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# INVESTMENT SPIKES: NEW FACTS AND A GENERAL EQUILIBRIUM EXPLORATION

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Investment Spikes: New Facts and a General Equilibrium Exploration
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**ABSTRACT**

Using plant-level data from Chile and the U.S. we show that investment spikes are highly pro-cyclical, so much so that changes in the number of establishments undergoing investment spikes (the "extensive margin") account for the bulk of variation in aggregate investment. The number of establishments undergoing investment spikes also has independent predictive power for aggregate investment, even controlling for past investment and sales. We re-calibrate the Thomas (2002) model (that includes fixed costs of investing) so that it assigns a prominent role to extensive adjustment. The recalibrated model has different properties than the standard RBC model for some shocks.

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## 1. Introduction

Economists are sharply divided over the aggregate significance of the heterogeneity of plant-level investment. On the one hand, there is unanimous agreement that individual plants sometimes forgo investing at all and at other times have dramatic surges in investment.[1] Caballero (1999), in his survey for the Handbook of Macroeconomics, argues that accounting for this "lumpiness" is critical: "it turns out the changes in the degree of coordination of lumpy actions play an important role in shaping the dynamic behavior of aggregate investment." On the other hand, Thomas (2002) presents a model where this is not true: "in contrast to previous partial equilibrium analyses, [the] model results reveal that the aggregate effects of lumpy investment are negligible. In general equilibrium, households' preference for relatively smooth consumption profiles offsets changes in aggregate investment demand implied by the introduction of lumpy plant-level investment." This "irrelevance result" inspired Prescott (2003) to argue "partial equilibrium reasoning to an inherently general equilibrium question cannot be trusted."

In this paper, we make three contributions to this debate. First, we introduce several new facts about surges in investment (that we call spikes). In particular, we show that for both U.S. and Chilean plants, most of the variation in the total investment rate is due to variation in investment of firms undergoing spikes. Moreover, this approximation derives its explanatory power from changes in the number of firms making large investments (the "extensive margin"), and not changes in the average size of the spikes (the "intensive margin"). We also find that information on prevalence of spikes in one year has predictive power for forecasting aggregate investment (even controlling for the past level of investment or sales): years with relatively more spikes are followed by years with relatively less investment.

We then try to construct a model that not only generates spikes on average, but also *variation* in spikes over the business cycle. To do this we start with the Thomas (2002) model, which is a tractable dynamic stochastic general equilibrium (DSGE) model that naturally yields lumpy investment. The heterogeneity in this model derives from variation in the fixed costs that firms must pay in order to invest. We find that the exact model, as originally calibrated, has trouble fitting the facts about cyclical patterns in lumpiness. But by changing the calibration we can match better these facts.

While we make several changes, the critical one is to alter the distribution of fixed costs that firms face. In order for the extensive margin to matter, this distribution must have the property that many firms face roughly the same sized fixed cost in deciding whether to invest. When the distribution has this type of compression, it becomes possible for a shock to move many firms across the threshold from not investing to investing. Conversely, if the distribution exhibits little compression, then firms become much less likely to synchronize their decisions and the extensive margin matters less. Importantly, even if part of the distribution is "compressed" there can still be substantial heterogeneity in the overall distribution and hence in the level of fixed costs that firms pay to adjust.

[1] See among others Becker et al. (2006), Caballero, Engel and Haltiwanger (1995), Cooper, Haltiwanger and Power (2000), Cooper and Haltiwanger (2006), Doms and Dunne (1998).

The third contribution is to explore the aggregate response of investment to various shocks when extensive adjustment is important. The Thomas model, as originally calibrated, implies that the fixed costs which generate spikes are essentially "irrelevant" for aggregate dynamics. In particular, the aggregate dynamics (summarized for example by the impulse response of investment to a productivity shock) are the same as the standard real business cycle (RBC) model, which has no adjustment costs of any kind. In our calibration, the qualitative response of investment to a productivity shock is somewhat different from the standard RBC model. More importantly, we find that the original Thomas model and the RBC model also exhibit virtually identical response when the distribution of firms capital levels move away from the steady-state distribution (for instance, as might occur if a temporary tax change leads firms to accelerate investment spending). In contrast, under our calibration, aggregate investment behaves differently than it would in the RBC model. Hence for this kind of shock the fixed cost seems to matter substantially.

We conclude, therefore, that although general equilibrium attenuates the differences between the fixed cost model and the RBC model, it does not eliminate these differences. In other words, the irrelevance result is not a generic finding that comes from the general equilibrium, but rather a result that depends on the details of how the model is calibrated, especially regarding the production side.

The remainder of the paper is organized into three sections. The first documents the aforementioned empirical regularities. Next we review the Thomas model and explain our calibration. We then explore the predictions of the re-calibrated model regarding the sensitivity to various disturbances. We close with a brief summary.

## 2. Empirical Evidence on Lumpiness over the Business Cycle

To analyze lumpiness we study two establishment-level data sets covering manufacturing plants in Chile and the U.S. Capital stocks are constructed through a perpetual inventory method; importantly, we do not have access to the underlying micro data for the U.S. Census, but instead have tabulations that group plants according to their current investment rates. A brief description of the data construction is given in Appendix 1. We start by reviewing three measurement issues before reporting our main results.

The first issue is how to handle very small rates of investment, for example where investment is not exactly zero, but less than one or two percent of capital. If fixed costs of investing are present, then we would expect to find few cases of this sort. Yet, it appears empirically many plants report making these tiny investments. We suspect that these cases represent some sort of maintenance or replacement investment (for which the fixed cost presumably does not apply). So in what follows, we will typically aggregate the plants with near zero investment with those that report exactly zero investment.

On the other side, there is no clear definition of what constitutes an investment spike. The papers by Cooper, Haltiwanger and Power (1999), Cooper and Haltiwanger (2005), and Becker et al (2006) all define spikes to be cases where investment relative to the beginning of period capital is greater than 20 percent. To maintain comparability with these papers we use this threshold as a primary definition. But the results for the case where we set the threshold to be 35 percent are very similar.

The last conceptual issue that arises relates to aggregation. To summarize the distribution of firms or establishments we must take a stand on whether each observation will be equally weighted or weighed by some other characteristic such as the plant's capital. We see equal-weighting as problematic (or at least inferior to capital-weighting) for several reasons.

First, at a sufficiently fine level of aggregation every decision is lumpy; no one disputes that integer constraints and the like are relevant for truly tiny firms.[2] Conversely for the entire economy there are never any zeros and spikes are rare. So as firm sizes vary, so will all measures of lumpiness. This means that as the size distribution of firms in a sample changes, either because of changes in the underlying population or because of changes in the sample coverage, the statistics on zeros and spikes will change. We would like our measurement to reflect more than just the mechanical effects that derive from the composition of the sample.

Conversely, one way to partially offset the attenuation of the zeros and spikes that results from aggregation is to weight the data based on firm size. Loosely speaking by giving firms with large capital stocks more weight when they report a zero or a spike we make up for the zeros or spikes that might be occurring within some of these organizations that are otherwise obscured. As a bonus, a capital-weighted average of investment rates delivers a measure that equals the aggregate investment in the sample divided by the total capital in the sample.

A final consideration comes from our specific interest in the general equilibrium effects of lumpiness. Intuitively we expect general equilibrium effects that operate through prices to depend on aggregate indicators of lumpiness. This suggests another potential reason that actions of larger firms (or establishments) are more important than smaller firms. For all these reasons we will emphasize our findings that pertain to the capital-weighted data.

Figures 1 and 2 show the effects of varying the definitions of spikes and zeros, and of changing the aggregation schemes. In each figure we report four panels; the two panels on the left show the time series patterns for the prevalence of zero (dashed lines) and near zero investment (defined to include establishments with I/K less than two percent). The bottom panel shows the data when the observations are aggregated according to the capital stock for each establishment, while the top panel treats all plants identically. The right hand panels graph spikes, with the solid lines showing the percentages based on I/K

[2] The model that we introduce below, like most models, abstracts from differences in size. So even if we wanted to account for this effect it would be difficult.

greater than 20 percent and the dashed lines showing the 35 percent spikes; again the top and bottom differ based on the weighing scheme. Figure 1 gives the results for the U.S. data, while Figure 2 shows the data for our Chilean sample.

For both the U.S. and Chilean samples it is clear that many establishments are not investing in any given year, whereas at the same time there are other establishments where investment is spiking. The full distribution of the investment rates for each sample is shown in Table 1. Fuentes, Gilchrist and Rysman (2006) stress the fact that emerging markets such as Chile tend to have more plants that are not investing than in developed economies such as the U.S. Comparing the dashed lines in the upper left panel in each figure shows that the (unweighted) percentage of establishments with exactly zero investment is two to three times higher in the Chilean sample.

The figures also show that the level of zeros is sensitive to the weighting schemes used. As would be expected, fewer large firms report literally zero investment, so the reported percentages of zeros drops precipitously in the capital-weighted figures compared to the equally-weighted figures. The capital weighting makes less of a difference for level estimates for the near zeros and even less difference for the spikes.[3] For the rest of this section, we concentrate on capital weighted series.

The figures show that regardless of the weighting scheme that is used, the 20 and 35 percent thresholds for spikes are extremely highly correlated. For example, the correlation between the capital weighted series for U.S. spikes of 20 percent and 35 percent (the lower right panel in Figure 1) is 0.95. For the remainder of the section, we concentrate on the 20 percent spikes.

