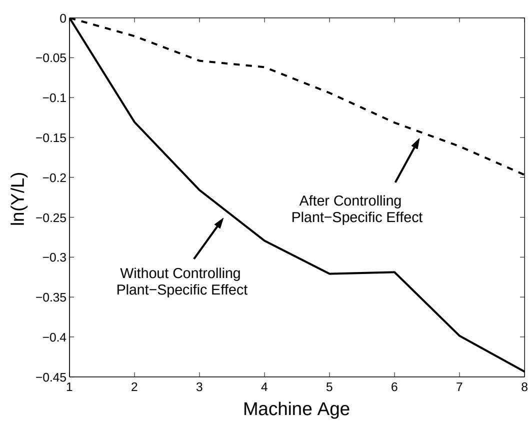

Figure 3: Labor Productivity and Machine Age

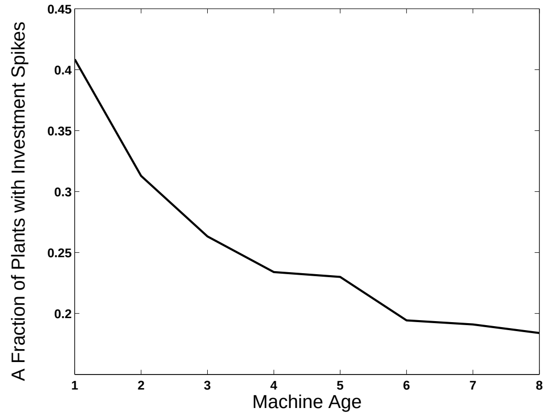

Figure 4: Empirical Hazard

between machine age and the log of plant labor productivity. The solid line plots the relationship without controlling plant-specific productivity and the dotted line plots the relationship after controlling plant-specific productivity.[10] While both lines show that plant labor productivity is negatively related to machine age, the negative relationship is much stronger before controlling plant-specific productivity (the average slope of -0.063) than after controlling 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. Without controlling for such differences across plants, it may appear that an increase in machine age has a larger negative impact on productivity than it actually has. 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, that a plant is more likely to replace if its machine is older. However, as is well known in the duration dependence

[10]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.

literature, and is discussed in the context of machine replacement problem by Cooper et al. (1999), the presence of unobserved heterogeneity may lead to downward-sloping hazard even if individual plants' hazards are increasing in machine ages. 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, in the empirical model, plants with higher ability to use machines, higher technological obsolescence rate, and lower replacement cost, are more likely to replace their machines conditional on machine age and thus their machines tend to be relatively young. In other words, the observed downward-sloping hazard may arise 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 a tariff increase on investment and productivity, I develop a structural dynamic optimization model that incorporates other potentially important factors. In particular, 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. I allow for three different sources of unobserved heterogeneity: plant specific productivity, replacement cost, and technological obsolescence rate [(B.1)]. I also allow for choice-dependent idiosyncratic cost shocks as well as idiosyncratic productivity shocks [(B.2)].

(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 tariff rates may affect replacement decisions. Highlighting the dependence of machine price on import price, the specification relates the time-dependent component of replacement cost, κ_t, to the log of the import price index—which is denoted by

p_t—as:

$$\kappa_t = \kappa \cdot \exp(\alpha_p p_t), \tag{5}$$

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. This specification allows me to examine whether the dynamics of import prices are relevant in determining replacement decisions. Note that if $\alpha_p = 0$, then the machine replacement cost is independent of the import price index.

(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. In particular, I incorporate serially correlated aggregate productivity shocks into the production function as

$$Y_{it} = A_{it} exp(\alpha_0 + \alpha_z z_t), \tag{6}$$

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. In practice, the Solow residuals are constructed from aggregate data on GDP, capital stock, and employed labor force and use its log after detrending as proxies for aggregate shocks.

(A.3) Tax on Profits In the sample period, there are two major tax reforms: in 1984-1986 and in 1991-1992.[11] 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.[12] "Unanticipation" of tax reforms tends to magnify the effect of the tax rate changes on replacement decisions. Thus, by assuming unanticipated tax rate changes rather than anticipated tax rate changes, the results constitute an upper bound on the effect of the tax rate changes in explaining variations of aggregate investment over time.

[11] 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.

[12] 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.

(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. After the abandonment of the fixed exchange rate regime in June 1982, the government reintroduced exchange control. The financial system collapsed in the midst of the recession; between the late 1981 and the end of 1983, and the government intervened 19 financial institutions—including the two largest banks in the private sector—which were either liquidated or rehabilitated and privatized [c.f., Barandiaran and Hernandez (1999)]. 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. This specification is motivated by the consideration that the collapse of domestic financial system and the reintroduction of exchange control may have increased the actual replacement cost; the former may have made it hard for plants to find the sources of funding; the latter may have increased the cost of purchasing imported machines. Further, I assume that the 1982-83 increase in replacement costs were unanticipated. This assumption seems reasonable 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. The large probability of further investment immediately following an investment spike 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 $j = 1, 2$. Formally, φ_j may be interpreted as the saving in fixed replacement cost when a plant replaces its machine across two or three years.

(B.1) Unobserved Heterogeneity As the discussion in Section 3.1 suggests, ignoring unobserved heterogeneity may bias the estimates toward the direction so that the empirical hazard rate is downward-sloping. Therefore, it is important to incorporate unobserved heterogeneity into the model. I consider three sources of unobserved heterogeneity: (i) plant-specific productivity, (ii) plant-specific replacement cost, and (iii) plant-specific technological obsolescence rate.

(i) I assume that individual plants differ in their ability to use machines and parameterize the plant-specific productivity by $u_{1,i}$. In particular, by modifying equation (6), the production function of the i^{th} plant at year t is assumed to be given by $Y_{it} = A_{it}exp(\alpha_0 + \alpha_z z_t + u_{1,i})$. Inclusion of plant-specific productivity is important in explaining a persistence in plant labor productivity over time that may not be captured by persistence in the machine age. Explicitly incorporating plant-specific productivity, I may 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 $u_{2,i}$. Specifically, a plant-time specific replacement cost, denoted by κ_{it}, is bifurcated into a time-specific component and a plant-specific component, $\kappa_{it} = \kappa_t exp(u_{2,i})$. Thus, together with equation (5), $\kappa_{it} = \kappa \cdot \exp(\alpha_p p_t + u_{2,i})$. 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.[13] To allow for such a possibility, it is assumed that the technological obsolescence rates are plant-specific. Denote the i^{th} plant-specific technological obsolescence rate by δ_i and 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

[13] 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.

technology level, A_t^*: $A_{it} = A_t^* \exp(-\delta_i a_{it})$.[14] Technological obsolescence is a key parameter, partially determining the degree of duration dependence. For example, if $\delta = 0$, then machine age is not systematically related to the probability of machine replacement.

Let the vector $u_i \equiv (u_{1,i}, u_{2,i}, \delta_i)$ represents the i^{th} plant-specific unobserved heterogeneity. I assume that plant-specific productivity is normally distributed with mean zero and variance $\sigma_{u_1}^2$. Further, (u_2, δ) is assumed to be independent of u_1 and multinomially distributed with the number of support points equal to K. The k^{th} type for $k = 1, 2, \ldots, K$ is characterized by a vector (u_2^k, δ^k) and the fraction of the k^{th} type in the population is denoted by 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 $\delta = 0$.[15] 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 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, and A_t^* is the frontier technology level. 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 conditional on other state variables. 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

[14] 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 $s_{it} \equiv -\delta_i a_{it}$.

