Abstract

We study the investment and productivity dynamics of Chilean manufacturing plants over the 1979-2000 period. We find that Chilean plants are much more likely to have periods of inaction (zero investment) than their U.S. counterparts. We propose a full information maximum likelihood estimation procedure to estimate a structural model of investment that allows for convex costs of adjustment and irreversible investment. We solve the model using smooth value function techniques. This procedure has advantages in terms of computational speed. It also allows us to easily characterize the likelihood function. Our results suggest that our model is able to capture key features of the Chilean investment data.
1 Introduction

Many developing and developed economies consider structural reforms to trade and fiscal policy that are designed to lower taxes and tariffs and stimulate investment and production of the manufacturing sector. A good example of such a country is Chile which went through a series of structural reforms in the late 1970s and early 1980s. The labor and financial markets were deregulated and price controls eliminated. Two major tax reforms were put into operation in 1975 and 1984, and a social security reform was introduced in 1980. In addition, Chile was one of the first countries in Latin America to begin a gradual but deep trade liberalization process. In 1967 the average effective protection rate was over 100%. Between 1973 and 1979, Chile eliminated the quantitative restrictions and reduced the import tariff to a uniform level of 10%. Responding to a debt crisis in 1982, some reforms were delayed and others were partially reversed, but by 1992 all of them were successfully in place.

Understanding the implications of such reforms for manufacturing production, productivity and investment requires a deep understanding of the nature of the costs to adjusting factor inputs such as labor and capital. The standard model of investment assumes that adjustment costs are convex and symmetric around zero investment or the replacement investment rate. In such a model, firms gradually adjust capital spending and production in response to the different economic stimuli that occur.

Recent empirical evidence challenges the notion of convex adjustment costs at the plant-level however and instead emphasizes notions of irreversibility and fixed costs to adjustment in the investment process. In the face of such non-convexities, the response of investment and production to shocks and economic fluctuations may be anything but gradual, as some firms are pushed over thresholds and respond with large immediate changes in capital, while other firms may not change their capital stock for a number of years following the shock.

Partial irreversibility is often modeled through asymmetric adjustment costs, and implies slower adjustment or gradual decay of the capital stock to its desired level on the downside and relatively rapid increases in capital to its desired level on the upside. Such asymmetries in response are well documented features of micro U.S. data (Caballero, Engel and Haltiwanger (1995)). The inclusion of fixed adjustment costs generates episodes of large but infrequent positive investment (lumpy investment), also a common feature of the U.S. data (Doms and Dunne (1998), Cooper, Haltiwanger and Power (1999)). Periods of inaction are introduced by assuming a wedge between the purchase price and sale price of capital. Studies with data from other countries include Nielsen
and Schiantarelli (1996) who find evidence of irreversibilities but not of non-convexities using data for Norwegian manufacturing plants. Similar findings for the manufacturing sectors in Mexico and Colombia are reported in Gelos and Isgut (2001). Except for these studies, detailed investigation about other countries, especially from Latin America, are modest.

In this paper, we extend the current literature and estimate a fully-structural model of investment for an emerging market economy, Chile. The period that we consider, 1979-2000, is characterized by aggregate shocks, structural reforms and volatility in macroeconomic variables. These features are desirable for our purpose, because they enhance the importance of irreversibilities, periods of inaction and lumpy investment. Emerging market economies such as Chile also appear to face inherently larger adjustment costs to investment than their developed country counterparts. In particular, our data imply that periods of inaction (no investment) occur, on average, 38% of the time for Chilean manufacturing plants. In the U.S., periods of inaction account for a much smaller fraction of the data – 10% on average. Chilean firms also rarely disinvest (only 5% of plant-year observations record capital sales), a fact that may reflect inherent differences in the liquidity of second-hand capital markets in developed versus developing economies. Overall, these findings imply that the investment process for an emerging market economy is unlikely to be similar to that of a developed economy. Understanding these dissimilarities within the context of a structural econometric framework is therefore likely to provide useful information regarding the nature of the investment process for an emerging economy.

In addition to characterizing the nature of the investment process for emerging market economies, our research makes a methodological contribution by estimating a fully specified structural model of plant-level investment using maximum likelihood techniques. We allow for both convex costs of adjustment and partial irreversibility by introducing a wedge between the purchase and sale price of capital. In this framework, we characterize both the decision of when to invest and how much to invest as functions of underlying observable state variables such as the current capital stock and current productivity parameter that governs plant-level profitability. Because our model is structural, it may be used to conduct policy experiments and trace out the effect of changes in tax and tariffs on plant-level investment decisions. The estimated parameters may also be used as inputs to calibrated general equilibrium models.

By solving an Maximum likelihood Estimation (MLE) version of an adjustment cost model, our methodology can be easily extended –by including both non-convex and convex adjustment costs– to other dynamic decision making environments such as the dynamic labor demand models of Sargent and Hammermesh, and dynamic price adjustment models along the lines of those considered by
2 Empirical Evidence: Investment irreversibility

In this section, we document the characteristics of capital adjustments for a our panel of Chilean manufacturing plants over the period 1979-2000. We analyze how investment patterns are related to observable plant characteristics and different capital types. We also document the degree of “lumpiness” in investment at the plant level and the implications on aggregate investment fluctuations of having such large capital adjustment episodes.

In particular, as shown in Table 1, the frequency of negative investment is significantly low, 5% for total investment. Second, the frequency of negative investment is related to capital type. Liquidation of installed capital is much more infrequent for building and machinery compared to vehicles, supporting the view that liquidation of second-hand markets are different across capital types. Third, the frequency of zero investment is considerable, reaching almost 38% for total investment. This number is substantially higher than the 10% share of zero-investment occurrences reported by Cooper, Haltiwanger and Power (1999) for U.S. manufacturing plants. It suggests that the investment process for manufacturing plants in a developing country are much more likely to be subject to investment irreversibilities and/or fixed costs to investment than their U.S. counterparts. Finally, episodes of investment rates above 20% are infrequent but account for 40% of total investment. This degree of “lumpiness” in investment also appears to be much greater than that reported by Cooper, Haltiwanger and Power (1999) for U.S. plants. Gelos and Isgut (2001) reported a frequency of zero investment between 40% and 70%, depending on the type of investment, for Mexican and Colombian manufacturing plants.
In Figure 1, we turn to analyze the within-plant investment behavior. We rank within-plant capital growth rate from highest (rank 1) to lowest (rank 21) and compute the within-plant investment share as the average share of total plant investment over the 21-year period that took place in each year.