One final noteworthy feature of Figures 1 and 2 is that several of the lumpiness proxies show trends; below when we look at the aggregate investment rates we will also find trends for those series too. These low frequency changes are outside of the scope of our investigation and in most of our analysis we will remove them by regressing the series on a linear time trend (although using a Hodrick-Prescott filter delivers very similar results for all of our findings).

The general facts that we have mentioned thus far about the prevalence of zeros and spikes have been documented in a number of other studies. Some of these studies also describe the cyclicality of the lumpiness. Figure 3 shows the (de-trended) capital weighted shares of establishments with either spikes or with near zeros, along with the (de-trended) aggregate investment rate for each sample; the aggregate rate is calculated by taking the capital weighted average of the establishment level rates and we denote this as Itot/K. (The weighting scheme also means that Itot/K is the ratio of aggregate investment to aggregate capital in our sample.)

[3] The pairwise correlations for the weighted and capital weighted series for Chile (US) are as follows: exact zeros = 0.82 (0.60), near zeros = 0.94 (0.23), 20 percent spikes = 0.92 (0.90), and 35 percent spikes = 0.90 (0.87).

In each country, the spikes are strongly pro-cyclical and near-zeros are strongly counter-cyclical. The correlation between the capital-weighted spikes and the aggregate investment rate (both detrended) is 0.87 for the US sample and 0.96 for the Chile sample; and the correlation between the capital-weighted near zeros and the aggregate investment rate (both detrended) is -0.94 for the U.S. sample and -0.56 for the Chilean sample. Thus, Figures 1, 2 and 3 show all the standard characteristics of plant-level investment.

In the remainder of this section we document several new facts regarding the connection between aggregate investment and investment spikes. In Figure 4, we decompose the aggregate investment rate into two parts. One part (shown by the lines with the circles) is the total investment done by those establishments where there is a spike (i.e. I/K > 20 percent), divided by the total stock of capital for all the firms in the sample; we label this series I20/K. The remainder of investment, that we dub I(0-20)/K, represents investment of plants with investment rates between 0 and 20 percent over total capital, and is shown in the line with inverted triangles.

The relative levels of I20/K and Itot/K indicate that the spikes account for about half of total investment in each country; in other words, I20/Itot is about 0.5. More importantly, the investment rate constructed for the spiking firms tracks the movements in the aggregate investment rate closely; the correlations between the de-trended series is 0.99 for each sample. Clearly, the bulk of the variation in the aggregate Itot/K is accounted for by changes in I20/K. The share of variance of Itot/K accounted to by I20/K (as opposed to the residual I(0-20)/K)) is 97 percent for the U.S. sample and 86 percent for the Chile sample.[4] The converse of these observations is that there is little variation in total investment explained by the firms investing between zero and 20 percent. Thus, for the purposes of modeling investment fluctuations it is critical to understand the timing of the investment spikes.[5]

To go further and understand how spikes matter for business cycles, we start from the following identity:

$$\frac{I20}{K} \equiv \frac{I20}{K20} \bullet \frac{K20}{K} \quad \equiv \quad IPA20 \bullet ADJ20 \qquad (1)$$

$$\rightarrow Log(\frac{I20}{K}) \equiv \quad \log(IPA20) + \log(ADJ20)$$

$$\text{where I20} \equiv \sum_{\frac{I_{i,t}}{K_{i,t-1}} > 0.20} I_{i,t}, \quad \text{K20} \equiv \sum_{\frac{I_{i,t}}{K_{i,t-1}} > 0.20} K_{i,t-1}, \quad \text{K} \equiv \sum_{\frac{I_{i,t}}{K_{i,t-1}} \geq 0} K_{i,t-1}$$

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[4] This is measured as Cov (I20/K,I/K) / Var (I/K). This calculation splits a covariance term and allocates its explanatory power equally between the two remaining terms. If instead we use an exact decomposition that preserves all three terms, for the U.S. the numbers are: Var(I20/K) / Var(I/K) = 0.964, Var( I(0-20)/K)) / Var(I/K)= 0.024 and 2Cov(I20/K, I(0-20)/K) / Var(I/K) = 0.012. For Chile, these numbers are Var(I20/K) / Var(I/K) = 0.759, Var( I(0-20)/K)) / Var(I/K)= 0.036 and 2Cov(I20/K, I(0-20)/K) / Var(I/K) = 0.205.

[5] This fact is also present, to a lesser degree, in Figure 8 of Cooper, Haltiwanger and Power (2000). The difference may be due to the fact that they use a balanced panel of rather large establishments. These authors also mention that spikes are procyclical but do not focus on this feature of the data.

In words, equation (1) simply says that the total investment done by the plants experiencing spikes can vary either because of a change in the investment per adjuster (IPA20, the intensive margin) or because of a change in the (capital-weighted) number of firms adjusting (ADJ20, the extensive margin). This approach is analogous to the one proposed by Klenow and Kryvstov (2005) for studying price dynamics, where they decompose inflation into changes in the number of firms resetting their prices and changes in the average size of price changes for those firms resetting their price.

Figure 5 shows a graph of Log(I20/K), along with Log(IPA20) and Log(ADJ20) (after each series has had a linear time trend removed) for the U.S. and Chilean samples. The striking conclusion is that the extensive margin, ADJ20, drives variation in spikes.

One way to conveniently summarize the information in the picture is to compute the following pair of statistics:

$$\text{ShareADJ20} \equiv \frac{\text{covariance}(\log(\text{ADJ20}),\log(\frac{\text{I20}}{\text{K}}))}{\text{variance}(\log(\frac{\text{I20}}{\text{K}}))} \text{ and ShareIPA20} \equiv \frac{\text{covariance}(\log(\text{IPA20}),\log(\frac{\text{I20}}{\text{K}}))}{\text{variance}(\log(\frac{\text{I20}}{\text{K}}))}$$

These shares by construction must sum to one. If the proportion of firms with spikes ADJ20 is constant, they would be zero and one, and if the average investment rate of firms with spikes is constant, they would be one and zero. For the U.S. sample ShareADJ20 is 0.87, while for the Chilean sample it is 0.925.[6] The dominant role of the extensive margin also appears when the threshold for identifying spikes is 35 percent instead of 20 percent. This fact also holds for different de-trending methods (e.g. the Hodrick-Prescott filter, or just considering growth rates).

Our last new fact about spikes is that they contain additional predictive content beyond just information that they convey about the past level of investment. The spirit of many models of lumpiness (e.g. Caballero and Engel (1999)) is that the cross-sectional distribution of firms' capital stock relative to the level that would prevail absent any adjustment costs should be an important determinant of aggregate investment. It is empirically difficult to construct this cross-sectional distribution, but there is a simple way to test for this possibility. We estimate regressions of the form:

$$\frac{Itot_t}{K_{t-1}} = \alpha + \beta Trend_t + \gamma \frac{Itot_{t-1}}{K_{t-2}} + \phi \frac{Sales_{t-1}}{\mathrm{K}_{t-2}} + \sum_{h=1}^{H} \omega_h ADJ20_{t-h} \qquad (2)$$

[6] Our decomposition splits a (small) covariance term equally between ShareADJ20 and ShareIPA20. If instead we use an exact three way decomposition, the results for the U.S. (Chile) are as follows: Var(logADJ20)/Var(logI20/K)= 0.850 (0.903), Var(logIPA20)/Var(logI20/K)= 0.114 (0.052) and Cov(logADJ20,logIPA20)/Var(logI20/K) = 0.036 (0.044).

So the novelty is that we add the (capital-weighted) share of adjusters to an otherwise standard accelerator type investment equation.[7] This type of accelerator style equation has repeatedly been shown to be an effective forecasting equation in horse-races of different specifications (Bernanke, Bohn and Reiss (1988) and Oliner, Rudebusch and Sichel (1995)).

Table 2 shows estimates of equation (2). The first six rows show the estimates for the U.S. data, while the last six rows show the estimates for the Chilean sample. For the U.S. data the lagged dependent variable is always estimated to have a positive and highly significant coefficient. The sales proxy is positively related to investment, but not always significant. Conversely in the Chilean sample the sales variable is always estimated to have a positive and very significant effect on investment, but the lagged dependent variable does not systematically influence investment.

Our main coefficients of interest are the ω's that measure the effects of past spikes on current investment. For the U.S. sample, the coefficients on both the first and second lags of ADJ20 are significant, whereas in the Chilean data, only the second lag is consistently significant.[8] Importantly, the estimated signs of the ω's are all *negative*, suggesting that investment is depressed in the period after an investment surge. This correlation is to be expected based on fixed costs models (and would be of the opposite sign if the past ADJ20 variable was standing in for productivity shocks or other factors that raise investment demand).

Taken literally, the coefficients suggest that the echoes from the spikes have a quantitatively important effect on investment. For the U.S. sample (Chile) the standard deviation of the spike variable is 0.046 (0.093), compared to the standard deviation of the investment rate of 0.017 (0.054). Taking the specifications where h=1, (shown in rows 5 and 11), the estimates for the U.S. (Chile) sample imply that a one standard deviation increase in ADJ20 predicts an increase of the investment rate of 0.7 (0.57) of a standard deviation.

Collectively, these new facts provide guidance about how to model lumpiness. Aggregate investment is largely driven by investment spikes; so a successful model should have the property that I20/Itot is substantial and that variations of I/K are accounted for by variation in I20/K. Moreover, the spikes matter because of adjustment along the extensive margin, i.e. a change in the number of firms making large investments; these spikes are sufficiently important that they have independent predictive power for aggregate investment, even controlling for past investment and sales. We now attempt to construct a model that has these properties, and we concentrate especially on matching the fact that ShareADJ20 is large.