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

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

$$Y_{it} = A_t^* \exp(\alpha_0 + \alpha_z z_t - (1 - \vartheta d_{it})\delta_i a_{it} + u_{1,i} + \xi_{it}). \tag{7}$$

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

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

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 innovations with the variance σ_z^2 and σ_p^2.[16]

[16] Note that z_t and p_t are assumed to be orthogonal to each other. I also estimated a joint stationary first-order

A typical plant manager's decision problem is: $\max E\sum_{t=0}^{\infty}\beta^t[\Pi(a_{it}, z_t, p_t, \gamma_t, D_t, u_i, \xi_{it}, d_{it})+\epsilon_{it}(d_{it})]$, where the expectation is taken with respect to the controlled stochastic process of $\{a_{it}, z_t, p_t, \gamma_t, D_t, u_i, \xi_{it}, \epsilon_{it}\}$. The corresponding Bellman's equation is 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 assumption on the additively separable error terms with the Type I extreme-value distribution, the following functional equation in terms of the expected value function $\bar{v}(\cdot)$ can be derived (c.f., Ben-Akiva and Lerman, 1985):

$$\begin{aligned} &\bar{v}_\theta(a, z, p, \gamma, D, u, \xi) = \\ &\quad \ln\left[\sum_{d'=0,1} exp\{\Pi(a, z, p, \gamma, u, \xi, d') + \beta E[\bar{v}_\theta((1-d')a+1, z', p', \gamma, D, u, \xi')|z, p]\}\right]. \end{aligned} \tag{8}$$

With the solution to the functional equation (8), the conditional choice probability is given by the binomial logit formula (c.f., McFadden, 1973; Rust, 1987),

$$\begin{aligned} &P_\theta(d|a, z, p, \gamma, D, u, \xi) = \\ &\quad \frac{\exp\{\Pi(a, z, p, \gamma, D, u, \xi, d) + \beta E[\bar{v}_\theta((1-d)a+1, z', p', \gamma, D, u, \xi')|z, p]\}}{\sum_{d'}\exp\{\Pi(a, z, p, \gamma, D, u, \xi, d') + \beta E[\bar{v}_\theta((1-d')a+1, z', p', \gamma, D, u, \xi')|z, p]\}}. \end{aligned} \tag{9}$$

Evaluation of (9) requires the solution to (8). 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. The integral in (8) is approximately evaluated using the

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.

Hermite quadrature formula (c.f., Tauchen and Hussey, 1991; Stinebricker, 2000). The appendix discusses the approximation method in greater detail.

Given the rate of technological progress, g, the frontier technology level at time t, $\ln A_t^*$, is related to the frontier technology level at time 0, $\ln A_0^*$, as $\ln A_t^* = \ln A_0^* + [\ln(1+g)]t$. Then, from equation (7), the log of labor productivity is given by $\ln(Y_{it}) = \alpha_{y0} + [\ln(1+g)]t + \alpha_z z_t - (1-\vartheta d_{it})\delta_i a_{it} + u_{1,i} + \xi_{it}$, where $\alpha_{y0} \equiv \ln A_0^* + \alpha_0$. It is plausible that observed labor productivity is measured with error. Thus, assume that the data generating process of the observed labor productivity in log form, denote by y_{it}, follows

$$y_{it} = \alpha_{y0} + [\ln(1+g)]t + \alpha_z z_t - (1-\vartheta d_{it})\delta_i a_{it} + u_{1,i} + \xi_{it} + \eta_{it}, \tag{10}$$

where η_{it} is an i.i.d. normal random measurement error with variance given by σ_η^2. Denote the sum of an idiosyncratic productivity shock ξ_{it} and a measurement error η_{it} by ω_{it} so that $\omega_{it} = \xi_{it} + \eta_{it}$.

3.3 Estimation

3.3.1 Likelihood Function

Let 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 shocks and import prices is given by:

$$L_1^p(\theta_1) \equiv q_z^*(z_{70}) q_p^*(p_{70}) \prod_{t=71}^{96} q_z(z_t|z_{t-1}) q_p(p_t|p_{t-1}) \tag{11}$$

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 $q(\cdot)$. Note that 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 $\{d_{it}\}_{t=80}^{96}$. Denote this sequence of machine ages for the i^{th} plant conditional on $a_{i,80}$—the initial machine age in 1980—as $\{a_{it}(a_{i,80})\}_{t=80}^{96}$. Given the initial machine age $a_{i,80}$ and the unobserved heterogeneity $u_i = (u_{1,i}, u_{2,i}, \delta_i)$, the (type-specific) likelihood contribution for labor productivity and replacement decision of the plant is

$$L_i(\theta; a_{i,80}, u_i) = \prod_{t=80}^{96} \frac{1}{\sigma_\omega}\phi\left(\frac{\tilde{\omega}_{it}(u_i, a_{it}(a_{i,80}))}{\sigma_\omega}\right)\int P_\theta(d|a_{it}(a_{i,80}), z_t, p_t, \gamma_t, D_t, u_i, \xi')f(\xi'|\tilde{\omega}_{it}(u_i, a_{it}(a_{i,80})))d\xi', \quad (12)$$

where $\tilde{\omega}_{it}(u_i, a_{it}) \equiv y_{it} - \{\alpha_{y0} + [\ln(1+g)]t + \alpha_z z_t - (1-\vartheta d_{it})\delta_i a_{it} + u_{1,i}\}$, $\sigma_\omega = \sqrt{\sigma_\xi^2 + \sigma_\eta^2}$, and $f(\xi|\omega) = \frac{1}{\sigma_\xi\sqrt{1-\rho^2}}\phi\left(\frac{\xi_{it}-\rho^2\omega}{\sigma_\xi\sqrt{1-\rho^2}}\right)$ which 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 partial likelihood function for productivity shocks and replacement decisions is a mixture of type-specific likelihood functions (12):

$$L_2^p(\theta; \{a_{i,80}\}_{i=1}^N) \equiv \prod_{i=1}^N \left[\sum_{k=1}^K \pi^k \int L_i(\theta; a_{i,80}, (u_1', u_2^k, \delta^k))\frac{1}{\sigma_{u_1}}\phi\left(\frac{u_1'}{\sigma_{u_1}}\right)du_1'\right]. \quad (13)$$

The full likelihood function is the product of the partial likelihood functions (11) and (13):

$$L_f(\theta; \{a_{i,80}\}_{i=1}^N) = L_1^p(\theta_1)L_2^p(\theta; \{a_{i,80}\}_{i=1}^N). \quad (14)$$

3.3.2 Initial Conditions Problem

Defining the machine age as the number of years passed since the last investment spike, the initial year's machine ages, $\{a_{i,80}\}_{i=1}^N$, are not observable. This is problematic since, if the initial machine ages are not observable, it is not possible to evaluate the likelihood (14).[17] One way to deal with this problem might be to assume a (type-specific) stationary distribution in the initial year 1980 and use it to integrate out the unobserved machine ages. Just before the sample period, however, Chile conducted a major trade liberalization and simultaneously experienced a major recession in the mid 1970s (c.f., 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 not be appropriate. 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.

[17] Even if the initial machine age $a_{i,80}$ is observable, how to treat the initial observation is an important issue; in particular, the initial observation is not independent of the type $u_i = (u_{1,i}, u_{2,i}, \delta_i)$ and hence cannot be treated as a nonstochastic starting point. This is the initial conditions problem (c.f., Heckman, 1981).