![Graph showing mean capital growth rates and investment shares by capital growth rate rank](image)

Figure 1:  Mean capital growth rates and investment shares by capital growth rate rank

The average maximum capital growth rate (rank 1) is 20%. The mean capital growth rate is
significantly lower after rank 1 and negative after rank 4. In general, this evidence suggests that plants experience very few episodes of positive and significant capital growth rates which account for a high proportion of total investment. At rank 1, one-year investment episode accounts for 41% of the total plant investment over the 21-year period. At the second largest capital growth rate, the plant investment share is on average 19% and 11% at rank 3. This suggests that on average 70% of total plant-level investment between 1980-2000 took place in only three years.

Now we report summary statistics on the relationship between aggregate patterns of the investment rate and the frequency of large investment episodes at the plant level. First, we compute the percentage of plants that have their maximum investment rate and capital growth rate in any given year. Figure 2 plots these percentages together with the aggregate investment rate over the period 1980-2000.

![Figure 2: Aggregate investment rate and plant spikes](image)

Three main features can be seen from this figure: (1) aggregate fluctuations in investment are highly correlated with the frequency of investment spikes at the plant level; (2) the correlation between aggregate investment and the frequency of maximum investment rate is 73%; and (3) the correlation between aggregate investment and the frequency of maximum capital growth rate is 90%. Investment fluctuations at the aggregate level are driven by a small group of plants.
experiencing large expansionary investment episodes that account for a significant proportion of
the capital stock already installed—the average maximum investment rate is 37%.

Figure 3 plots the aggregate investment rate and the proportion of plants that invest in new
capital in any given year. Both the aggregate investment rate and the proportion of plants that
invest exhibit a strong positive correlation over the twenty-one year sample period. The timing
of these investment patterns coincides with the proportion of plants experiencing their maximum
investment rates and capital growth rates as shown in Figure 2.

![Figure 3: Frequency positive investment](image)

Tables 2 and 3 provide information about the distribution of investment for alternative plant
types. In particular, size is defined as: a plant is small (large) if its value added is less than or
equal to (greater than) the median value added. Plant type is defined as whether plants belong
to a uni-plant or multi-plant firm.

<table>
<thead>
<tr>
<th>Plant size</th>
<th>I/K&lt;0</th>
<th>I/K=0</th>
<th>I/K&gt;0</th>
</tr>
</thead>
<tbody>
<tr>
<td>Small plants</td>
<td>4.4%</td>
<td>54.5%</td>
<td>41.1%</td>
</tr>
<tr>
<td>Large plants</td>
<td>5.2%</td>
<td>22.8%</td>
<td>72.0%</td>
</tr>
</tbody>
</table>
Table 3: Frequency of negative, zero and positive investment by plant type

<table>
<thead>
<tr>
<th></th>
<th>I/K&lt;0</th>
<th>I/K=0</th>
<th>I/K&gt;0</th>
</tr>
</thead>
<tbody>
<tr>
<td>Small uniplant</td>
<td>3.9%</td>
<td>59.3%</td>
<td>36.7%</td>
</tr>
<tr>
<td>Large uniplant</td>
<td>6.4%</td>
<td>25.9%</td>
<td>67.8%</td>
</tr>
<tr>
<td>Small multiplant</td>
<td>2.5%</td>
<td>61.6%</td>
<td>36.0%</td>
</tr>
<tr>
<td>Large multiplant</td>
<td>5.7%</td>
<td>22.2%</td>
<td>72.1%</td>
</tr>
</tbody>
</table>

The frequency of zero investment is significantly related to firm size. In Table 2, the share of zero investment goes from 55% to 23% if we compare small versus large plants. The share of negative investment is higher for large plants. Also, large plants have a significantly higher frequency of positive investment compared to small plants (72% versus 41%). Interestingly, in Table 3 we do not see important distinctions in either the investment rates or occurrence of investment zeros across uni-plant and multi-plant firms. This finding, combined with the fact that the vast majority of plants are single-plant firms,\(^1\) suggests that to a first approximation, analyzing and modeling the investment decision at the plant level is a reasonable decision. Also, even though we have data on three types of investment—building, vehicles and machinery—machinery accounts for 75% of total investment at the plant level, as reported in Table 4. This provides some justification for our decision to model a single capital good as starting point for our structural estimation.\(^2\)

Table 4: Decomposition of total investment by plant type

<table>
<thead>
<tr>
<th></th>
<th>Building</th>
<th>Machinery</th>
<th>Vehicles</th>
</tr>
</thead>
<tbody>
<tr>
<td>Small plants</td>
<td>5.0</td>
<td>70.7</td>
<td>24.3</td>
</tr>
<tr>
<td>Large plants</td>
<td>9.5</td>
<td>76.6</td>
<td>13.9</td>
</tr>
<tr>
<td>All plants</td>
<td>7.8</td>
<td>74.5</td>
<td>17.7</td>
</tr>
</tbody>
</table>

3 Baseline Model and Estimation Procedure

Our structural econometric model is designed to measure the parameters that govern investment decisions by firms. Given structural disturbances, our model, provides a full characterization of when firms invest and how much they invest. A particular advantage of our econometric technique is its emphasis on Maximum Likelihood Estimation. Estimation by ML is desirable because we

---

\(^1\) Approximately 90% of the plants are single-plant firms.

\(^2\) Although there is evidence that the investment process depends on the size of the plant, we choose to estimate a simpler version of the adjustment cost of investment that does not include a variable cost component dependent on size. Our specification for the investment cost function is introduced in section 3, and includes partial irreversibility and a convex adjustment component.
specify all of the features of the model and ML takes advantage of that information in a way that GMM or indirect inference does not. Our emphasis on maximum likelihood techniques sets us apart from other econometric approaches which are either less efficient or not fully structural. Indeed, a major contribution of our research is to develop MLE procedures for models of input choice within a structural framework that allows for partial irreversibility, convex and non-convex adjustment costs.

3.1 The investment decision

We define flow profit (ignoring investment costs) to be:

$$\pi_{it}(K_{it}, \Omega_{it}) = \Omega_{it}K_{it}^\alpha$$

where $\alpha$ parameterizes the curvature of the profit function and reflects returns to scale and the producer market power. This function for flow profit assumes that firms pick labor optimally in each period. The choice of labor is ignored for the time being, as it has no dynamic content.