## 3. A DSGE model with fixed costs of adjusting capital

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[7] For the U.S. sample, we have shipments data which correspond to sales for establishment data.

[8] When the spikes are measured with the 35 percent threshold then both lags one and two are significant in both samples.

We first review the Thomas model and then discuss how we calibrate it.

### 3.1 A brief review of the Thomas model

Thomas (2002) offers an elegant and compact model for analyzing the importance of fixed costs of adjusting capital on aggregate investment in a dynamic, stochastic general equilibrium framework.[9]

The economy has a fixed number of plants (normalized to be of measure one). In what follows, we refer to these as "plants" or "firms" interchangeably. Each plant has the production function: $y = Ak^{\psi}n^{\upsilon}$, where y is output, A is aggregate productivity (TFP), k is capital, and n is labor. There are decreasing returns to scale so that $\psi + \upsilon < 1$ and there is no entry or exit.

In each period, each plant has the opportunity to adjust its factor usage. Labor can be freely varied, but adjusting capital can only be done if the firm pays a fixed cost. The fixed cost, $\xi$, is a random variable that is independently and identically distributed across time and plants and comes from the cumulative distribution G. This distribution has finite support and the maximum fixed cost is called B. The firms that choose to pay the fixed cost, which we call "adjusters", bear no marginal adjustment costs: they can buy or sell capital at price 1. The fixed cost is measured in units of labor. Owing to the fixed cost, firms will not always adjust capital.

Much of the model's tractability derives from its inherent symmetry that leads all firms choosing to invest at a given point to pick the same new level of capital, $k_{0,t+1}$; this is because there is no heterogeneity except in the fixed cost drawn today and the current capital. So firms are distinguished by the time since their last investment. Regardless of whether a firm invests, its capital depreciates at rate $\delta$. Therefore,

$$k_{0,t+1} = (1-\delta)k_{j,t} + i_{j,t} \text{ when } i_{j,t} > 0 \text{ and otherwise } k_{j+1,t+1} = (1-\delta)k_{j,t},$$

where $k_{j,t}$ is the capital of a plant of vintage j at time t, and $i_{j,t}$ is the investment of a plant of vintage j at time t, conditional on the plant deciding to pay the fixed cost.

A firm that last adjusted capital j periods ago, henceforth a vintage j firm, will operate with capital $k_j$ (and labor $n_j$). This implies the following maximization problem for a plant:

$$\max_{i_{jt}, n_{jt}} \mathbb{E}_0 \left( \sum_{t \geq 0} m_t (A_t k_{jt}^{\psi} n_{jt}^{\upsilon} - w_t n_{jt} - i_{jt} - \xi_t w_t 1_{i_{jt} \neq 0}) \right),$$

subject to the capital accumulation laws above, where $m_t$ is the stochastic discount factor (the ratio of marginal utilities in period t to period 0), and $w_t$ is the real wage.

[9] The setup is similar to the sticky price model of Dotsey, King and Wolman (1999).

The TFP process, $A_t$, evolves according a first-order autoregressive process around a deterministic trend:

$A_t = \Theta_A^t z_t$, $\log\ z_t = \rho \log z_{t-1} + \varepsilon_t$, $\varepsilon_t$ is distributed independently $N(o, \sigma^2)$.

The combination of the fixed depreciation rate and the finite upper bound on the fixed cost guarantees that all firms will eventually find it optimal to invest; in other words, this structure delivers a maximum vintage J by which time all firms will invest. The solution to the problem involves finding that maximum vintage (J), along with the capital stock for each of the intervening vintages ($k_j$), and the percentage of total firms in each vintage ($\theta_j$).

Thomas shows that firm's investment decisions follow a cutoff rule: in any given vintage, and in any period, there is a threshold fixed cost, such that firms which draw a fixed cost below the threshold will invest and upgrade their capital, and firms which draw a fixed cost above the threshold will let the capital depreciate. We call $\alpha_j$ the proportion of firms which are below the threshold (and so choose to adjust). In her simulations Thomas chooses a uniform distribution for the fixed costs, between 0 and B. The level of fixed costs B is chosen to match two facts reported by Doms and Dunne (1998): i) in the average year, 8 percent of plants raise their real capital stocks by 30 percent or more; ii) these plants account for 25 percent of aggregate investment.

The rest of the model is intentionally chosen to follow the real business cycle (RBC) literature. So, for instance, Thomas adopts a utility function with indivisible labor of the form $U_t = \log c_t - \zeta n_t$. Thus, aside from the fixed costs and the mild decreasing returns, the calibrated parameters, displayed in the second column of Table 3, are very standard.[10] Indeed, when the upper bound of fixed costs, B, is set to 0, all firms adjust their capital each period, and equate their marginal product of capital and labor; in this case, there is a representative firm, and the model collapses to a standard RBC model with decreasing return to scale.

This model is solved numerically by a standard log-linearization around the steady-state. First, one finds the optimal J, the maximum time-since-last-adjustment such that all firms want to invest. Second, one solves the system of non-linear equations that define the non-stochastic steady-state. Finally, one computes the log-linear approximation itself. The log-linear method is advantageous here since the state space of the model is large: it includes the TFP shock, and the cross-sectional distribution of capital (the $\theta_j$'s and the $k_j$'s). [11]

[10] Also, the model is calibrated to annual rather than quarterly data, because the plant-level evidence is based on annual surveys.

[11] For more details on the solution, we refer the reader to our separate technical appendix (available on http://people.bu.edu/fgourio).

### 3.2 Calibration of the Model

In the first three rows of Table 4 we report several statistics comparing the prominence of spikes in both of our samples and in the baseline model. Given that Thomas chose B to match the Doms-Dunne facts on spikes, it is not surprising that the model also matches the prevalence of spikes in our sample. In her original calibration of the model, however, spikes only account for about 62 percent of the total variance of investment and the extensive margin accounts for only 51 percent of the variance of spikes; in the data both these percentages are roughly 90 percent.

In Appendix 2, we describe several exercises that show how varying different parameters one at a time change the extensive-intensive decomposition. We focus on three key parameters in these experiments: the maximum size of fixed costs, B, the distribution of fixed costs, G, and the curvature of the production function ($\psi+\upsilon$). Intuitively one expects these parameters to be critical since B and G govern the costs of adjusting capital and the curvature governs the benefits (by determining the loss in profits that result from having an inefficient plant size).

The results in Appendix 2 suggest that the key determinant of this decomposition is the shape of the CDF. The intuition for this conclusion is that increasing the number of plants doing positive investment requires marginal plants to switch from inaction to action; this decision depends on the fixed costs for the indifferent plants. If marginally inactive plants face the same fixed cost as marginally active plants, increasing the number of plants investing is inexpensive. Hence, the marginal cost of changing the extensive margin depends on the shape of the CDF of fixed costs.

Thomas, following Caballero and Engel (1999), chooses G to be uniform. With this type of CDF (or any other that has a second derivative that is close to zero everywhere), increasing the number of plants investing requires activating plants that have substantial differences in the fixed costs they are facing. Put differently, for any particular level of fixed costs, even a marginal change in the number of investing plants always involves firms with relatively different levels of fixed costs. In this case it will be efficient to rely more on intensive adjustment. On the other hand, when the CDF is sufficiently "compressed", i.e. so that many firms face nearly-identical fixed costs, the opposite result obtains: increasing the number of plants investing need not be very costly. This means that the extensive margin can be important.

The compressed CDF that is considered in most of the experiments that follow is displayed in Figure 6. This particular CDF implies that the fixed costs for most firms bunch around B and B/2, but as we show below all of our results also obtain if there was bunching only around one level of fixed cost and there is considerable heterogeneity in the rest of the distribution.[12] Hence, what matters is the "compression" and not the lack of heterogeneity.

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[12] The formula for this CDF is G(x) = H(x/B) where B is the upper support and H is defined on the interval [0,1] as H(x) = (F(x)-F(0))/(F(1)-F(0)), with $F(x) = 1/(2*\pi)*(\arctan(\sigma_1*(x-1/2)) + \arctan(\sigma_2*(x-1)))$. This

Before turning to the results, we note one other observation regarding the original Thomas calibration. As reported in the fourth column of Table 4, total expenditure due to adjustment costs is roughly 1/5 of one percent of total investment spending. This cost seems small on an anecdotal basis, if we think of the costs of the planning, budgeting, and committee work that accompany most investments. There are also obvious cases when adjustment costs are much larger: think of the re-tooling of a factory, or the temporary closure of a retail store to redesign it.

One recent study that computes adjustment costs is by Cooper and Haltiwanger (2006). They study a host of specifications that include convex and non-convex adjustment costs, including fixed costs, quadratic costs, gaps between the buying and selling price of capital, and productivity distortions created by capital adjustment. Using U.S. plant level data, they find statistically significant costs of each type, either when estimated in isolation or when several costs are simultaneously present. The total implied adjustment costs in this model and all the others (e.g. the one including just fixed costs) are substantial. For instance, their preferred estimates suggest that profits are reduced 20 percent during investment spikes. They simulate the model and find that on average spending on adjustment costs is equal to 0.91 percent of capital. Given that investment for their sample is about 12.2 percent of capital, this implies that adjustment costs average roughly 7.5 percent of investment; in other words, they find adjustment costs roughly 40 times the size assumed by Thomas. Abel and Eberly (2002) in their study of listed firms find a similar magnitude of adjustment costs (between 1.1 and 9.7 percent of investment). So in what follows we also explore the predicted variation in total adjustment costs paid relative to investment. From a theoretical standpoint, it is hardly surprising that lumpiness is quantitatively irrelevant when fixed costs are small. This is another motivation to explore the effect of varying B, the parameter which governs the level of fixed costs.