To deal with this issue, for each candidate parameter vector 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 as follows. Denote the probability distribution of plants with machine age a at year t conditional on the type u by $m_{\theta,t}(a|u)$. At the beginning of 1970, $m_{\theta,70}(a|u)$ is assumed to be an invariant distribution.[18] In order to obtain the 1971 distribution $m_{\theta,71}(a|u)$, I update the 1970 distribution $m_{\theta,70}(a|u)$ using the conditional choice probability (9) 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 (type-specific) transitory machine age distribution in the beginning of 1980, $m_{\theta,80}(a|u)$, which is conditioned on $\{(z_t, p_t)\}_{t=70}^{79}$. I use this 1980 distribution to integrate out the unobserved initial machine age from the partial likelihood function (13) as:

$$L_2^{*p}(\theta) \equiv \prod_{i=1}^{N} \left[\sum_{k=1}^{K} \pi^k \int \sum_{a'_{80}} L_i(\theta; a'_{80}, (u'_1, u_2^k, \delta^k)) m_{\theta,80}(a'_{80}|(u'_1, u_2^k, \delta^k)) \frac{1}{\sigma_{u_1}} \phi\left(\frac{u'_1}{\sigma_{u_1}}\right) du'_1 \right]. \tag{15}$$

The full likelihood function after integrating out the initial machine age is the product of the partial likelihood functions (11) and (15):

$$L_f^*(\theta) = L_1^p(\theta_1) L_2^{*p}(\theta). \tag{16}$$

The parameter θ is estimated by maximizing the logarithm of the likelihood (16).[19]

3.4 Variable Definitions

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

[18] The invariant distribution is computed under the transition probability function of a implied by (9) when aggregate shocks and import prices are constant over time at the means of estimated AR(1) processes, $z^* = c_z/(1-\psi_z)$ and $p^* = c_p/(1-\psi_p)$.

[19] To maximize the likelihood, I first use the simplex method of Nelder and Mead to reach the neighborhood of the optimum and then use the BFGS quasi-Newton method.

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

the previous year.[21] The measure of gross investment here includes machinery and equipment and vehicles but excludes buildings.[22] Furthermore, since the model focuses on the replacement of old machines by new machines embodying the frontier technology, I exclude the purchase and sales 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 perpetual inventory method.[23]

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.[24] Then, I regress lnZ_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.[25] For plants' labor productivity, y_{it},

[21]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.

[22]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.

[23]Since the reported book values are evaluated at the end of year t, the book values of capital are deflated by the (geometric) average deflator 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.

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

[25]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*

I use the log of the ratio of value added, deflated by the respective output price deflators, to the number of workers.[26] Trade orientation is classified into two categories: export-oriented 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.[27] 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 of the machine replacement model and their asymptotic standard errors, which are computed using the outer product of gradients estimator, for all manufacturing sectors.[28] 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

Nacionales for the years 1986-1996.

[26]I excluded from the sample the plants with negative value added. The labor productivity variables are then trimmed using the sample 1st percentile and the sample 99th percentile.

[27]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 Industy) 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.

[28]The discount rate β is not estimated but set to 0.95.

Table 1: Maximum Likelihood Estimates: All Manufacturing Sectors

Parameters			Parameters		
c_p	-0.017	(0.033)	φ_2	0.339	(0.051)
ψ_p	0.842	(0.115)	α_D	0.693	(0.064)
σ_p	0.095	(0.016)	g	0.012	(0.000)
c_z	-0.011	(0.019)	ϑ	0.486	(0.037)
ψ_z	0.792	(0.240)	σ_ω	0.478	(0.001)
σ_z	0.069	(0.006)	ρ	0.072	(0.140)
α_0	6.175	(0.014)	σ_{u_1}	0.592	(0.005)
α_z	1.156	(0.022)	δ^H	0.081	(0.001)
α_p	0.819	(0.060)	u_2^H	0.625	(0.035)
α_{y0}	-2.017	(0.837)	π_1	0.347	(0.030)
κ	1.321	(0.062)	π_2	0.181	(0.023)
φ_1	0.677	(0.048)	π_3	0.265	(0.028)
$\bar{\delta}$	0.031				
$\bar{\kappa}$	1.862				
$\bar{exp}(\alpha_0)/\bar{\kappa}$	0.096				
$\ln L^f$	-31830.7				

Notes: Standard errors are in parentheses. $\bar{\delta} \equiv \sum_{k=1}^{4} \pi^k \delta^k$ is the average technological obsolescence rate. $\bar{\kappa} \equiv \sum_{k=1}^{4} \pi^k \kappa \exp(u_2^k)$ is the average replacement cost. $\bar{exp}(\alpha_0) \equiv \exp(\alpha_0 + 0.5\sigma_{u_1})$ is the average value added with the frontier technology.

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. The estimate of ϑ implies that only a fraction 0.486 of a new machine becomes productive at the year of investment. 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. The coefficients φ_1 and φ_2 are significantly positive, indicating that a multiyear investment phenomenon is present in the data. These point estimates 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 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: 8.1 percent. Thus, there exists substantial heterogeneity in technological obsolescence rates across plants. The average technological obsolescence rate $\bar{\delta} = \sum_{k=1}^{4} \pi^k \delta^k$ is estimated at 3.1 percent.

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.[29] The model appears to replicate well the observed aggregate investment patterns. As shown in Figures 6, the model also performs well in replicating the observed machine age distribution.[30] Table 2 compares the actual and predicted proportion of plants with investment spikes by machine ages for the years 1994 to 1996.[31] 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. As discussed before, this is because of the composition effect: 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 the labor productivity. The model quantitatively misses, however, a large decline in the average labor productivity that occurred during 1986-

[29] 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 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.

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

[31] 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.

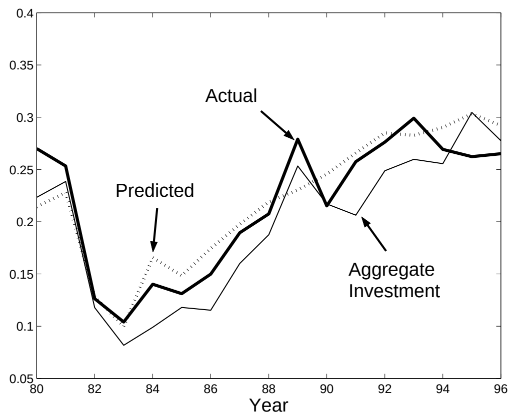

Figure 5: Fraction of Plants with Investment Spike (Predicted vs. Actual)

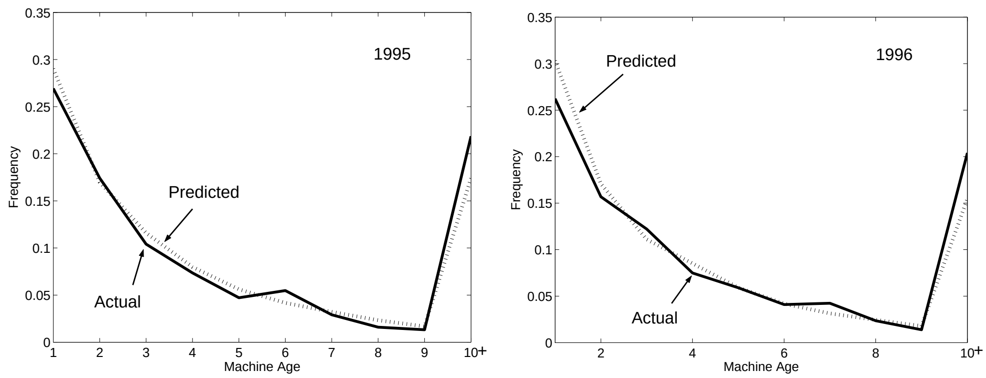

Figure 6: Machine Age Distributions in 1995 and 1996 (Actual vs. Predicted)