Capital is determined by the law of motion:

$$K_{it+1} = (1 - \delta)K_{it} + I_{it}$$

where $I_{it}$ is the cost of investment. To account for the main features of the data documented above, we assume that firms face an investment cost $c(I_{it}, K_{it}, \varepsilon_{it})$ which includes both a wedge between the purchase and sale price of capital that will help explain the presence of a significant degree of zeros in the investment data, and a convex cost component that potentially captures the serially correlated movements in investment that are documented in section 4.2 (Table 7). Accordingly, we parameterize the investment cost function as

$$c(I_{it}, K_{it}, \varepsilon_{it}) = \frac{\phi I_{it}^2}{2K_{it}} + (p^- \{I_{it} < 0\} + p^+ \{I_{it} > 0\} + \varepsilon_{it}) I_{it}$$

The first term represents a quadratic and hence convex adjustment cost to altering the size of a firm. This cost decreases at an increasing rate in capital and is parameterized by $\phi$. The second term can be thought of as the pecuniary cost of investment, where $\varepsilon_{it}$ represents idiosyncratic costs that affects the level of investment. Partial irreversibility is introduced by assuming that the sale price $p^-$ is lower than the purchase price of capital, $p^+$. The term $\{I_{it} > 0\}$ takes on a value of 1 when $I_{it}$ is positive and 0 otherwise. Firms choose investment $I_{it}$ to maximize the expected discounted sum of profits. In each period, each firm solves:

$$\max_{I_{it}} E \left[ \sum_{\tau=t}^{\infty} \beta^{\tau-t} \pi_{it}(K_{i\tau}, \Omega_{i\tau}) - c(I_{i\tau}, K_{i\tau}, \varepsilon_{i\tau}) | K_{it}, \Omega_{it}, \varepsilon_{it} \right]$$
Firms can determine capital but not the productivity parameter $\Omega_{it}$. The term $\Omega_{it}$ moves according to the Markov process $p(\Omega_{it+1}, \Omega_{it})$.

We can specify this problem as a sequence of one period decisions using standard techniques. The state variables in this formulation are the capital level $K_{it}$, the productivity parameter $\Omega_{it}$, and the idiosyncratic shocks $\varepsilon_{it}$. Define the value function $V(K_{it}, \Omega_{it}, \varepsilon_{it})$ as the discounted sum of future profits conditional on the state variables assuming profit maximizing choices of investment. We assume that $\varepsilon_{it}$ is distributed iid according to the normal distribution $N(0, \sigma)$. We can define the value function iteratively as:

$$V(K_{it}, \Omega_{it}, \varepsilon_{it}) = \max_{I_{it}} \left\{ \pi_{it}(K_{it}, \Omega_{it}) - c(I_{it}, K_{it}, \varepsilon_{it}) + \beta E[V(K_{it+1}, \Omega_{it+1}, \varepsilon_{it+1})|K_{it}, \Omega_{it}, \varepsilon_{it}] \right\}$$

where $K_{it}$ follows the law of motion (1). Noting that $\varepsilon_{it}$ is independent across time and that the problem is stationary conditional on state variables (that is, $t$ is not a state variable), we can define $E[V(K, \Omega)]$ as the expectation over $\varepsilon_{it}$ as:

$$E[V(K, \Omega)] = E \left[ \max_{I} \pi(K, \Omega) - c(I, K, \varepsilon) + \beta \int_{\Omega'} E[V(K', \Omega')]p(\Omega', \Omega) \right]$$

(2)

where we have suppressed the subscripts to emphasize that equation (2) holds for all firms in all periods and the prime symbol indicates a variable one period ahead. Equation (2) is a fixed point equation determining $E[V(K, \Omega)]$. We exploit this equation extensively in our estimation routine.

Firms can be thought of as making two decisions: whether or not to invest and how much to invest. Let $\hat{I}(K_{it}, \Omega_{it}, \varepsilon_{it})$ be the optimal amount to invest conditional on investing at all. The function $\hat{I}(K_{it}, \Omega_{it}, \varepsilon_{it})$ solves the following first-order conditions:

$$\beta \int_{\Omega'} E[V_K((1-\delta)K_{it} + \hat{I}_{it}, \Omega_{it+1})]p(\Omega_{it+1}, \Omega_{it}) = \phi \hat{I}_{it} K_{it} + p^- + \varepsilon_{it} \quad \hat{I}_{it} < 0 \quad (3)$$

$$\beta \int_{\Omega'} E[V_K((1-\delta)K_{it} + \hat{I}_{it}, \Omega_{it+1})]p(\Omega_{it+1}, \Omega_{it}) = \phi \hat{I}_{it} K_{it} + p^+ + \varepsilon_{it} \quad \hat{I}_{it} > 0 \quad (4)$$

Here, $V_K$ refers to the derivative of $V$ with respect to the first term and we have substituted for $K_{it+1}$ according to Equation (1). The firm chooses to invest if:

$$\beta \int_{\Omega'} \left( E[V((1-\delta)K_{it} + \hat{I}_{it}, \Omega_{it+1})] - E[V((1-\delta)K_{it}, \Omega_{it+1})] \right) p(\Omega_{it+1}, \Omega_{it}) > \frac{\phi \hat{I}_{it}^2}{2K_{it}} + \left( p^- \mathbb{I}\{\hat{I}_{it} < 0\} + p^+ \mathbb{I}\{\hat{I}_{it} > 0\} + \varepsilon_{it} \right) \hat{I}_{it} \quad (5)$$

The left-hand side represents the improvement in future profits from investing. The right hand side is $c(\hat{I}_{it}, K_{it}, \varepsilon_{it})$, the cost of investing today.
We use these two equations to construct our likelihood function. Let \( I_{it} \) be the observed level of investment for firm \( i \) in period \( t \). For reasonable parameter values, there exists a value of \( \varepsilon_{it} \) such that \( \hat{I}_{it} = I_{it} \) for any \( I_{it} \neq 0 \). Let \( \hat{\varepsilon}(K_{it}, \Omega_{it}, I_{it}) \) be the value of \( \varepsilon_{it} \) such that equations (3) and (4) imply that \( \hat{I}_{it} = I_{it} \). Similarly, to obtain the probability of observing \( I_{it} = 0 \), let \( \varepsilon^+(K_{it}, \Omega_{it}, I_{it}) \) be the value of \( \varepsilon_{it} \) that makes firms indifferent between investing and not investing and \( \varepsilon^-(K_{it}, \Omega_{it}, I_{it}) \) be the value that makes firms be indifferent between disinvesting and not investing. Then, our log likelihood function is:

\[
L_nT(\psi) = \ln \prod_{i=1}^{n} \prod_{t=1}^{T} \phi \left( \frac{\hat{\varepsilon}(K_{it}, \Omega_{it}, I_{it})}{\sigma} \right) \Phi \left( \frac{\varepsilon^-(K_{it}, \Omega_{it}, I_{it})}{\sigma} \right) - \Phi \left( \frac{\varepsilon^+(K_{it}, \Omega_{it}, I_{it})}{\sigma} \right)
\]

(6)

The function \( \phi \) is the normal PDF (an abuse of notation as we use \( \phi \) above as well), the function \( \Phi \) is the normal CDF, and \( \psi \) is the vector of model parameters.