Our first experiment is to substitute the compressed distribution of fixed costs from Figure 6 for the uniform distribution. If we keep Thomas choice of B=0.002, then plants adjust continuously[13]; hence to obtain some lumpiness, we set B=0.008. The results are shown in row 4 of Table 4. With these changes the extensive margin in the model rises to 92.6 percent and the variance of Itot/K due to I20/K rises to 99.9 percent. Thus, the model becomes much closer to the data on these two critical dimensions. The only shortcoming is that expenditure on adjustment costs remains less than one percent of total investment spending.

To see that the improvement in fit comes solely from the compression, the next row in the table shows the findings when the uniform distribution is used and B is set to 0.0053.

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distribution implies that many firms draw either a cost around B/2 or a cost close to B. The parameters sigma1 and sigma2 govern how concentrated around B/2 and B the fixed costs are. For all the experiments in Table 3 we set $\sigma_1$ =150 and $\sigma_2$=33.3.

[13] This is because the chance of getting a very low fixed cost is low, so that in contrast to Thomas, there is no option value of waiting for a low fixed cost.

With this level of B the average adjustment costs faced by firms is the same as in row 4. With this specification ShareADJ20 drops back towards the level in the baseline Thomas specification. The contrast between rows 4 and 5 quantifies the intuition given above about the importance of compression.

Our next step is to increase B to move the expenditure in adjustment costs to a more plausible level. Row 6 shows the result when B is equal to 0.03. This change increases the resources spent on adjustment so that they are nearly two percent of investment. Notice that the number of vintages also rises so that J=24. This occurs because as the costs become higher, firms tolerate larger deviations from their target capital before adjusting. Indeed, if we double B again, to B=0.06, then J=45 and the expenditure on adjustment costs rises to just over three percent of investment. In this case, roughly 96 percent of the plants do not invest.

To limit this waiting it is necessary to give firms higher benefits from adjusting their capital stock; to do so we change the curvature of the profit function (which in this model comes from the decreasing returns to scale but could also have been introduced by assuming monopolistic competition in the product market). The curvature determines the cost to having the capital stock deviate from its static optimal level. Subsequent to Thomas' paper a large empirical literature has estimated this curvature to be between 0.5 and 0.7, markedly lower than one (see e.g., Cooper and Haltiwanger (2005), Fuentes, Gilchrist and Rysman (2006), and Hennessy and Whited (2005)). Thus, there are both empirical and theoretical reasons to consider calibrations with more curvature.

Comparing rows 6 and 7 shows the effect of changing curvature. Here we set the return to scales to 0.6, and find that relative to row 6 this doubles the resources spent on adjustment costs, and reduces the maximum vintage J, so that firms adjust faster. The extensive margin remains dominant.

This suggests that a calibration that raises B and involves more curvature could lead to a model that has both non-trivial spending on adjustment and important extensive adjustment. Our preferred calibration confirms this hunch. For these results we increase B to 0.06 and keep the returns to scale equal to 0.6; the full set of parameters we choose are shown in the last column of Table 3 and the resulting moments are shown in row 8 of Table 4. We now find that the extensive margin is critical and that spending on adjustment costs is substantial.

This calibration is not fully optimized, i.e. it is likely that by changing more of the baseline parameters we can match the moments more closely. But, we believe that further improvements would not change our main conclusions that compression in the distribution of fixed costs is key to matching the dominant role of the extensive margin, and a combination of high fixed costs and curvature leads to non-trivial spending on adjustment costs.

One defect of our preferred specification is that nearly all the investment is spikes. This comes because we have no maintenance motives for investing. Row 9 adds a maintenance motive to our calibration. Maintenance is modeled as follows. At the beginning of the period, a fraction of plants is hit by a "breakdown shock" which decreases its capital stock. The plants that suffer these breakdowns must invest immediately 8% of their capital to compensate for the capital destruction. This investment is not subject to the fixed cost. Once the breakdown has (or not) occurred, the usual sequence of events takes place, with each plant drawing a fixed cost and then deciding to adjust or to wait. We chose the fraction of firms to be 30%. Clearly, adding these breakdowns improves our ability to match the cross-sectional distribution of investment rates, by generating small investments. Hence spikes now make up only 77% of total investment. Most importantly, introducing these breakdowns does not affect our other results noticeably (and it does not affect the impulse responses shown in the next Section).[14]

Other Distributions of Fixed Costs

Given the central role played by the CDF of fixed costs, it is important to check that the feature of our distribution that is driving our results is indeed the "compression". For this purpose, we consider two other distributions, which are displayed in Figure 7. The distribution in the top panel has much more variance than the one we use in our preferred calibration, since about 50% of firms draw a fixed cost that is roughly uniformly distributed between 0.03 and 0.06 (i.e. the cumulative distribution function is linear in this interval). Thus, studying this distribution allows us to check whether compression rather than lack of heterogeneity is important.

The distribution from the bottom panel has only one point of compression rather than two as in our preferred calibration.[15] With this distribution virtually all firms draw B, in which case the model is closer to the first generation of Ss models[16] rather than the ones studied by Caballero and Engel (1999) and Thomas (2002). Therefore, this distribution exhibits compression with even less heterogeneity than our baseline CDF.

As rows 10 and 11 illustrate, the extensive margin remains dominant when either of these distributions for fixed costs is substituted for our benchmark distribution. Based on other cases we considered we are convinced that compression is a necessary ingredient for

[14] This is not surprising. Consider an exogenous breakdown process which requires firms to have small investment rates; this will create some small investment rates in every period, but since this "maintenance investment" will not change over the business cycle it will have almost no effect on aggregate dynamics. Indeed, if there are types of investment for which the fixed cost does not apply or is different, calibrating the model to match the cross-sectional distribution of investment rates is not informative about the business cycle behavior. These considerations are why we concentrate on matching the (capital-weighted) business cycle statistics of the cross-section (rather than the average properties).

[15] The formulas for the CDF of the top panel of Figure 8 is $G(x) = H(x / B)$, with $H(x) = (F(x)-F(0))/(F(1)-F(0))$, and $F(x) = 1/\pi*(1/4*\arctan(\sigma_1*(x-1/2)) + 3/4*\arctan(\sigma_2*(x-1)))$, and $\sigma_1 = 30$ and $\sigma_2=5$. The formula for the CDF of the bottom panel of Figure 8 is $G(x) = H(x / B)$, with $H(x) = (F(x)-F(0))/(F(1)-F(0))$, and $F(x) = 1/(2*\pi)*(\arctan(\sigma_1*(x-.95)) + \arctan(\sigma_2*(x-1)))$, and $\sigma_1 = 80$ and $\sigma_2=10$.

[16] Sheshinksi and Weiss (1977) and (1983), Caplin and Spulber (1987), Caplin and Leahy (1991).

delivering substantial extensive adjustment, but the exact nature of the compression is not critical.[17] In particular, the only heterogeneity in this set up comes from the differences in fixed costs, and therefore we believe the results in row 10 are especially important because they show that allowing for not trivial heterogeneity does not necessarily overturn the basic intuition about the importance of compression.

Relation to the Literature

While these findings are robust to the changes that we have investigated, the literature on this class of models is growing quickly and suggests several additional experiments that merit consideration. Khan and Thomas (2006) extend the Thomas (2002) model to allow for idiosyncratic productivity shocks. They do not find any significant effect of fixed costs on aggregate dynamics. Their baseline calibration has relatively low adjustment costs and only modest curvature. Moreover, they maintain the assumption of a uniform distribution of fixed costs. Given this, and that the productivity shocks are log-normally distributed, the marginally inactive firms will not be similar to the marginally active ones. They also concentrate on the response of investment to TFP shocks (and not other shocks), and on whether the model generates nonlinearities. We concentrate on the simpler question of whether aggregate dynamics are different in the fixed cost model and in the RBC model. Interestingly, Khan and Thomas emphasize that general equilibrium feedbacks affects plant-level investment dynamics, which would imply that the panel data estimates from partial equilibrium models that we use may be misleading.

We conjecture that our results would hold if the idiosyncratic productivity shocks do not eliminate the compression associated with our parameterization of the fixed costs, but would go away if they did. The shape of the distribution of idiosyncratic shocks would likely matter as well, and we conjecture that a compressed distribution for idiosyncratic shocks could also generate results close to ours. For instance, if the distribution of idiosyncratic shocks was degenerate with only a few very different values, then one could have firms with different and extremely volatile histories, but at any given time the relevant cross-sectional distribution could still be compressed.

Bachmann, Caballero and Engel (2006) also explore issues that we do not consider. Like us, their model presumes higher curvature, and higher fixed costs to reproduce "sectoral level" volatility. They then calibrate the intertemporal elasticity of substitution of consumption to match aggregate volatility. With these features, they obtain like us differences between the impulse responses of their model and the RBC model. They emphasize that their specification also implies that the elasticity of aggregate investment with respect to a TFP shock is time-varying. This feature is absent from our model because it is log-linear. There are two main differences between our paper and theirs. First, we keep the same preferences as Thomas (2002), i.e. log utility of consumption and linear disutility of leisure (as in Hansen (1985) and Rogerson (1988)). Since the dispute is about whether general equilibrium offsets are central to this debate, we believe this is the appropriate place to start. Second, we focus on the shape of the distribution of fixed costs while they emphasize the role of sectors.[18] If we follow Bachmann et al. and allow for preferences with higher intertemporal elasticity of substitution (than the log case) we find also more smoothing than in our baseline.