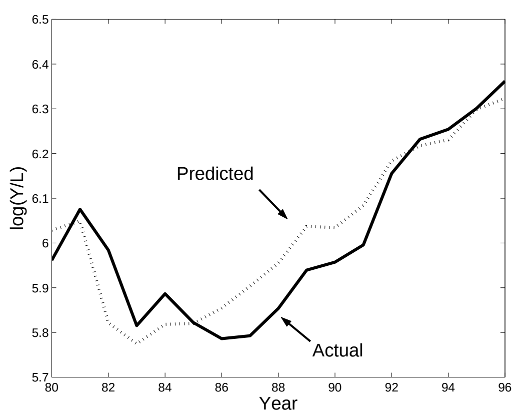

Figure 7: Average Labor Productivity (Actual vs. Predicted)

Table 2: Actual and Predicted Machine Replacement Rate by Years and Machine Ages

	Year					
	1994		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 3: Maximum Likelihood Estimates of Selected Coefficients: Export-Oriented and Import-Competing

Parameters	Export-Oriented	Import-Competing
α_p	0.909 (0.082)	0.850 (0.098)
g	0.015 (0.001)	0.001 (0.001)
$\bar{\delta}$	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.

1988; there were other important factors that are largely responsible for the observed decline in the average labor productivity in the mid-1980s.

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 and productivity during the period of high tariffs. To examine this issue, I estimate the model while identifying trade-sectors. Table 3 presents the maximum likelihood 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. They are within a reasonable range. The estimated rate of technological progress, g, in export-oriented industry is larger than that in import-competing industry. Indeed, the higher technological progress in export-oriented industry might have been an important factor for the successful export performance in Chile during this period (c.f., Dornbusch and Edwards, 1994).

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 appear to capture aggregate investment patterns as well as their differences between export-oriented and import-competing industries reasonably well. To examine how much of the difference in investment rates across trade-sectors is attributable to a

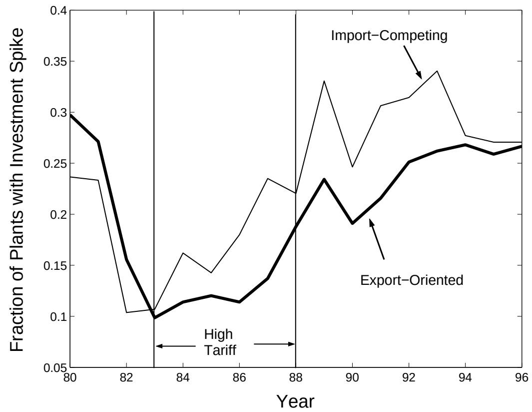

Figure 8: Actual Fraction of Plants with Investment Spike by Trade Sectors

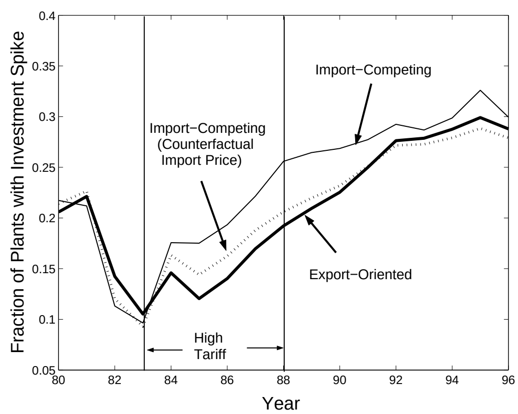

Figure 9: Predicted Fraction of Plants with Investment Spike by Trade Sectors

Table 4: Maximum Likelihood Estimates of Selected Coefficients: Import-Material-Intensive vs. Domestic-Material-Intensive

Parameters	Domestic-Material-Intensive	Import-Material-Intensive
α_p	0.628 (0.070)	1.473 (0.144)
g	0.012 (0.000)	0.013 (0.001)
$\bar{\delta}$	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.

difference in relative import prices, 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. The difference between the thin line and the dotted line in Figure 9 therefore captures the difference in investment rates between export-oriented and import-competing industries attributable to the difference in relative import prices. The observed difference in the dynamics of relative import prices explains a substantial portion of the difference in investment rates between export-oriented and import-competing industries. In particular, 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.[32]

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

Plants that are importing materials may have a better access to foreign machines and hence might be more likely to use the imported machines, as oppose to the domestic machines, than other plants.[33] 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

[32] I also conducted a counterfactual experiment to test what would happen to the investment rate of export-oriented industry if the realization of its relative import prices were identical to that of import-competing 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 65.5 percent on average for the period of 1984-1988.

[33] 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.

this issue, I estimate the model 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 sample years. Table 4 presents the maximum likelihood estimates of selected coefficients. The column of "Import-Material-Intensive" presents the parameter estimates for the plants using imported material intensively while "Domestic-Material-Intensive" presents the estimates for those using domestic material intensively.[34] As expected, the estimate of import price elasticity of replacement cost, α_p, is substantially higher for import-material-intensive plants than for domestic-material-intensive plants. 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.[35] One important implication of this result is that plants using the imported materials may have experienced a larger decline in investment than others during the period of high import price due to a larger increase in machine replacement cost.

To examine the extent to which the higher import price elasticity of replacement cost is responsible for a large decline in investment for import-material-intensive plants during the period of high tariffs, I conduct 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. This counterfactual experiment is presented in Figure 10, together with the actual and the predicted fractions of plants with investment spikes among import-material-intensive plants. While the dashed line shows the predicted investment rates of import-material-intensive plants given the actual elasticity ($\alpha_p = 1.473$), the dotted line shows the model's prediction of what would happen to investment rates of import-material-intensive plants given the counterfactual elasticity ($\alpha_p = 0.628$). Figure 10 demonstrates the importance of the import price elasticity of replacement cost in determining

[34]See Section 3.4 for the classification of "Import-Material-Intensive" plants and "Domestic-Material-Intensive" plants.

[35]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.