3.2 Solving the value function

We now discuss the computation of \( E[V(K, \Omega)] \). This step distinguishes our project from much of the previous work in this area. Following Rust (1987), we nest a fixed point algorithm based on equation (2) in our optimization algorithm and solve for \( E[V(K, \Omega)] \) for each set of parameter values that our optimization algorithm tries. Typically, researchers proceed by discretizing \( K \) and \( \Omega \) and solving \( E[V(K, \Omega)] \) at these points. However, because we require the derivative of the value function and because our maximum likelihood procedure requires that we determine the exact \( \varepsilon_{it} \) that justifies a particular observed level of investment, discretizing \( K \) is not helpful for us. Instead, we specify a smooth approximation of \( E[V(K, \Omega)] \) and solve the fixed point using projection methods outlined in Judd (1998).

By definition \( E[V(K, \Omega)] = E_{\varepsilon} \{ V(K_{it}, \Omega_{it}, \varepsilon_{it})|\Omega_{it}, K_{it} \} \), is the expected value of the firm conditional on \( K_{it} \) and \( \Omega_{it} \). We use the notation \( E_{\varepsilon} \{ \} \) to denote the fact that we are integrating over an iid shock \( \varepsilon_{it} \). The key to our solution procedure is to note that, although \( V(K_{it}, \Omega_{it}, \varepsilon_{it}) \) is not smoothly differentiable, \( E[V(K, \Omega)] \) is smoothly differentiable in \( K, \Omega \) and can therefore be approximated using continuous and differentiable functions. In effect, integrating over the iid cost shock produces a smoothed version of the value function that may be approximated using projection methods. Projection methods approximate \( E[V(K, \Omega)] \) as a polynomial function of \( K \) and \( \Omega \). We use Chebyshev polynomials for our approximating procedures. Specifically, let \( X(K, \Omega) \) denote the \( kth \) order Chebyshev polynomial of \( K, \Omega \). We approximate the value function as

\[
\tilde{V}(K, \Omega; A) = \exp(X(K, \Omega)A)
\]
for some parameter vector $A$. We then search for the parameter vector $A$ that solves the fixed point problem defined above. By taking exponents and therefore approximating the log of $\tilde{V}$, we guarantee a positive value function. This also has better approximation properties (less curvature) which allows us to restrict our attention to lower order polynomials.

Using a polynomial approximation, it is straightforward to compute the derivative of $\tilde{V}(K, \Omega; A)$ with respect to $K$:

$$\tilde{V}_K(K, \Omega; A) = \frac{dX(K, \Omega)}{dK}A.$$ 

To insure that this approach is valid, we need to be able to specify the firm’s decision in terms of $\tilde{V}(K, \Omega; A)$. To see that this can be done, let $I(K, \Omega, \varepsilon; A)$ denote the optimal level of investment. Inserting this into the value function and taking expectations over $\varepsilon_{it}$, we obtain

$$\tilde{V}(K, \Omega; A) = E_{\varepsilon}\{\pi(K, \Omega) - c(I(K, \Omega, \varepsilon; A), K, \varepsilon)$$

$$+ \beta E[\tilde{V}((1 - \delta)K + I(K, \Omega, \varepsilon; A), \Omega'; A)[K, \Omega] \}

where $K_{it}$ follows the law of motion in (1).

Again, let $\hat{I}(K, \Omega, \varepsilon; A)$ be the optimal amount to invest conditional on investing. The function $\hat{I}(K, \Omega, \varepsilon; A)$ solves the following first-order conditions:

$$\beta \int_{\Omega'} \tilde{V}_K((1 - \delta)K + \hat{I}, \Omega'; A]p(\Omega', \Omega) = \phi \frac{\hat{I}}{K} + p^- + \varepsilon \quad \hat{I}_{it} < 0 \tag{8}$$

$$\beta \int_{\Omega'} \tilde{V}_K((1 - \delta)K + \hat{I}, \Omega'; A]p(\Omega', \Omega) = \phi \frac{\hat{I}}{K} + p^+ + \varepsilon \quad \hat{I}_{it} > 0 \tag{9}$$

The firm chooses to invest if:

$$\beta \int_{\Omega'} \left(\tilde{V}((1 - \delta)K + \hat{I}(K, \Omega, \varepsilon; A), \Omega'; A) - \tilde{V}((1 - \delta)K, \Omega'; A)\right) p(\Omega', \Omega)$$

$$> \frac{\phi \hat{I}^2}{2K} + \left(p^- \{\hat{I} < 0\} + p^+ \{\hat{I} > 0\} + \varepsilon\right) \hat{I} \quad \hat{I}_{it} > 0 \tag{9}$$

Otherwise, the firm sets $I(K, \Omega, \varepsilon; A)$ equal to zero.

Equations (7), (8), and (9) completely characterize the firm problem for any given coefficient vector $A$. We can simplify this problem further by noting that equation (9) defines two cutoff values $\varepsilon^- = \varepsilon^-(\hat{I}, K, \Omega; A)$ and $\varepsilon^+ = \varepsilon^+(\hat{I}, K, \Omega; A)$ that set equation (9) to equality:

$$\varepsilon^- : \beta \int_{\Omega'} \left(\tilde{V}((1 - \delta)K + \hat{I}(K, \Omega, \varepsilon^-; A), \Omega'; A) - \tilde{V}((1 - \delta)K, \Omega'; A)\right) p(\Omega', \Omega)$$

$$= \left((p^- + \varepsilon^-)\hat{I} + \frac{\phi \hat{I}^2}{2K}\right) \quad \hat{I}(K, \Omega, \varepsilon; A) < 0 \quad \hat{I}_{it} < 0 \tag{10}$$
\[ \varepsilon^+ : \beta \int_{\Omega'} \left( \tilde{V}((1 - \delta)K + \tilde{I}(K, \Omega^+; A), \Omega'; A) - \tilde{V}((1 - \delta)K, \Omega'; A) \right) p(\Omega', \Omega) \]  
\[ = \left( (p^+ + \varepsilon^+) \tilde{I} + \frac{\phi \tilde{I}^2}{2K} \right) \tilde{I}(K, \Omega, \varepsilon; A) > 0 \]  
such that
\[ I(K, \Omega, \varepsilon; A) = \tilde{I}(K, \Omega, \varepsilon; A) \text{ if } \varepsilon < \varepsilon^+ \text{ and } I > 0 \]
\[ I(K, \Omega, \varepsilon; A) = \tilde{I}(K, \Omega, \varepsilon; A) \text{ if } \varepsilon > \varepsilon^- \text{ and } I < 0 \]
\[ I(K, \Omega, \varepsilon; A) = 0 \text{ if } \varepsilon \geq \varepsilon^+ \text{ and } \varepsilon \leq \varepsilon^- \]