## 4. Aggregate Dynamics and the Irrelevance Result

We conclude our analysis by revisiting the Thomas (2002) "irrelevance result" using our new calibration of the fixed cost model.

### 4.1. The Thomas result

Thomas compared the effect that aggregate productivity shocks have on investment when the fixed cost is positive and when the fixed cost is zero. In the latter case, the model simplifies to the standard RBC model (with decreasing returns to scale) without any adjustment cost. The bottom panel of Figure 8 plots the impulse response of the two models to the productivity shock.[19] The striking result is that the two models are virtually indistinguishable, with the two lines sitting on top of each other. The response on impact of the fixed cost model is about 99.8 percent of the response of the RBC model.

This result holds for many variations of parameter values. For instance, changing the elasticity of labor supply or the source of shocks does not affect the result. Increasing the level of fixed costs (B), while maintaining a uniform distribution, also makes little difference: for instance, when B is multiplied by a factor of 10, i.e. B = 0.02, so that the maximum vintage is J=20, the impact response of the fixed cost model is 98 percent of the response of the RBC model. That is, larger fixed costs lead to a slightly smaller response of investment, but the difference between the two models remains negligible.

This is in stark contrast with the partial equilibrium analysis, where fixed cost models typically generate two features in the impulse response: first, aggregate investment becomes of course smoother than without any adjustment costs; second, investment becomes subject to oscillatory dynamics (aka "echo effects", or replacement cycle). Thomas argued that the general equilibrium nature of the model was responsible for the inconsequential impact of the micro lumpiness.

While there is little doubt that general equilibrium effects are important, there is still a tension between the preference for smooth consumption of households and the lumpy investment demand of firms. We see no good theoretical reason why *all* the effects of fixed costs would disappear in general equilibrium. Intuitively, this has to be a quantitative question: depending on the curvature of the utility function *and* the parameters that govern the investment demand of firms, the race between consumption

[18] Another recent paper on the topic is Svenn and Weinke (2005). In contrast to Thomas (2002) or Caballero and Engel (1999), they use a Calvo-style time-dependent adjustment rule for capital. Interestingly, they find that given this rule, the irrelevance result holds in the RBC model but not in a New Keynesian model.

[19] In a one-shock linear model, the impulse response function (IRF) summarizes the full dynamics of the system. Hence, models which have the same IRF have exactly the same dynamics in all respects.

smoothing and investment lumpiness will go one way or the other. Consistent with this intuition, we show below that general equilibrium is not the whole story. Depending on microeconomic assumptions, features typical of the partial equilibrium responses with fixed costs may still arise in general equilibrium.

## 4.2 Impulse response to a technology shock with our calibration

We start by displaying in the top panel of Figure 8 the impulse response function of aggregate investment to a productivity shock for our preferred calibration from Section 3, along with the RBC model with the same parameters but zero fixed costs. While the general shape of the impulse response is the same, the two models differ qualitatively in two respects. First, the response is initially smaller in the fixed cost model: on impact the response of the fixed cost model is only 89 percent of the response of the RBC model. This reflects simply that investment becomes smoother in the presence of adjustment costs. Second and more interestingly, the fixed cost model exhibits a noticeable hump 12 periods after the shock. We call this hump an "echo effect" because it is caused by the initial surge in investment: as many firms adjust initially, the distribution shifts toward more recent vintages, which are less likely to invest. This makes the investment response smaller than the RBC model for a while, until the units which invested at time 0 need to invest again to replace their capital. Clearly, this result depends on the shape on the hazard rate (the probability of adjusting as a function of vintage, i.e. alpha). For our calibration, the hazard rate is initially steeply convex: the alphas (probability of adjustment) are very small for the first vintages before rising noticeably after 12 periods. (Of course, adjustment is random, and probabilities of adjustment move over time, but the average shape of the hazard rate still plays an important role.) The quantitative differences between the responses of the two models to a TFP shock are modest.[20]

## 4.3 The dynamic effects of a change in the cross-sectional distribution with our calibration

When we consider disturbances which affect more directly the shape of the cross-sectional distribution, the differences between the two models become much larger. In general the cross-sectional distribution is endogenous to shocks, but there are several cases when we might expect it to shift abruptly for exogenous reasons: for instance, Bloom (2006) considers the effect of a rise in uncertainty which leads many firms to delay capital adjustment. Another trigger could be an investment tax cut. In Appendix 3, we simulate the effects of an unexpected, temporary cut in the price of capital, such as an investment tax credit. That experiment is somewhat complicated to analyze, because not only must one specify the size and duration of the change, but one must also account for the fact that the tax change changes the level of capital by different amounts in the fixed cost model and the RBC model (since they are not equivalent any more).

[20] With different parameter values (e.g. higher fixed costs, higher depreciation rate, or lower returns to scale), the two qualitative differences (smoothing and echo) between the RBC model and fixed cost model can be made somewhat larger.

To side-step these complications, we consider the following thought experiment: assume that many firms have invested in the past two years, so that the distribution is distorted with more firms in the first two vintages and fewer firms in all the other vintages. Does changing the initial cross-sectional distribution in this way affect aggregate investment? This experiment is at the heart of the debate in the fixed cost literature. Figure 9 presents the exact perturbations that we consider and Figure 10 gives the aggregate investment responses. The RBC model displays the usual, monotonic, smooth convergence to the steady-state given a high starting initial capital (since many firms have invested recently). The fixed cost model, for our calibration, differs in two respects from the RBC model: first, the response of investment is smaller than in the case of the RBC model (except in the first two periods). This is because many firms have invested recently, so that there is less investment demand as fewer firms are close to the point where they want to invest. Second, we obtain a magnified "echo effect" when firms which had invested recently finally re-invest after 8 to 11 periods. These features are typical of partial equilibrium fixed cost models.

These features arise largely because of our choice of fixed cost distribution: this distribution G implies that the hazard rate is initially very low and then rises steeply; the initially lower response of aggregate investment stems directly from the first feature, and the echo stems from the second feature. In other words, the compression of the CDF that is necessary for amplifying the importance of extensive adjustment essentially guarantees that the change in the initial cross-sectional distribution will matter for the subsequent aggregate dynamics. Overall, we conclude that a shock which affects the shape of the cross-sectional distribution has very different effects when fixed costs are positive than when they are nil.[21]

We emphasize that all of these results are obtained with log utility. As a point of reference the bottom panel of Figure 10 shows the same experiment in the baseline Thomas model. The RBC model and the Thomas model yield essentially identical predictions even for this experiment. This equivalence for us is proof that general equilibrium effects are not the only reason why Thomas found no aggregate effect of fixed costs. Depending on microeconomic assumptions, i.e. on the calibration, the equivalence result need not hold.

## 5. Conclusions

We make three contributions to the debate over the aggregate significance of plant-level investment lumpiness. Remarkably, the basic plant-level facts on the lumpiness of investment are fairly similar in Chile and the U.S. In each country, we show that investment spikes drive total investment. The spikes draw their predictive power from changes in number of plants making large investments, rather than changes in the size of average investment per plant. We use these statistics regarding the decomposition

[21] To keep our experiment simple, we picked the initial cross-sectional distribution arbitrarily, but similar results are obtained when one runs a true investment tax credit in the model.

between the intensive and extensive margins of adjustment to summarize the microeconomic facts about lumpiness that we ask a model to match.

We use the Thomas (2002) model to examine these facts. This model augments a relatively standard RBC model by assuming that firms must pay a fixed cost (that is randomly drawn each period) in order to adjust its capital. As originally calibrated, however, the model fails to generate a dominant role of investment spikes and a dominant role of the extensive margin. To fit these facts we change the distribution of fixed costs from which firms sample and make it more "compressed" than the distribution considered by Thomas. We also argue that the original calibration has an average level of fixed costs which is too low and a profit function that has too little curvature.

Our final contribution is to study the properties of the model using our preferred calibration. In the original Thomas model the aggregate dynamics for investment following a productivity shock were indistinguishable from an RBC model with no adjustment costs. In our model this type of shock plays out somewhat differently. Moreover, for shocks that directly reshape the cross-sectional distribution of capital, the two models have very different implications: in general, the fixed cost model predicts that investment is more depressed for a while; moreover, the fixed cost model generates an echo effect which is absent in the RBC model.

Our conclusion from the last exercise is that there is nothing generically related to DSGE models that guarantees that plant-level investment lumpiness is smoothed away. Rather we agree with Thomas that there can be substantial differences between the importance of lumpiness in a GE models and partial equilibrium models. However, many have gone farther and concluded that GE makes fixed costs to investment completely irrelevant for the business cycle. Both our empirical and theoretical work shows this conclusion is premature; in particular, the details of how the production side is modeled matter. Given the currently available information our calibration is reasonable, but we recognize much more work needs to be done in this respect to determine how these models should be estimated and calibrated.

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**Appendix 1: Data**

The purpose of this appendix is to briefly describe the data that we analyze in section 2.

US Census data:

One of our data sets relates to U.S. establishment-level data between 1972 and 1998. These data were kindly provided by Shawn Klimek of the Census Bureau. The capital expenditure data are taken from the Census Bureau's Annual Survey of Manufactures (ASM) and the details of the data construction are given in Becker et al (2006). Their core calculation involves building up a capital stock series using a perpetual inventory method.