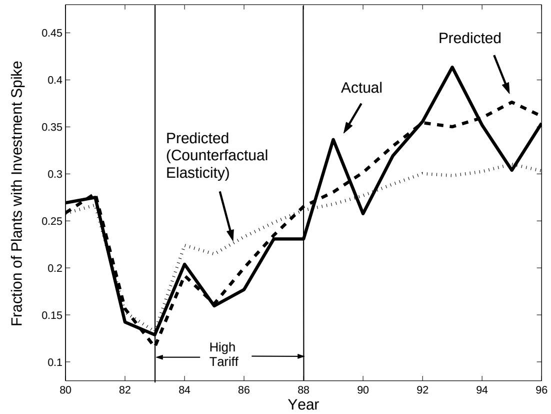

Figure 10: Actual and Predicted Fraction of Plants with Investment Spike for Import-Material-Intensive Plants

the investment dynamics during the period of substantial tariff changes. In particular, 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 tariff increase, 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 this assumption (dotted line) and the fraction of plants with investment spikes for the actual import prices (dashed line). The gap between the two lines captures the effect on investment of the high import prices between 1983-1987. 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

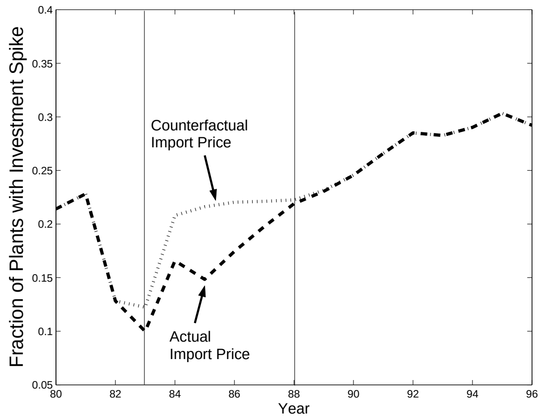

Figure 11: Experiment: Investment — All Manufacturing Sector

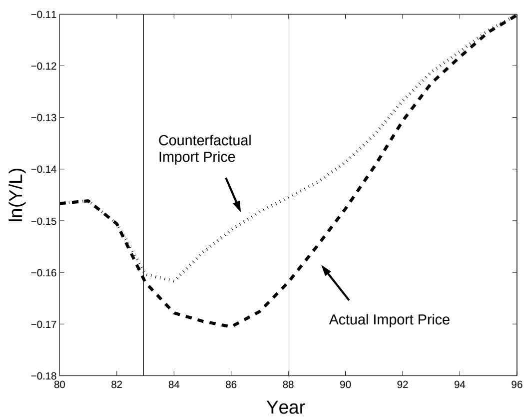

Figure 12: Experiment: Productivity — All Manufacturing Sector

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 substantial: 11.1 percent of annual output.

The results of similar experiments for export-oriented industry and import-competing industry are presented in Figures 13(a)-(d). Reflecting the larger increase in relative import prices for export-oriented industry than for import-competing industry, the negative impact of tem-

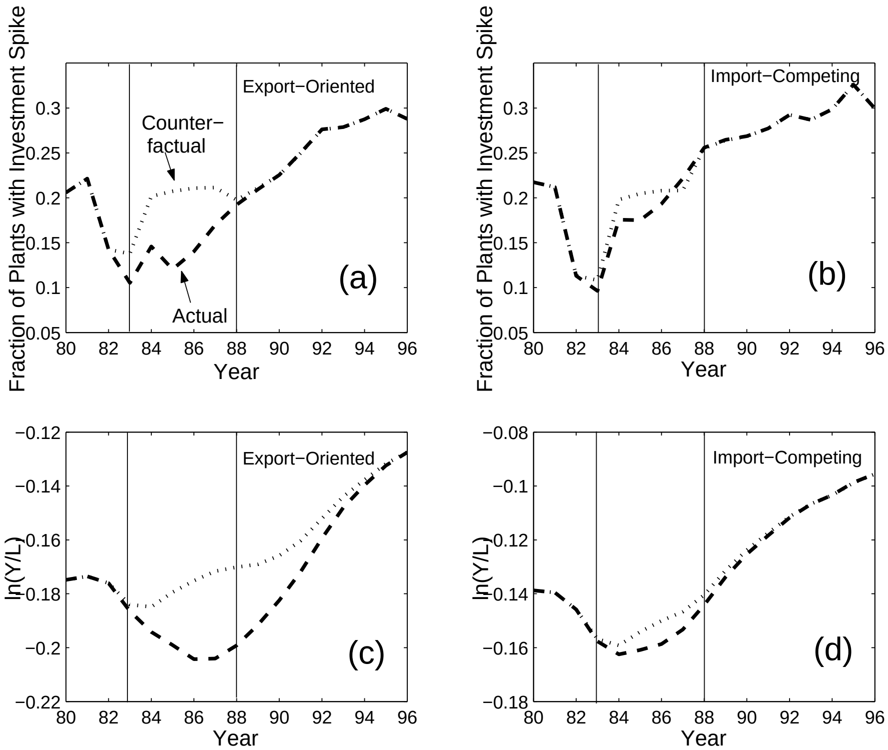

Figure 13: Experiment: Export-Oriented vs. Import-Competing

porarily high import prices on investment and productivity during the high tariff period was substantially larger for export-oriented industry than for import-competing industry. While the investment rate of export-oriented industry would have been higher by 8.7 percent in 1985 had there been no temporary increase in import prices from 1983 to 1987, the investment rate of import-competing industry would have been higher only by 3.0 percent [Figures 13(a)-(b)]. The output per worker of export-oriented industry would have been higher by 2.9 percent in 1986 if the import prices of 1983-1987 had remained at the 1982 level [Figure 13(c)]; on the other hand, the impact of temporarily high import prices on import-competing industry's productivity in 1986 is calculated as only 0.9 percent [Figure 13(d)]. The accumulated output loss from 1983 to 1996 associated with the high import prices of 1983-1987 for export-oriented industry is 18.7 percent of annual output, which is much larger than the accumulated loss for import-competing industry, calculated as 3.5 percent of annual output.

Finally, the results of similar experiments for import-material-intensive plants and domestic-material-intensive plants are presented in Figures 14(a)-(d). While the 1985 investment rate of

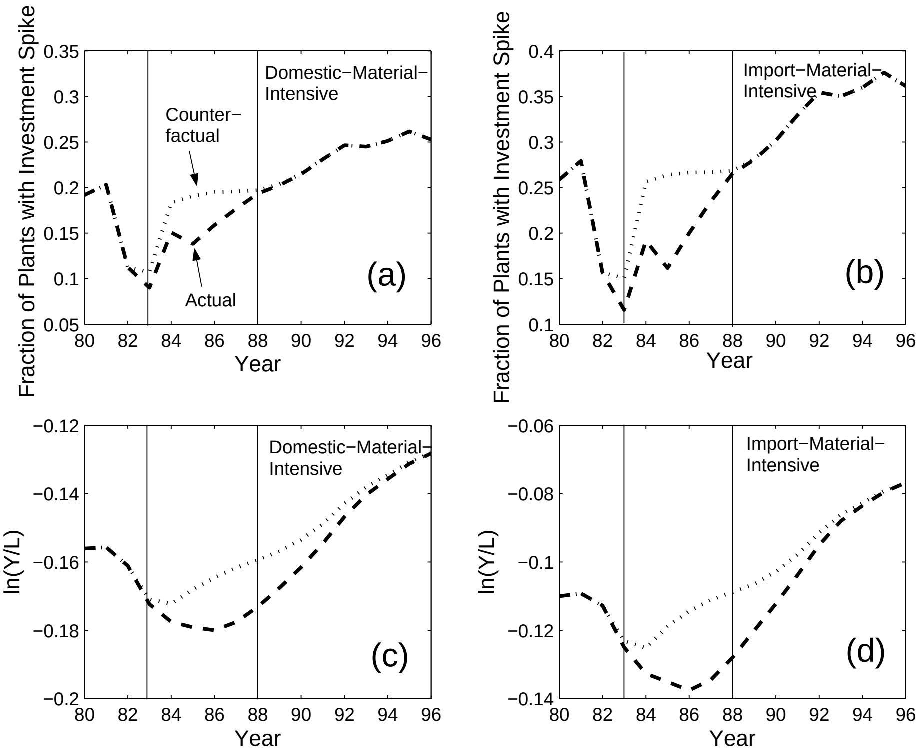

Figure 14: Experiment: Domestic-Material-Intensive vs. Import-Material-Intensive

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 [Figures 14(a)-(b)]. 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. Therefore, reflecting the higher import price elasticity of replacement cost among import-material-intensive plants, the temporarily high import prices during the high tariff period had much larger negative impacts on investment and productivity among import-material-intensive plants than among domestic-material-intensive plants.