Let \( \sigma \) denote the standard deviation of \( \varepsilon \), and let \( \phi \) and \( \Phi \) denote the PDF and CDF of \( \varepsilon \), which we assume to be normally distributed. We can compute the probability of observing zero investment as
\[ \text{Prob}(0) = \Phi\left( \frac{\varepsilon^-}{\sigma} \right) - \Phi\left( \frac{\varepsilon^+}{\sigma} \right) \]  

We may write the value function as
\[ \tilde{V}(K, \Omega; A) = E_\varepsilon \left\{ \begin{array}{l}
(1 - \text{Prob}(0)) \left[ \pi(K, \Omega) - \left( \frac{\phi \varepsilon}{2\sigma} + \left( p^-\{\tilde{I} < 0\} + p^+\{\tilde{I} > 0\} + \varepsilon \right) \tilde{I} \right) \right] + \text{Prob}(0) \left[ \pi(K, \Omega) + \beta E[\tilde{V}((1 - \delta)K + \tilde{I}, \Omega'; A)|K, \Omega] \right]
\end{array} \right\} \]

The right hand side of equation (13) contains two terms. The first term is the expected reward plus value tomorrow, conditional on investing, times the probability that the firm invests. The second bracketed term is the value of not investing, times the probability of not investing.

We now propose a computational recipe to solve for the unknown coefficient vector \( A \). We first pick a grid in \( K, \Omega \). We then choose \( A \) to make sure that the fixed point holds exactly at these grid points. Approximation methods using Chebyshev polynomials imply that efficient grid points are the zeros of the Chebyshev polynomial \( X(K, \Omega) \). Let \( n \) denote the size of grid. We consider starting at some initial guess \( A_i \). For each value of \( \{K_i, \Omega_i\} \) in the grid space, we must compute the right-hand side of equation (13) by taking expectations over both \( \varepsilon \) and \( \Omega' \). To compute expectations, we rely on quadrature methods. Specifically, we choose a grid of investment rates points \( \{I_j\}, j = 1..m_j \) (to compute the exact \( \varepsilon_{ij} \) that justify a particular \( I_j \)) and a set of quadrature points and weights \( \{\nu_k, \omega_k^+\} \) where \( k = 1..m_k \) to approximate the integrals with respect to \( \nu_i = \Omega' - E(\Omega'|\Omega_i) \).
To compute the right hand side of (13), for each value \( \{K_i, \Omega_i\} i = 1..n \), we follow the following algorithm:

1. Pick a grid over \( I_j, j = 1..m_j \)
2. Solve for \( \varepsilon_{ij} (K_i, \Omega_i; I_j; A) \) in equation (8) directly for a given \( I_j \).
3. Determine the probability of investing \( I_j \) by computing \( \phi(\varepsilon_{ij} (K_i, \Omega_i; I_j; A) / \sigma) \).
4. Solve for cutoffs \( \varepsilon^- (I_j, K_i, \Omega_i; A) \) and \( \varepsilon^+ (I_j, K_i, \Omega_i; A) \) that set equation (9) to equality. Then, compute the probability of zero investment as \( \text{Prob}(0)_i = \Phi(\varepsilon^- / \sigma) - \Phi(\varepsilon^+ / \sigma) \).
5. Use \( [I_j, \varepsilon_{ij} (K_i, \Omega_i, I_j; A), \varepsilon^- (I_j, K_i, \Omega_i; A), \varepsilon^+ (I_j, K_i, \Omega_i; A)] \) to compute the right hand side of (13). Here, we compute the term inside the brackets for each combination of \( (K_i, \Omega_i, \varepsilon_{ij}) \).

We denote this term as \( y_{ij} \):

\[
y_{ij} = (1 - \text{Prob}(0)_i) \left[ \frac{\pi(K_i, \Omega_i) - (p^- \{I_j < 0\} + p^+ \{I_j > 0\} + \varepsilon_{ij})I_j - \frac{\phi I^2}{\sigma K_i}}{\pi(K_i, \Omega_i) + \beta E[\tilde{V}((1 - \delta)K_i + I_j, \Omega'; A)|K_i, \Omega_i]} \right] + \text{Prob}(0)_i \left[ \frac{\pi(K_i, \Omega_i) + \beta E[\tilde{V}((1 - \delta)K_i, \Omega'; A)|K_i, \Omega_i]}{\pi(K_i, \Omega_i)} \right]
\]

Again, terms such as \( E[\tilde{V}((1 - \delta)K_i + I_j, \Omega'; A)|K_i, \Omega_i] \) are computed by integrating over \( \Omega_i' \) using the quadrature points and weights \( \{\nu_k, \omega_k^{\Omega}\} \ k = 1..m_k \). As a result, we approximate the right-hand side of (13) as:

\[
y(K_i, \Omega_i; A) = \sum_{j=1}^{m_j} \phi \left( \frac{\varepsilon_{ij}}{\sigma} \right) y_{ij}(K_i, \Omega_i; A).
\]

Our fixed point problem is then to find a coefficient matrix \( A \) that satisfies

\[
\tilde{V}(K_i, \Omega_i; A) = y(K_i, \Omega_i; A) \text{ for } i = 1..n
\]

Let \( y(K, \Omega; A) \) denote the \( n \times 1 \) vector with \( i \)th element \( y(K_i, \Omega_i; A) \). Let \( X(K, \Omega) \) denote the matrix of Chebyshev polynomials of \( K, \Omega \). This can be done using the least squares updating rule. Given a guess \( A_s \), we update according to:

\[
X(K, \Omega)A_{s+1} = y(K, \Omega; A_s).
\]

---

3We pick a grid over \( I_j \) and solve for \( \varepsilon_{ij} \) instead of choosing a set of quadrature points and weights \( \{\varepsilon_j, \omega_j\} \), \( j = 1..m_j \) and then solve for \( \hat{I}_{ij} = I(K_i, \Omega_i, \varepsilon_j; A) \) for a given \( \varepsilon_j \) to avoid solving a numerical problem in equation (8).
4 Application: metal industry

4.1 Empirical evidence for the metal industry

We choose the metal industry, one of the largest industries in the Chilean manufacturing sector, to show the results of our MLE procedure. The metal industry accounts for 7% of total value added for the manufacturing sector over the period 1979-2000; and utilizes approximately 8% of total employment and capital stock over the same time interval. Given that our panel is unbalanced, we only consider plants that appear in the sample at least 10 years of the 22-year period for which we have information. We also drop observations if the plant reports zero investment for 10 consecutive years or more. Our sample for the metal industry contains 2,207 observations across plants and years. Table 5 reports descriptive statistics.