The data provided to us were sorted establishments into different categories according to the ratio of investment to beginning of period capital ($I_{i,t}/K_{i,t-1}$). Totals for investment and (beginning of period) capital were computed by summing across all establishments in a given category for each year; for example, data for total investment for firms with $I_{i,t}/K_{i,t-1} > 0.2$ would be one entry in the spreadsheet that we received. By summing across categories we get total investment (or total capital) for the year.

Chilean data:

Our second data set is a plant-level census of manufacturing plants with ten or more employees from Chile. These data are collected by the National Statistics Institute of Chile and the series we exploit were provided to us by Olga Fuentes and Simon Gilchrist, who constructed real capital stocks and real investment series from a perpetual inventory equation, with industry-specific investment prices and depreciation rates. The data we use is an unbalanced panel which has on average 1780 plants per year, from 1981 to 1999. We delete firms with missing observations. We sort firms based on their investment-capital ratio using the same procedure we use for the Census data.

The spreadsheets with these data are available on the following web page: http://people.bu.edu/fgourio/extintpaper.html

## Appendix 2: Additional Comparative Dynamics and the Extensive-Intensive Decomposition

This appendix studies how different parameters affect the extensive-intensive decomposition that we emphasize in the paper. The key finding is that some parameters have a weak or counter-intuitive effect on this decomposition. Understanding this "negative" result seems relevant from a technical point of view, because similar issues have arisen in the sticky price literature following the work of Klenow and Kryvstov (2005). Our results raise warning flags regarding some intuitive approaches to calibrating these models, because these approaches may not be robust. For instance, we show a higher fixed cost can increase, not decrease, the importance of the extensive margin over the business cycle.

To start, consider first the Thomas model when there are no aggregate shocks. Due to depreciation, there is some firm-level variation in investment: firms let their capital depreciate, and readjust after a few periods, depending on their draws of fixed costs. The model thus generates a cross-sectional distribution of investment rates. We can think of the aggregate investment in this economy (which is constant over time) as the product of the number of investing firms, times the average investment that each of these firms is doing. In this economy, which is the non-stochastic steady-state[22] of the full Thomas model, the following intuitive results hold:

- an increase in the level of fixed costs leads to an increase in the maximum vintage J, a reduction in the number of firms investing, and an increase in the average amount invested per firm investing;

- an increase in the curvature of the profit function (i.e. a reduction in returns to scale) leads to a decrease in J, an increase in the number of firms investing, and a reduction in the average amount invested per firm investing;

- an increase in the depreciation rate or in the growth rate of the economy reduces J, increases the number of firms investing, and reduces the average investment per firm investing.

Hence, these parameters all have intuitive effects on the relative importance of the extensive and intensive margins: increasing the cost of adjusting the extensive margin (the fixed cost) reduces its importance, and increases the importance of the intensive margin.

Next consider the business cycle implications when aggregate shocks are added to this model. To gain some intuition, suppose that a positive technology shock occurs. This will raise the marginal product of capital and lead firms to want to accumulate more capital. As a result, more firms find it worth paying the fixed cost and the number of firms "adjusting" rises. But, a second margin is also important: the capital stock of firms

[22] By "nonstochastic" we mean the model without aggregate productivity shocks; we maintain the random idiosyncratic shocks to the level of the fixed cost.

that do adjust, denoted by $k_{0,t+1}$, increases too. This means that the typical investment per adjuster will increase. Hence the model will generate a mix of extensive and intensive margins: both the number of adjusters and the investment per adjuster will typically be procyclical.

A natural conjecture is that the results for the nonstochastic steady-state quoted above extend to the business cycle extensive-intensive decomposition. That is, one may think that higher fixed costs lead not only to a smaller number of firms adjusting on average, but also to a smaller importance of the variation over time in the number of firms adjusting. The panel A of Table A-1 considers the effect of increasing solely B, starting from the Thomas calibration. The main result is that ShareADJ20 actually increases. (And so does ShareADJ0, the number of firms which are doing any kind of positive investment, not only spikes.) Quantitatively, this effect is not very large: comparing rows 1 and 6 shows that a ten fold increase in B moves ShareADJ20 by 12 percentage points. (Moreover, we found that with other parameter values, this effect was often even smaller.)

Our interpretation of these results (related to Klenow and Kryvstov (2005)) is as follows. In the low B economy, no matter if you choose to change your adjustment threshold in response to a shock, the probability of adjusting in the next two or three years is very large. So there is a limited incentive to tie an adjustment to aggregate shock and the variation in the amount of investment per adjusting firm is naturally low.

In contrast, when B is high, the maximum vintage rises and most firms will wait many periods and undertake larger investments when they do adjust. In this case, making sure that capital is high when productivity is high becomes more important and firms have a stronger incentive to invest when there is a favorable aggregate shock. Thus, in a high B environment two opposing forces are operative. There are more vintages and hence more variation in the investment per adjuster, but there also is a stronger incentive to synchronize when investments occur, leading to more variation in the number of adjusting firms. Because of these two countervailing effects, varying B has ambiguous effects on how a productivity shock will change the extensive/intensive decomposition.

In a number of experiments that we considered besides those reported in Table A-1, these two effects seem to roughly cancel, so that the amount of extensive adjustment is little affected by varying B. Dotsey, King, and Wolman (1999) and Klenow and Kryvstov (2005) mention similar "counterintuitive" results when discussing the effect of trend inflation rate on business cycle dynamics. Hence, these considerations seem to arise in other contexts as well.[23]

When we change the benefits to adjusting, by changing either the depreciation rate or the curvature of the profit function, we obtain similarly counterintuitive results. Panel B in

[23] See Foote (1998) and Campbell and Fisher (2001) for a similar debate on the theoretically unclear effect of trend growth on employment dynamics, and Caballero (1992) for a general exposition of the problem. These models have a somewhat different microeconomic structure (e.g., linear costs of adjustment and idiosyncratic shocks) but appear to be related to our findings.

Table A-1 shows that lowering the curvature has mixed effects. Neither the percentage of firms adjusting or the extensive margin monotonically responds to this change. Moreover, the total effect on ShareADJ20 is modest, even though range of curvature parameters in these experiments varies all the way from 0.95 to 0.6.

Panel C shows that raising the depreciation rate lowers the number of firms investing and has ambiguous effects on the share of adjusters; notice the non-monotonicity in ShareADJ20 in these experiments. Thus, it seems that even if the changes in the incentive to adjust on average are clear, the effect of how firms respond to shocks may not be.

In contrast, changing the CDF of fixed costs has strong and reliable effects on both the steady-state of the model and the importance of the share of adjusters over the business cycle. This was already clear from Table 4. Another interesting experiment is to add a small probability of drawing a zero fixed cost. This captures the idea of very large idiosyncratic shocks which dwarf the fixed cost, and which lead firms to adjust. As expected, firms then tend to wait until they draw this zero fixed cost to adjust. Consequently, the share of firms adjusting is almost constant over the business cycle, equal to the number of firms drawing this zero fixed cost.

## Appendix 3: An investment tax credit

The four panels of Figure A-1 show the response to an investment tax credit (ITC) in our model. The experiment we consider is an unexpected decrease in the price of capital goods by 1%, which is financed by lump-sum taxes, and which lasts for two years. The first panel shows the response of aggregate investment in the RBC model and in the preferred calibration of the cost model in section 3. On impact, the adjustment costs of course lead to a more muted response. The more interesting part is what happens once the ITC has ended, i.e. starting in period three. The two year reduction in the cost of capital leads many firms to pull forward their investment and thus the distribution of plants is distorted. The second panel of Figure A-1 drops the first two years to highlight what happens starting in period 3. The responses for the two models are not strictly comparable since the total investment during the ITC differs so that the total level of capital as of period 3 differs.

The third panel rescales the response of the RBC model so that it enters period 3 with the same level of capital as the model with our preferred calibration. With this adjustment, investment in the wake of the ITC is now smaller in the fixed cost model and the fixed cost model continues to show echo effects. Finally, the fourth panel plots the difference between the fixed cost model and the (rescaled) RBC model, multiplied by 10 to demonstrate the effect of a 10% ITC. Looking at the last two panels the qualitative differences between the RBC and fixed cost models that we saw the ad-hoc experiment in section 4.3 are preserved in this ITC experiment, though they are smaller.

The four panels of Figure A-2 give the same analysis for the Thomas calibration. Importantly, the key third panel shows no difference between the RBC model and the fixed cost model. Consequently, the comparison of the fourth panels of Figures A-1 and A-2 respectively quantifies the importance of our calibration for this ITC experiment. In the Thomas calibration, the difference between the two models is extremely small (less than 0.15%, on impact), while for our calibration it is substantial (more than 2% on impact).

We also considered ITCs which were anticipated, and found similar effects.

Table 1: Distribution of Investment Rates for U.S. and Chilean Plants

| | U.S. Sample Equal Weighted (Percent) | U.S. Sample Capital Weighted (Percent) | Chilean Sample Equal Weighted (Percent) | Chilean Sample Capital Weighted (Percent) |
|---|---|---|---|---|
| I/K=0 | 15.8 | 3.4 | 41.31 | 18.55 |
| 0<I/K<2 | 15.1 | 12.1 | 11.04 | 17.24 |
| 2≤I/K<8 | 29.7 | 33.3 | 17.78 | 26.32 |
| 8≤I/K<12 | 11.5 | 14.4 | 6.76 | 9.44 |
| 12≤I/K<20 | 11.6 | 16 | 8.44 | 11.84 |
| 20≤I/K<35 | 8 | 10.8 | 7.36 | 8.83 |
| 35≤I/K | 8.3 | 10 | 7.31 | 7.78 |

Table 2: Forecasting of Aggregate Investment by Share of Plants undergoing Investment Spikes.