These results 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, export-oriented industry suffered larger negative effects than did import-competing industry due to the increase in relative import prices. The negative effects of import price increase are particularly large among import-material-intensive plants.

There are caveats. First, we should be cautious of interpreting these numbers as the effects of a temporary increase in *tariffs*; they rather reflect the effect of a temporary increase in *relative import prices*. Although an increase in tariffs may have been the primary factor that led to higher relative import prices in the mid-1980s, there may have been other factors (e.g., the real exchange rate) that were also important determinants of relative import prices. Second, I did not consider a general equilibrium framework. As discussed in Caballero (1999), in general equilibrium, the effect of the shocks on aggregate investment is smoothed further; the extent of synchronized investment may be limited because of the short-run inelastic supply of capital goods, although such a bottleneck might be less important in a small open economy like Chile.

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 examined 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 main empirical findings are summarized as follows. First, a temporary increase in import prices in the mid-1980s had a substantial impact on aggregate investment and average productivity. According to the counterfactual experiment, had there been no temporary increase in import prices in the period from 1983 to 1987, the aggregate investment rate would have been higher by 6.8 percent in 1985, the year of the highest tariff rates, and the average output per worker would have been higher by 1.9 percent in 1986. The accumulated loss in output for 1984-

1996 is calculated as 11.1 percent of annual output. Second, I identify the differential impact of a tariff increase on output prices across trade-sectors by comparing export-oriented industry with import-competing industry. On average for 1984-1988, 60.0 percent of the investment rate difference between export-oriented industry and import-competing industry is attributable to the difference in relative import prices. Finally, plants using imported materials intensively are found to have a much larger import price elasticity of replacement cost and thus have experienced a larger negative impact of temporarily high import prices on investment and productivity than those using domestic materials intensively. The finding that the estimated model explains the differences across trade-sectors and across plants differing in their use of imported materials provides particularly important evidence for the role of tariff changes in determining investment and productivity since other potentially important factors (e.g., the tax reform of 1984-1986) are not likely to be able to explain these differences.

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 (c.f., 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 (c.f., 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.

Appendix

We first provide Proposition A which states the existence and the uniqueness of a fixed point of the functional equation (3).

Proposition A There exists an unique fixed point of the functional equation (3). Further, the unique fixed point is bounded, continuous, and strictly increasing in s and strictly decreasing in (τ^L, τ^H).

Proof By the standard argument found in Stokey and Lucas (1989). ∎

Proof of Proposition 1 By Proposition A, $v(s, \tau)$ is continuous and strictly increasing in s. Then, $v^R(s, \tau) - v^N(s, \tau) = -\tau p + \beta E[v(0, \tau') - v(s - \delta, \tau')|\tau]$ is strictly decreasing in s. Therefore, for each τ, there exists the unique $s^*(\tau)$ such that $v^R(s^*(\tau), \tau) - v^N(s^*(\tau), \tau) = 0$, $v^R(s, \tau) - v^N(s, \tau) > 0$ if $s < s^*(\tau)$, and $v^R(s, \tau) - v^N(s, \tau) < 0$ if $s > s^*(\tau)$. ∎

Proof of Proposition 2 Let $\tau_1^H < \tau_2^H$. Let $s^*(\tau_1^H)$ and $s^*(\tau_2^H)$ be the threshold value of s under the high tariff regime for τ_1^H and τ_2^H. We need to show $s^*(\tau_1^H) > s^*(\tau_2^H)$. Note that $s^*(\tau_i^H)$ for $i = 1, 2$ is characterized by:

$$0 = -(1 + \tau_i^H)p + \beta\lambda^H[v(0, \tau_i^H) - v(s^*(\tau_i^H) - \delta, \tau_i^H)] + \beta(1 - \lambda^H)[v(0, \tau^L) - v(s^*(\tau_i^H) - \delta, \tau^L)].$$

By taking the difference and using $v(s^*(\tau_i^H) - \delta, \tau_i^H) = e^{s^*(\tau_i^H)-\delta} - (1 + \tau_i^H)p + \beta[\lambda^H v(0, \tau_i^H) + (1 - \lambda^H)v(0, \tau^L)]$ for $i = 1, 2$, we find

$$\begin{aligned} \beta\lambda^H e^{-\delta}[e^{s^*(\tau_1^H)} - e^{s^*(\tau_2^H)}] \quad = \quad & -(1 - \beta\lambda^H)(\tau_1^H - \tau_2^H)p + \beta\lambda^H(1 - \beta\lambda^H)[v(0, \tau_1^H) - v(0, \tau_2^H)] \\ & +\beta(1 - \lambda^H)[v(s^*(\tau_2^H) - \delta, \tau^L) - v(s^*(\tau_1^H) - \delta, \tau^L)]. \end{aligned} \tag{17}$$

Suppose, on the contrary, $s^*(\tau_1^H) \leq s^*(\tau_2^H)$. Then, the right hand side of (17) is strictly positive since (i) the first term is strictly positive by $\tau_1^H < \tau_2^H$, (ii) the second term is strictly positive by Proposition A $[v(0, \tau_1^H) > v(0, \tau_2^H)]$ with $\tau_1^H < \tau_2^H$, and (iii) the third term is non-negative by Proposition A if $s^*(\tau_1^H) \leq s^*(\tau_2^H)$. On the other hand, the left hand side of (17) is non-negative if $s^*(\tau_1^H) > s^*(\tau_2^H)$. A contradiction. Therefore, if $\tau_1^H < \tau_2^H$, then $s^*(\tau_1^H) > s^*(\tau_2^H)$. This proves (a). From (a), (b) follows since (i) $s^*(\tau^H) = s^*(\tau^L)$ if $\tau^H = \tau^L$, (ii) $s^*(\tau^H)$ is strictly increasing in τ^H by (a), and (iii) $s^*(\tau^L)$ is independent of τ^H. ∎

The Approximated Solution to (8) and the Evaluation of (12) and (15) Let 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 $q_p(p'|p) = \phi\left(\frac{p' - \psi_p p}{\sigma_p}\right)/\sigma_p$. Denote the density function of ξ by $q_\xi(\xi) = \phi\left(\frac{\xi}{\sigma_\xi}\right)/\sigma_\xi$. To obtain the approximated solution to (8), it is required to evaluate the conditional expectation $E[\bar{v}_\theta(z', p', \xi')|z, p] =$