<table>
<thead>
<tr>
<th>Table 5: Descriptive statistics for industry 381</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inaction rate</td>
</tr>
<tr>
<td>Frequency I/K&lt;0</td>
</tr>
<tr>
<td>Median investment rate if positive</td>
</tr>
<tr>
<td>In 1980 thousand pesos:</td>
</tr>
<tr>
<td>Median capital stock</td>
</tr>
<tr>
<td>Min-max capital stock</td>
</tr>
<tr>
<td>Median value added</td>
</tr>
<tr>
<td>Min-max value added</td>
</tr>
</tbody>
</table>

The inaction rate of investment is 31%, close to the one reported for the entire manufacturing sector. The median investment rate is 8.4% and there is large heterogeneity as reported by the minimum and maximum values for capital stock and value added. To perform our estimation procedure, we remove the fixed effect component of the data by normalizing the variables by their plant-specific mean. More details regarding the transformation of the variables are given in the next section.

4.2 Input to our MLE procedure: returns to scale and productivity estimates

We are primarily concerned with modeling investment and productivity at the plant level in an econometric environment that accounts for the high fraction of zeros, as well as the irreversibility and indivisibility (lumpiness) suggested by the plant-level data. Our structural econometric model is designed to measure the parameters that govern investment decisions by firms. Given structural disturbances, our model, provides a full characterization of when firms invest and how much they invest.
Inputs into our model are returns to scale and productivity realizations for individual firms. In principal, one can estimate production function parameters jointly with the investment decision, within our MLE framework. We currently follow a different approach however. We estimate directly from the data the curvature of the profit function and the productivity measure at the plant level by ordinary least squares (OLS).

Let $L_{it}$ be the amount of labor used, and $K_{it}$ be the amount of capital at the beginning of period $t$. We assume the following Cobb-Douglas production function:

$$y = A_{it}K_{it}^{\beta_k}L_{it}^{\beta_l}$$

Also, we assume the producer has market power and faces an isoelastic demand curve given by:

$$p = y_{it}^{-\eta}$$

The maximization of profits with respect to the variable input, $L$, leads to the following reduced form profit equation:

$$\Pi_{it}(\Omega_{it}, K_{it}) = \Omega_{it}K_{it}^\alpha$$

$$\alpha = \frac{\beta_k(\eta - 1)}{\beta_l(1 - \eta) - 1}$$

where $\Omega_{it}$ captures productivity (including labor costs) and $\alpha$ measures the curvature of the profit function. We normalize the data by the plant fixed effect and take logs to obtain:

$$\tilde{\pi}_{it} = \log(\Pi_{it}) - \log(\Pi_i) = \log \left( \frac{\Omega_{it}}{\Omega_i} \right) + \alpha \log \left( \frac{K_{it}}{K_i} \right) = \tilde{\omega}_{it} + \alpha \tilde{k}_{it}$$

where $\Omega_i$ is the within-plant mean of $\Omega_{it}$ for $X_{it}=\{\Pi_{it}, \Omega_{it}, K_{it}\}$. Since $\Omega_{it}$ is unknown, we estimate $\alpha$ from an OLS regression of $\tilde{\pi}_{it}$ on $\tilde{k}_{it}$.

Once we have $\hat{\alpha}$, we can compute $\tilde{\omega}_{it}$ using equation (14). We obtain the estimated value of $\tilde{\omega}_{it}$ as $\tilde{\omega}_{it} = \tilde{\pi}_{it} - \hat{\alpha}\tilde{k}_{it}$.

The last parameter we need for our model is the persistence in technology ($\rho$). To estimate it we assume an AR(1) process for $\tilde{\omega}_{it}$ given by:

$$\tilde{\omega}_{it} = \rho \tilde{\omega}_{it-1} + \nu_{it}$$

The estimated parameters $\hat{\alpha}$, $\hat{\rho}$, and $\hat{\sigma}_\nu$ (the standard deviation of the technology shock) are reported in Table 6.

---

4 Instead of using the log value of profits, we use the log of value-added, given the relation:

$$\Pi_{it} = \{1 - \beta_l(1 - \eta)\} VA_{it}$$
Table 6: Estimated parameters for industry 381

<table>
<thead>
<tr>
<th>Estimated parameter</th>
<th>$\hat{\alpha}$</th>
<th>$\hat{\rho}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Std. Err.</td>
<td>0.036</td>
<td>0.015</td>
</tr>
<tr>
<td>$\hat{\sigma}_\nu$</td>
<td>0.40</td>
<td></td>
</tr>
<tr>
<td>Adj. R²</td>
<td>0.12</td>
<td>0.53</td>
</tr>
<tr>
<td>n. obs.</td>
<td>2,207</td>
<td>2,030</td>
</tr>
</tbody>
</table>

Before performing our MLE procedure, we report preliminary estimates of a reduced form probit equation characterizing the zero-one decision of whether to invest or not. These results are reported in Table 7. The explanatory variables are the log-level and log-difference in our plant-specific productivity measure $\tilde{\omega}_{it}$, the log of the capital stock (which captures a firm size effect), and past investment measured both as the zero-one investment decision last period, and the rate of investment ($I_{it-1}/K_{it-1}$).