Dependent variable is $Itot_t/K_{t-1}$ , the ratio of the sum of investment across all plants to the sum of beginning of period capital across all plants; the lag of this variable is denoted $Itot_{t-1}/K_{t-2}$, Rows of the table show regressions with different right hand side variables. $Sales_{t-1}/K_{t-2}$ is the (lag of) total plant-level shipments divided by the (lag of) the total capital at all establishments. A time trend is always included (but not shown). ADJ20 is defined below the table. For the U.S. sample, the time period is 1974 to 1998. For the Chilean sample the time period is 1981 to 1999. The standard errors are computing using the Newey-West (1987) correction with three lags.

| | | | Coefficient estimates (standard errors) | | | |
|---|---|---|---|---|---|---|
| Row | Sample | $\bar{R}^2$ | $Itot_{t-1}/K_{t-2}$ | $Sales_{t-1}/K_{t-2}$ | $ADJ20_{t-1}$ | $ADJ20_{t-2}$ |
| 1 | U.S. | 0.748 | 0.743<br>(0.101) | | | |
| 2 | U.S. | 0.738 | 0.690<br>(0.094) | 0.0078<br>(0.0098) | | |
| 3 | U.S. | 0.776 | 1.255<br>(0.180) | | -0.204<br>(0.044) | |
| 4 | U.S. | 0.893 | 1.553<br>(0.165) | | -0.228<br>(0.035) | -0.161<br>(0.048) |
| 5 | U.S. | 0.786 | 1.257<br>(0.153) | 0.0199<br>(0.009) | -0.258<br>(0.039) | |
| 6 | U.S. | 0.866 | 1.531<br>(0.167) | 0.010<br>(0.008) | -0.250<br>(0.033) | -0.157<br>(0.055) |
| 7 | Chile | 0.809 | 0.353<br>(0.292) | | | |
| 8 | Chile | 0.848 | 0.151<br>(0.257) | 0.055<br>(0.017) | | |
| 9 | Chile | 0.802 | 0.999<br>(0.804) | | -0.331<br>(0.341) | |
| 10 | Chile | 0.847 | 1.152<br>(0.753) | | -0.454<br>(0.272) | -0.405<br>(0.061) |
| 11 | Chile | 0.839 | 0.462<br>(0.764) | 0.054<br>(0.018) | -0.156<br>(0.339) | |
| 12 | Chile | 0.856 | 0.790<br>(0.629) | 0.034<br>(0.12) | -0.323<br>(0.264) | -0.331<br>(0.075) |

ADJ20 is defined as

$$\frac{I20}{K} \equiv \frac{I20}{K20} \bullet \frac{K20}{K} \equiv IPA20 \bullet ADJ20$$

$$\text{where I20} \equiv \sum_{\frac{I_{i,t}}{K_{i,t-1}}>0.20} I_{i,t}, \quad \text{K20} \equiv \sum_{\frac{I_{i,t}}{K_{i,t-1}}>0.20} K_{i,t-1}, \quad \text{K} \equiv \sum_{\frac{I_{i,t}}{K_{i,t-1}}\geq 0} K_{i,t-1}$$

Table 3: Parameters in the Thomas (2002) Calibration and in our Preferred Calibration.

| Parameter | Thomas (2002) | Preferred Calibration |
|---|---|---|
| Depreciation rate (δ) | 0.06 | 0.06 |
| Persistence of TFP shock (ρ) | 0.9225 | 0.9225 |
| Returns to scale ($\psi + \upsilon$) | 0.905 | 0.60 |
| Share of capital in Production Function $\psi$ | 0.325 | 0.2155 |
| Share of capital in Output $\psi / \psi + \upsilon$ | 0.359 | 0.359 |
| B (maximum fixed cost) | 0.002 | 0.06 |
| Discount factor (β) | 0.954 | 0.954 |
| Intertemporal elasticity of substitution | 1 | 1 |
| Frisch elasticity of labor supply | Infinite | Infinite |

In our preferred calibration, the CDF for G is G(x) = H(x / B) where B is the upper support and H is defined on the interval [0,1] as H(x) = (F(x)-F(0))/(F(1)-F(0)), with F(x) = 1/(2*π)*(arctan($\sigma_1$*(x-1/2)) + arctan($\sigma_2$*(x-1))). We set $\sigma_1$ =150 and $\sigma_2$=33.3.

Table 4: Steady-State and Business Cycle Lumpiness Statistics for various calibrations.

| Row | | J | Total Adjustment Costs / Total I % | Mean % Plants I/K>0.20 | Mean I20/Itot | % Variance of Itot/K due to I20/K | Share ADJ 20 |
|---|---|---|---|---|---|---|---|
| 1 | Data US | NA | NA | 20.8 | 49.9 | 97.0 | 87.0 |
| 2 | Data Chile | NA | NA | 16.6 | 57.3 | 86.0 | 92.5 |
| 3 | Thomas (2002) Calibration | 5 | 0.21 | 19.7 | 85.9 | 62.4 | 51.7 |
| 4 | Thomas with Compressed CDF and B=0.008 | 11 | 0.87 | 12.2 | 99.9 | 99.9 | 92.6 |
| 5 | Thomas with Uniform CDF and B=0.0053 (i.e. same mean as row 4) | 9 | 0.34 | 17.1 | 93.9 | 81.9 | 55.2 |
| 6 | Thomas with Compressed CDF and Higher B (B=0.03) | 24 | 1.97 | 6.4 | 99.9 | 99.9 | 100.0 |
| 7 | Thomas with Compressed CDF and Lower return to scales (0.6), and Higher B=0.03 | 16 | 3.97 | 8.3 | 99.9 | 99.9 | 115.6 |
| 8 | Preferred Calibration = Thomas with Compressed CDF and Lower return to scales and higher B=0.06 | 23 | 6.24 | 5.9 | 99.9 | 99.9 | 84.5 |
| 9 | Preferred Calibration with Breakdowns | 23 | 5.58 | 5.9 | 77.4 | 100.1 | 86.0 |
| 10 | CDF with more variance | 22 | 5.27 | 9.7 | 99.7 | 99.5 | 81.2 |
| 11 | CDF with only one spike | 16 | 7.41 | 7.8 | 99.9 | 99.9 | 75.8 |

Notes: Results from simulations of the model (500 simulations of 200 periods each). See the text for the full characteristics of the alternative calibrations. The definitions of I20, Itot, and ShareADJ20 are:

$$\text{I20} \equiv \sum_{\frac{I_{i,t}}{K_{i,t-1}}>0.20} I_{i,t}, \quad \text{Itot} \equiv \sum_{\frac{I_{i,t}}{K_{i,t-1}}\geq 0.0} I_{i,t},$$

$$\text{K20} \equiv \sum_{\frac{I_{i,t}}{K_{i,t-1}}>0.20} K_{i,t-1}, \quad \text{K} \equiv \sum_{\frac{I_{i,t}}{K_{i,t-1}}\geq 0.0} K_{i,t-1}$$

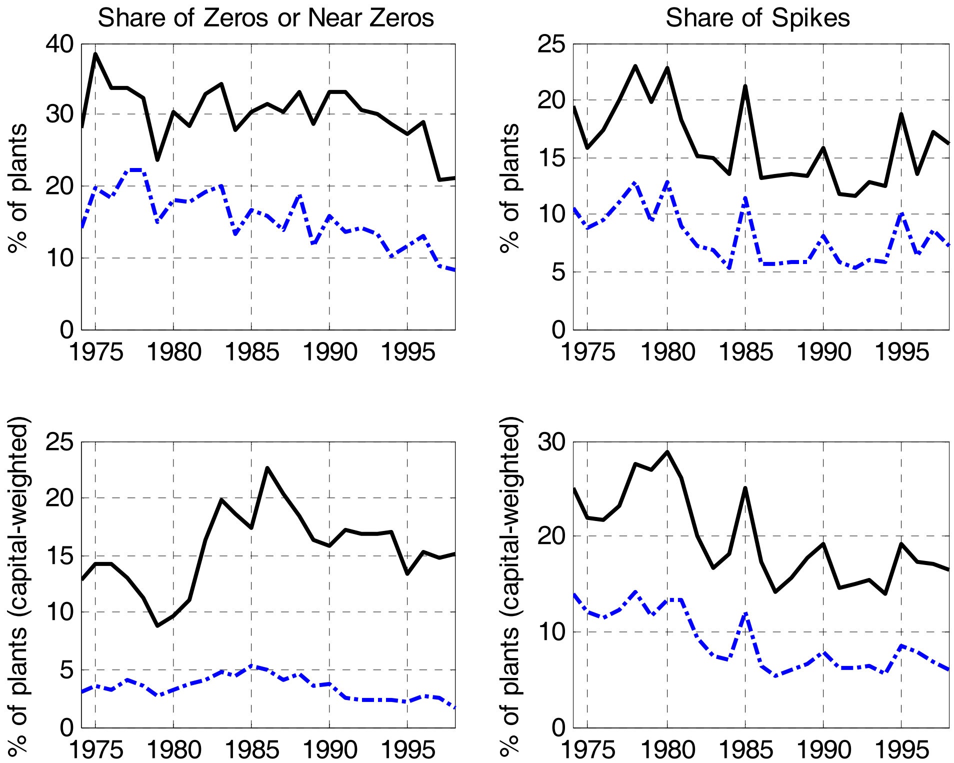
The %Variance of Itot/K due to I20/K is Cov(I20/K, Itot/K)/Var(Itot/K), and the ShareADJ20 is Cov(log(K20/K),log(I20/K))/Var(log(I20/K)) where the logs of the various series are de-trended using the Hodrick-Prescott filter (with a smoothing parameter equal to 100 since these are annual simulations).