$\int\int\int \bar{v}_\theta(z',p',\xi')q_z(z'|z)q_p(p'|p)q_\xi(\xi')dz'dp'd\xi'$, where other arguments for $\bar{v}_\theta(\cdot)$ are suppressed for brevity. To evaluate this three-hold integrals, I use the Gauss-Hermite quadrature methods together with the use of an "importance" density as suggested by Tauchen and Hussey (1991) and Stinebricker (2000). Specifically, by choosing an "importance" density $\phi\left(\frac{z}{\sigma_z}\right)/\sigma_z$, $\phi\left(\frac{p}{\sigma_p}\right)/\sigma_p$, and $\phi\left(\frac{\xi}{\sigma_\omega}\right)/\sigma_\omega$ for z, p, and ξ, respectively, I approximate the conditional expectation as

$$\int\int\int \bar{v}_\theta(z',p',\xi')q_z(z'|z)q_p(p'|p)q_\xi(\xi')dz'dp'd\xi' \approx \sum_{k_1}^{N}\sum_{k_2}^{N}\sum_{k_3}^{N}\bar{v}_\theta(z^{k_1},p^{k_2},\xi^{k_3})q^*(z^{k_1},p^{k_2},\xi^{k_3}|z,p),$$

where

$$q^*(z^{k_1},p^{k_2},\xi^{k_3}|z,p) = \frac{q_z^*(z^{k_1}|z)q_p^*(p^{k_2}|p)q_\xi^*(\xi^{k_3})}{\sum_{j_1}\sum_{j_2}\sum_{j_3} q_z^*(z^{j_1}|z)q_p^*(p^{j_2}|p)q_\xi^*(\xi^{j_3})}$$

defines a Markov chain that approximates the true law of motion of (z,p,ξ) with $q_z^*(z^k|z) = \frac{\lambda^k}{\sqrt{\pi}}\frac{q_z(z^k|z)}{\phi(z^k/\sigma_z)/\sigma_z}$, $q_p^*(p^k|p) = \frac{\lambda^k}{\sqrt{\pi}}\frac{q_p(p^k|p)}{\phi(p^k/\sigma_p)/\sigma_p}$, and $q_\xi^*(\xi^k) = \frac{\lambda^k}{\sqrt{\pi}}\frac{q_\xi(\xi^k)}{\phi(\xi^k/\sigma_\omega)/\sigma_\omega}$. The grid points are chosen as: $z^k = \sqrt{2}\sigma_z v^k$, $p^k = \sqrt{2}\sigma_p v^k$, and $\xi^k = \sqrt{2}\sigma_\omega v^k$.[36] Here, v^k and λ^k $(k = 1,...,N)$ are the points and weights associated with the Gauss-Hermite quadrature.

Define a discretized Bellman operator:

$$\begin{aligned}&[\Gamma_N(\bar{v}_{\theta,N})](a,z,p,\cdot,\xi)\\ &= \ln\left[\sum_{d'=0,1}\exp\left\{\pi(a,z,p,\cdot,\xi,d') + \beta\sum_{k_1,k_2,k_3}\bar{v}_\theta((1-d)a+1,z^{k_1},p^{k_2},\cdot,\xi^{k_3})q^*(z^{k_1},p^{k_2},\xi^{k_3}|z,p)\right\}\right].\end{aligned}$$

The approximate solution to (8), which we denote by $\bar{v}_{\theta,N}$, is obtained as a fixed point of Γ_N that satisfies $\Gamma_N(\bar{v}_{\theta,N}) = \bar{v}_{\theta,N}$. The fixed point $\bar{v}_{\theta,N}$ is defined only on the set of finite grid points of (z,p). We may evaluate nonetheless the value function at any point (z,p) by $\bar{v}_{\theta,N}(a,z,p,\cdot,\xi) = [\Gamma_N(\bar{v}_{\theta,N})](a,z,p,\cdot,\xi)$ using the *self-approximating* property of the operator Γ_N as discussed in Rust (1996). This allows us to evaluate (9) on the *realized value* of (z_t,p_t).

To evaluate (12), we need to compute an integral $\int P_\theta(d|a_{it},z_t,p_t,\gamma_t,D_t,u_i,\xi')f(\xi'|\tilde{\omega}_{it}(u_i,a_{it}))d\xi'$.

[36] We may use $\xi^k = \sqrt{2}\sigma_\xi v^k$ for the grid points of ξ in place of $\xi^k = \sqrt{2}\sigma_\omega v^k$; in such a case, the "importance" density for ξ is $\phi(\xi/\sigma_\xi)/\sigma_\xi$.

The integral in (12) can be approximated as:

$$\int P_\theta(d|a_{it}, z_t, p_t, \gamma_t, D_t, u_i, \xi')f(\xi'|\tilde{\omega}_{it}(u_i, a_{it}))d\xi$$
$$= \int P_\theta(d|a_{it}, z_t, p_t, \gamma_t, D_t, u_i, \xi')\frac{f(\xi'|\tilde{\omega}_{it}(u_i, a_{it}))}{\phi\left(\frac{\xi'}{\sigma_\omega}\right)/\sigma_\omega}\frac{1}{\sigma_\omega}\phi\left(\frac{\xi'}{\sigma_\omega}\right)d\xi'$$
$$\approx \sum_k P_\theta(d|a_{it}, z_t, p_t, \gamma_t, D_t, u_i, \xi^k)\frac{f(\xi^k|\tilde{\omega}_{it}(u_i, a_{it}))}{\phi\left(\frac{\xi^k}{\sigma_\omega}\right)/\sigma_\omega}\frac{\lambda^k}{\sqrt{2}},$$

where the last line used the Gauss-Hermit quadrature method. Here, $\xi^k = \sqrt{2}\sigma_\omega v^k$ for $k = 1, 2, ..., N$ where v^k and λ^k are the points and weights associated with the Gauss-Hermite quadrature. The integral in (15) is evaluated similarly by using the Gauss-Hermit quadrature method with the number of grids equal to N.

In practice, I set $N = 10$ for p, z, ξ , and u_1. This means that the state space for (p, z, ξ, u_1) is approximated by 10000 grid points. The maximum machine age is also set to 10 by assuming that, once the machine is 10 years or older, machine quality is constant over time. Since there exist four types for (u_2, δ), the state space for $(a, p, z, \xi, u_1, u_2, \delta)$ is approximated by 400000 grid points.

References

[1] Akerlof, George A. (1970) "The Market for Lemons: Qualitative Uncertainty and the Market Mechanism," *Quarterly Journal of Economics* 84: 488-500.

[2] Baker, Michael and Angelo Melino (2000) "Duration Dependence and Nonparameteric Heterogeneity: A Monte Carlo Study," *Journal of Econometrics* 96: 357-393.

[3] Banco Central De Chile (2000) *Anuario De Cuentas Nacionales.*

[4] Barandiaran, Edgardo, and Leonardo Hernandez (1999) "Origins and Resolution of a Banking Crisis: Chile 1982-86," *Central Bank of Chile Working Papers No. 57.*

[5] Ben-Akiva, Moshe and Steven R. Lerman (1985) *Discrete choice analysis: theory and application to travel demand*, Cambridge: MIT Press.

[6] Bergoeing, Raphael, Patrick J. Kehoe, Timothy J. Kehoe, and Raimundo Soto (2001) "A Decade Lost and Found: Mexico and Chile in the 1980s," *Central Bank of Chile Working Papers No. 107.*

[7] Bernard, Andrew B., Jonathan Eaton, J. Bradford Jensen, and Samuel Kortum (2003) "Plants and Productivity in International Trade," *American Economic Review* 93(4): 1268-1290.

[8] Caballero, Ricardo J. "Aggregate Investment," in J. Taylor and M. Woodford (eds.) *Handbook of Macroeconomics*, Amsterdam: North Holland.

[9] Caballero, Ricardo J. and Engel, Eduardo M.R.A. (1999) "Explaining Investment Dynamics in U.S. Manufacturing: A Generalized (S,s) Approach," *Econometrica*, 67 (4): 783-826.