Table 7: Probit estimation

<table>
<thead>
<tr>
<th>Dummy for $I_{it}/K_{it}&gt;0$</th>
<th>dy/dx</th>
<th>Std. Err.</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\tilde{\omega}_{it-1}$</td>
<td>0.076</td>
<td>0.022</td>
</tr>
<tr>
<td>$\Delta \tilde{\omega}_{it}$</td>
<td>0.128</td>
<td>0.030</td>
</tr>
<tr>
<td>$\tilde{K}_{it-1}$</td>
<td>0.030</td>
<td>0.037</td>
</tr>
<tr>
<td>$I_{it-1}/K_{it-1}&gt;0$</td>
<td>0.286</td>
<td>0.033</td>
</tr>
<tr>
<td>$I_{i,t-1}/K_{i,t-1}$</td>
<td>0.044</td>
<td>0.063</td>
</tr>
</tbody>
</table>

The reduced form results in Table 7 imply that the plant-specific productivity estimate $\tilde{\omega}_{it}$ is an important determinant of the decision to invest. The parameter estimates suggest that both current and last year’s productivity have a positive impact on the decision to invest. The size effect, measured by the coefficient on the log of the capital stock, is not significant however. Finally, having invested last period is a strong predictor of whether or not a plant invests this period. The marginal increase in the probability of investment is 29%. This finding runs counter to the evidence on investment lumpiness documented by Cooper, Haltiwanger and Power (1999) which suggests that investment episodes are likely to be negatively rather than positively correlated. It is consistent with the notion that there are serially correlated benefits to extending episodes of positive investment over several years, either owing to systematic price movements or convex adjustment costs.
4.3 Estimation of the model

4.3.1 Identification

The intuition for how the parameters are identified is fairly straightforward. We normalize the value of \( p^+ \) to one and estimate directly from the data the curvature of the profit function \( \alpha \) and productivity realizations for individuals firms (see section 4.1). So, the parameters to estimate within our MLE procedure are the sale price of capital \( p^- \) (measured relative to \( p^+ \)), the convex adjustment cost parameter, \( \phi \), and the standard deviation of the cost shock \( \sigma_\varepsilon \). These parameters are identified by the level and variance of investment (conditional on the level and variance of the productivity disturbance). The difference between \( p^+ \) and \( p^- \) moderate the frequency of zeros and negative investment we observe in the data.

4.3.2 MLE results

The goal of the estimation is to find the set of structural parameters which maximizes the likelihood that the investment model generates the actual observations from the data. The set of structural parameters to be estimated is \( \{p^-, \phi, \sigma_\varepsilon \} \). The maximization of the log-likelihood function \( L_{nT}(\psi) \) in equation (6) is performed in two steps. First, we do an extensive grid search over the three parameters to be estimated and select the parameter values that maximizes \( L_{nT}(\psi) \). Then, we take this parameter configuration as the vector of starting values for the actual optimization routine. The non-linear optimization procedure of maximizing \( L_{nT}(\psi) \) is then performed by using the MATLAB routine \textit{fminsearch}. We perform this two-step estimation procedure to make sure that a global maximum is attained. Table 8 presents the estimated parameters as well as the standard errors.

<table>
<thead>
<tr>
<th>Structural parameters</th>
<th>Industry 381</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficient</td>
</tr>
<tr>
<td>\textit{Sale price of capital (relative to p\textsuperscript{+})}</td>
<td>( p^- )</td>
</tr>
<tr>
<td>\textit{Convex adjustment cost parameter}</td>
<td>( \phi )</td>
</tr>
<tr>
<td>\textit{Standard deviation of the cost shock}</td>
<td>( \sigma_\varepsilon )</td>
</tr>
<tr>
<td>n. obs.</td>
<td></td>
</tr>
<tr>
<td>Log-Likelihood</td>
<td></td>
</tr>
</tbody>
</table>

Table 8: MLE results
Overall, the structural parameters are precisely estimated. The small standard errors give information about the curvature of the log-likelihood function at the point estimates and the potential errors in achieving a global maximum. Figure 4 plots the log-likelihood for different combinations of \( \sigma_\varepsilon \) and \( p^- \) for a value of \( \phi \) equal to zero.

![Figure 4: Log-likelihood for \( \sigma_\varepsilon \) and \( p^- \) (at \( \phi^* = 0 \))](image)

The estimate for \( \phi \) is almost zero which is low compared with estimates from previous literature. The standard approach used in the literature is to assume that the profit function is linear in \( K \) and the cost of adjustment is convex and homogeneous of degree one. In this framework, \( \phi \) is estimated from a regression of the investment rate on the average value of the firm (average Q). The estimates of \( \phi \) under these assumptions range from 20 to 3 (Hayashi 1982, Gilchrist and Himmelberg 1995). Yet, when there is curvature in the profit function, as in our case (\( \hat{\alpha} = 0.62 \)), the values mentioned above about the magnitude of the convex adjustment cost parameter may not be valid. In fact, Cooper and Haltiwanger (2000) and Cooper and Ejarque (2001) report significantly lower estimates for \( \phi \) in a range between 0.15 and 2.1, in a model that introduces market power and convex and non-convex adjustment costs. They consider different specifications that include all or some of the following components: convex, non-convex adjustment costs, and irreversible investment. When all components are considered, their estimate of \( \phi \) is close to 2. When the fixed cost component is not considered, their estimate of \( \phi \) decreases to a value close to 0.2. Given that our specification

---

5 The standard errors of the parameters are computed as the square root of the main diagonal elements of the outer product of gradients estimator (OPG estimator) obtained by numerical differentiation of \( L(\psi) \) around the optimal parameters values with a step-size factor for computation of the gradient equal to \( 10^{-6} \). More details in Greene, “Econometric Analysis”, 5th edition, page 481.
for adjustment costs does not include fixed costs, our low estimate of $\phi$ may be explained by the presence of investment spikes in the data that are not completely captured by our combination of convex adjustment costs, irreversible investment and idiosyncratic cost shocks.

The second parameter of interest is the sale price of capital $p^-$. The estimated $p^-$ is 0.37 which is consistent with the high proportion of zero investment and low frequency of negative investment found in the data. In particular, Cooper and Haltiwanger (2000) estimate a value of $p^-$ equal to 0.84 for a balanced panel of U.S. manufacturing plants over the period 1972-1988. The degree of investment irreversibility in their dataset—inaction rate of 8% and frequency of negative investment of 10%—is considerably lower compared with our sample of Chilean plants. Our results are therefore consistent with having a higher inaction rate and lower occurrence of negative investment in our data when compared with U.S. plants.

Finally, our estimate of the standard deviation of the price shock, $\sigma_\varepsilon$, is 0.33 which is in line with the variance of the productivity disturbance and investment in the data.

### 4.3.3 Evaluation: model simulations

We now consider a numerical example for our solution routine. We use the estimated values of the parameters of the model to illustrate the flexibility of the solution, and its ability to reproduce key features of the data, such as the zeros in investment. Accordingly, we set the curvature of the profit function at $\alpha = 0.62$. We assume that $\Omega$ follows an AR(1) in logs, with autocorrelation of 0.72 and that the standard deviation for the log of $\Omega$ is 0.4. Finally, consistent with the estimation results in the previous section, we set $\phi = 0$, $p^- = 0.37$ and $\sigma_\varepsilon = 0.33$.