[10] Caballero, Ricardo J., Engel, Eduardo M.R.A., and John Haltiwanger (1995) "Plant-Level Adjustment and Aggregate Investment Dynamics," *Brookings Papers on Economic Activity*, (2): 1-39.

[11] Coe, David T. and Elhanan Helpman (1995) "International R&D Spillovers," *European Economic Review* 39: 859-887.

[12] Coe, David T., Elhanan Helpman, and Alexander W. Hoffmaister (1997) "North-South R&D Spillovers," *Economic Journal* 107: 134-149.

[13] Cooley, Thomas, Greenwood, Jeremy and Yorukoglu, Mehmet (1997) "The Replacement Problem," *Journal of Monetary Economics*, 40(3): 457-499.

[14] Cooper, Russell, and John Haltiwanger (1993) "The Macroeconomic Implications of Machine Replacement: Theory and Evidence," *American Economic Review*, 83 (3): 360-382.

[15] Cooper, Russell, John Haltiwanger, and Laura Power (1999) "Machine Replacement and the Business Cycle: Lumps and Bumps," *American Economic Review*, 89 (4): 921-946.

[16] Cooper, Russell and John Haltiwanger (2000) "On the Nature of Capital Adjustment Costs," *NBER Working Paper* No. 7925.

[17] de la Cuadra, S., and D. Hachette (1990) "Chile," in D. Papageorgiou, M. Michaely, and A. Choksi (eds.) *Liberalizing Foreign Trade*, Oxford: Blackwell.

[18] De Long, B., Summers, L. (1991) "Equipment Investment and Economic Growth," *Quarterly Journal of Economics* 106:445-502.

[19] Dornbusch, R. and S. Edwards (1994) "Exchange Rate Policy and Trade Strategy," in Bosworth, B.P., R. Dornbusch, and R. Laban, eds., *The Chilean Economy: Policy Lessons and Challenges* Washington, D.C.: The Brookings Institution.

[20] Doms, Mark and Timothy Dunne (1998) "Capital Adjustment Patterns in Manufacturing Plants," *Review of Economic Dynamics* 1: 409-30.

[21] Eaton, Jonathan and Samuel Kortum (2001) "Trade in Capital Goods," *European Economic Review* 45: 1195-1235.

[22] Eckstein, Zvi, and Kenneth I. Wolpin (1989) "Dynamic Labor Force Participation of Married Women and Endogenous Work Experience," *Review of Economic Studies* 56(3): 375-390.

[23] Eckstein, Zvi, and Kenneth I. Wolpin (1999) "Why Youths Drop Out of High School: The Impacts of Preferences, Opportunities, and Abilities," *Econometrica*, 67(6): 1295-1339.

[24] Greenwood, Jeremy, Zvi Hercowitz, and Per Krusell (1997) "Long-Run Implications of Investment Specific Technological Change," *American Economic Review* 87:342-362.

[25] Grossman, G.M. and E. Helpman (1991) *Innovation and Growth in the Global Economy* Cambridge, MA: MIT Press.

[26] Haddad, Mona and Ann Harrison (1993) "Are There Positive Spillovers from Direct Foreign Investment? Evidence from Panel Data for Morocco," *Journal of Development Economics* 42: 51-74.

[27] Harrison, Ann (1994) "Productivity, Imperfect Competition and Trade Reform: Theory and Evidence," *Journal of International Economics* 36: 53-73.

[28] Heckman, James J. (1981) "The Incidental Parameters Problem and the Problem of Initial Conditions in Estimating a Discrete Time-Discrete Data Stochastic Process," in Charles Manski and Daniel McFadden, eds., *The Structural Analysis of Discrete Data* Cambridge, MA: MIT Press.

[29] Heckman, James J. and B. Singer (1984) "A Method for Minimizing the Impact of Distributional Assumptions in Econometric Models for Duration Data," *Econometrica* 52: 271-320.

[30] Hopenhayn, H.A. (1992) "Entry, Exit, and Firm Dynamics in the long run," *Econometrica* 60: 1127-1150.

[31] Hulten, Charles R. (1992) "Growth Accounting when Technical Change is Embodied in Capital," *American Economic Review*, 82:964-980.

[32] Jones, Charles I. (1994) "Economic Growth and the Relative Price of Capital," *Journal of Monetary Economics* 34: 359-382.

[33] Jovanovic, B. and R. Rob (1998) "Solow vs. Solow" mimeo, New York University.

[34] Keane, Michael P. and Kenneth I. Wolpin (1997) "The Career Decisions of Young Men," *Journal of Political Economy* 105(3): 473-522.

[35] Melitz, Mark J.(2003) "The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity," *Econometrica* 71: 1695-1725.

[36] McFadden, D. (1973) "Conditional Logit Analysis of Qualitative Choice Behavior," in P. Zarembka, ed., *Frontiers in Econometrics*, New York: Academic Press.

[37] Nilsen, ∅ivind Anti, Fabio Schiantarelli (1996) "Zeros and Lumps: Investment Patterns of Norwegian Plants and Firms," mimeo.

[38] Pavcnik, Nina (2002) "Trade Liberalization, Exit, and Productivity Improvements: Evidence From Chilean Plants," Review of Economic Studies, 69(1): 245-276.

[39] Power, Laura (1998) "The Missing Link: Technology, Investment, and Productivity," *Review of Economics and Statistics*, 80(2):300-313.

[40] Ramey, Valerie A., and Matthew D. Shapiro (2001) "Displaced Capital: A Study of Aerospace Plant Closings," *Journal of Political Economy* 109(5): 954-992.

[41] Restuccia, Diego and Carlos Urrutia (2001) "Relative Prices and Investment Rates," *Journal of Monetary Economics* 47:93-121.

[42] Rust, John (1987) "Optimal Replacement of GMC Bus Engines: An Empirical Model of Harold Zurcher," *Econometrica*, 55(5): 999-1033.

[43] Rust, John (1996) "Numerical Dynamic Programming in Economics," in H. Amman et al., eds., *Handbook of Computational Economics* Amsterdam: Elsevier.

[44] Stinebrickner, Todd (2000) "Serially Correlated Variables in Dynamic, Discrete Choice Models," *Journal of Applied Econometrics*, 15: 595-624.

[45] Stokey, Nancy L., and Robert E. Lucas with Edward C. Prescott (1989) *Recursive Methods in Economic Dynamics* Cambridge: Harvard University Press.

[46] Tauchen, George, and Robert Hussey (1991) "Quadrature-Based Methods for Obtaining Approximate Solutions to Nonlinear Asset Pricing Models," *Econometrica* 59(2): 371-396.

[47] Tybout, James R. (2000) "Manufacturing Firms in Developing Countries: How Well Do They Do, and Why?" *Journal of Economic Literature* Vol. XXXVIII: 11-44.

[48] Tybout, James, Jaime de Melo, and Vittorio Corbo (1991) "The Effects of Trade Reforms on Scale and Technical Efficiency: New Evidence from Chile," *Journal of International Economics* 31: 231-250.

[49] Tybout, James, and M. Daiel Westbrook (1995) "Trade Liberalization and Dimensions of Efficiency Change in Mexican Manufacturing Industries," *Journal of International Economics* 39: 53-78.

[50] Xu, Bin and Jianmao Wang (1999) "Capital Goods Trade and R&D Spillovers in the OECD," *Canadian Journal of Economics* 32: 1258-1274.