Figures 5 through 7 illustrate the characteristics of the solution. Figure 5 plots the value function, $\tilde{V}(K, \Omega)$, assuming that the cost shock ($\varepsilon_{it}$) is zero. Figure 6 plots the investment policy function.
The value function is concave in capital and increasing in $\Omega$ as we would expect. The investment policy exhibits smooth continuous episodes combined with periods of inaction. Conditional on the capital stock, the plant’s investment rate is monotonically increasing in $\Omega$. Also, as expected, the investment rate is decreasing in $K$. As $K$ rises above some cutoff value, the plant stops investing. As $\Omega$ increases, the point of zero investment occurs at higher values of $K$.

Figure 7 plots the probability of having positive investment. The probability of observing
positive investment is decreasing in $K$. Also, for a given $K$ the probability of positive investment increases for higher values of $\Omega$.

![Figure 7: Probability of positive investment as a function of K, omega](image)

Finally, we report a set of moments obtained from a stochastic simulation over 2000 periods. We also report similar moments for the metal industry. The results of Table 9 indicate that the model does relatively well at reproducing certain aspects of the data.

<table>
<thead>
<tr>
<th></th>
<th>Data</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inaction rate: $\text{Prob}(I=0)$</td>
<td>0.31</td>
<td>0.37</td>
</tr>
<tr>
<td>Frequency positive investment ($I/K&gt;0$)</td>
<td>0.63</td>
<td>0.63</td>
</tr>
<tr>
<td>Investment spike: $I/K&gt;0.2$</td>
<td>0.16</td>
<td>0.07</td>
</tr>
<tr>
<td>$\sigma_{I/K}$</td>
<td>0.23</td>
<td>0.08</td>
</tr>
<tr>
<td>$\sigma_{\log\Omega}$</td>
<td>0.60</td>
<td>0.56</td>
</tr>
<tr>
<td>$\sigma_{\log K}$</td>
<td>0.36</td>
<td>0.14</td>
</tr>
<tr>
<td>$\rho_{I/K}$</td>
<td>0.22</td>
<td>0.03</td>
</tr>
<tr>
<td>$\rho_{\log\Omega}$</td>
<td>0.72</td>
<td>0.72</td>
</tr>
<tr>
<td>$\text{cor}(I/K,\log(\Omega))$</td>
<td>0.22</td>
<td>0.44</td>
</tr>
</tbody>
</table>

The frequency of positive investment is the same as in the data. Interestingly, the estimation of the model implies complete irreversibility while in the data the frequency of negative investment
is low but positive (5.8%). We can see this in more detail in Figure 8 and Table 10. In Figure 8 we plot the log-likelihood as a function of the sale price of capital, and Table 10 presents the implied frequency of negative investment obtained from simulated data for different values of $p^-$. In particular, any sale price of capital below 0.7 implies complete irreversibility. The value of $p^-$ (0.37) that maximizes \( L_nT(\psi) \) is in the range of complete irreversibility. In this sense, the model is able to match the frequency of positive investment observed in the data but not the frequency of negative investment.

The model also reproduces the positive correlation of investment and productivity, even though the correlation in the model is twice the correlation observed in the data (see Table 9). This is potentially given by the fact that the model is able to replicate half of the probability of observing a positive investment spike, and hence the correlation between investment and profitability is higher in the model than in the data.

<table>
<thead>
<tr>
<th>$p$</th>
<th>$I/K&gt;0$</th>
<th>$I/K=0$</th>
<th>$I/K&lt;0$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.00</td>
<td>0.824</td>
<td>0.000</td>
<td>0.177</td>
</tr>
<tr>
<td>0.95</td>
<td>0.794</td>
<td>0.161</td>
<td>0.046</td>
</tr>
<tr>
<td>0.90</td>
<td>0.758</td>
<td>0.228</td>
<td>0.015</td>
</tr>
<tr>
<td>0.85</td>
<td>0.755</td>
<td>0.243</td>
<td>0.002</td>
</tr>
<tr>
<td>0.80</td>
<td>0.732</td>
<td>0.267</td>
<td>0.001</td>
</tr>
<tr>
<td>0.70</td>
<td>0.691</td>
<td>0.309</td>
<td>0.000</td>
</tr>
<tr>
<td>0.60</td>
<td>0.660</td>
<td>0.340</td>
<td>0.000</td>
</tr>
<tr>
<td>0.50</td>
<td>0.642</td>
<td>0.358</td>
<td>0.000</td>
</tr>
<tr>
<td><strong>0.37</strong></td>
<td><strong>0.630</strong></td>
<td><strong>0.370</strong></td>
<td><strong>0.000</strong></td>
</tr>
<tr>
<td>0.30</td>
<td>0.614</td>
<td>0.388</td>
<td>0.000</td>
</tr>
<tr>
<td>0.20</td>
<td>0.583</td>
<td>0.418</td>
<td>0.000</td>
</tr>
<tr>
<td>0.00</td>
<td>0.559</td>
<td>0.442</td>
<td>0.000</td>
</tr>
</tbody>
</table>
5 Conclusions

This paper extends the current literature and estimates a fully-structural model of investment for an emerging market economy. We characterize the nature of the investment process for a panel of Chilean manufacturing plants over the period 1979-2000. In particular, we find that Chilean plants are much more likely to have periods of inaction (zero investment) than their U.S. counterparts. Owing to illiquid second hand markets and a smaller size distribution of firms, such non-convexities are a prevalent feature of plant-level investment in developing economies.

Our research makes a methodological contribution by estimating a fully specified structural model of plant-level investment using maximum likelihood techniques. We allow for both convex costs of adjustment and partial irreversibility by introducing a wedge between the purchase price and sale price of capital. In this framework, we characterize both the decision of when to invest and how much to invest as functions of underlying observable state variables such as the current capital stock and current productivity parameter that governs plant-level profitability. We solve the model using smooth value function techniques which allows us to easily characterize the likelihood function. The results imply that our model is able to capture key features of the Chilean investment data.
for which irreversibility plays an important role in determining plant-level investment dynamics.
References


[31] Liu, Lili and James Tybout (1996) “Productivity Growth in Chile and Colombia: The role of entry, exit and learning” in M. Roberts and J. Tybout eds., Industrial Evolution in Developing Countries, Oxford University Press.