Table A-1: Additional Comparative Dynamics in the Thomas Model.

| Row | | J | Mean % of Plants with I/K=0 | Mean % Plants I/K>0.20 | Share ADJ0 | Share ADJ 20 |
|---|---|---|---|---|---|---|
| Panel A: Effect of Changing B (the maximum value of fixed costs) in the Thomas calibration | | | | | | |
| 1 | B=0.002 (Thomas) | 5 | 72.7 | 19.7 | 66.1 | 51.8 |
| 2 | B=0.004 | 8 | 77.6 | 18.0 | 68.2 | 53.9 |
| 3 | B=0.005 | 9 | 79.1 | 17.3 | 68.8 | 54.7 |
| 4 | B=0.008 | 11 | 81.9 | 15.7 | 70.3 | 58.0 |
| 5 | B=0.01 | 13 | 83.1 | 14.9 | 71.3 | 59.6 |
| 6 | B=0.02 | 20 | 86.4 | 12.5 | 74.0 | 64.1 |
| Panel B: Effect of Changing returns to scale in the Thomas calibration | | | | | | |
| 7 | Scale = 0.95 | 7 | 76.6 | 18.5 | 67.9 | 53.4 |
| 8 | Scale = 0.905 (Thomas) | 5 | 72.7 | 19.7 | 66.3 | 51.6 |
| 9 | Scale = 0.8 | 4 | 69.0 | 20.0 | 64.7 | 54.6 |
| 10 | Scale = 0.6 | 4 | 68.0 | 20.0 | 65.8 | 59.3 |
| Panel C: Effect of changing the depreciation rate in the Thomas calibration | | | | | | |
| 11 | Delta = 0.04 | 7 | 76.8 | 13.6 | 67.4 | 66.7 |
| 12 | Delta = 0.06 (Thomas) | 5 | 72.7 | 19.7 | 65.5 | 51.5 |
| 13 | Delta = 0.08 | 4 | 68.6 | 28.2 | 64.9 | 54.4 |
| 14 | Delta = 0.10 | 3 | 64.8 | 30.3 | 61.5 | 47.0 |

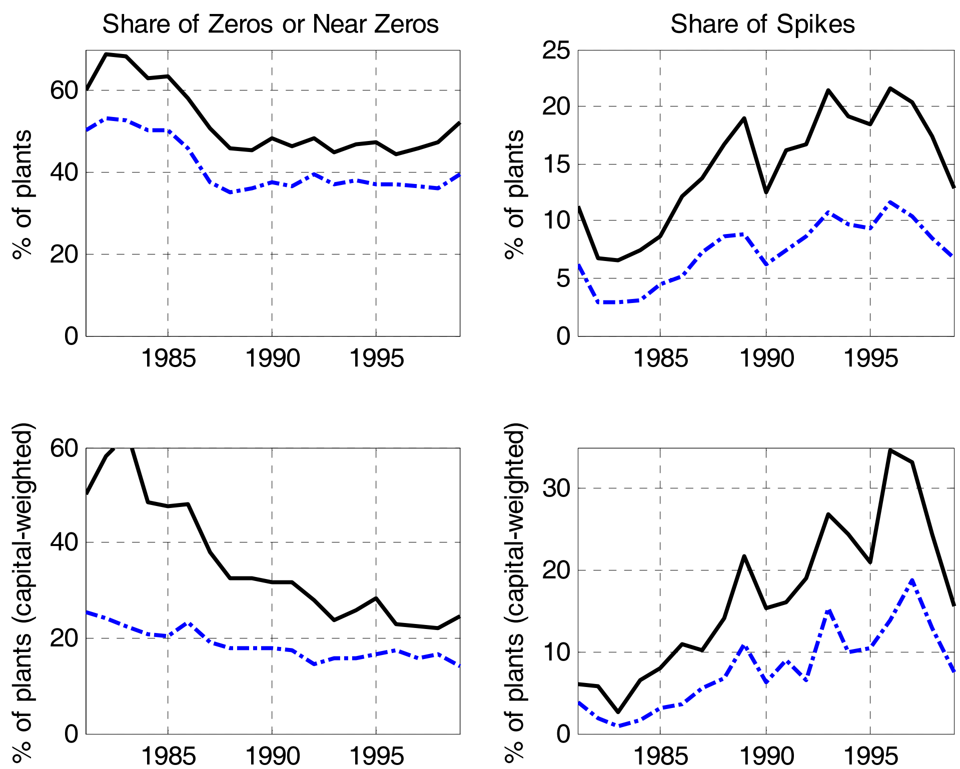
Notes: Results from simulations of the model (500 simulations of 200 periods each). The parameters are as in Thomas (2002), i.e. the first column of Table 3, except for one different parameter in each row. Share ADJ0 is defined as Cov(log(K0/K),log(I/K))/Var(log(I/K)) where K0 is the total of capital of plants doing a positive investment. Share ADJ20 is Cov(log(K20/K),log(I20/K)/Var(log(I20/K)). All series in logs are HP filtered (with a smoothing parameter equal to 100 since these are annual simulations).

Figure 1: Investment Lumpiness in U.S. Manufacturing Plants




Notes:
Left Panels: "Near Zeros" are defined as plants with $0 \leq I/K < 0.02$ and are shown in the solid line. Plants with $I/K = 0$ are shown with dashed line.
Right panels: Solid line is plants with $I/K > 0.2$. Dashed line is $I/K > 0.35$.
Top-panel is in number of plants, and bottom-panel is capital-weighted.

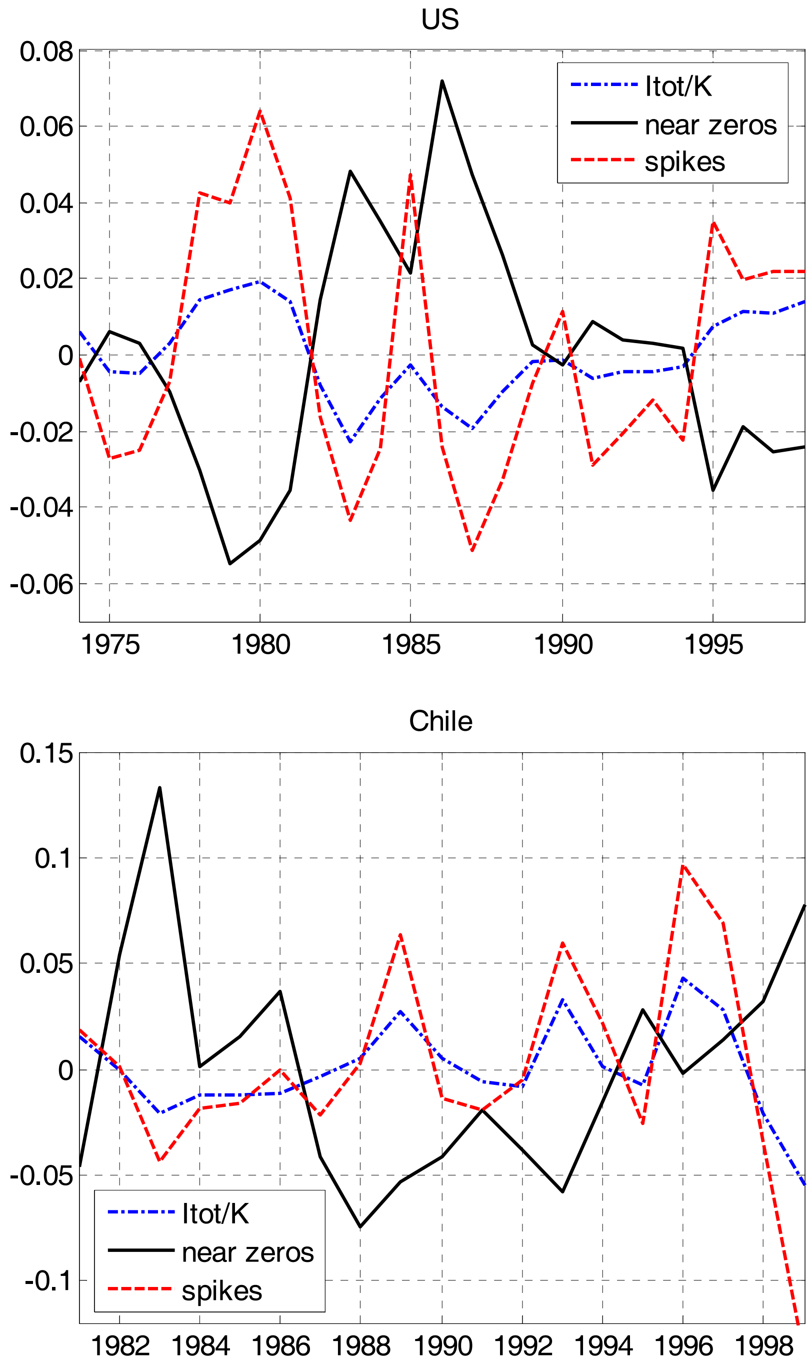
Figure 2: Investment Lumpiness in Chilean Manufacturing Plants




Notes:
Left Panels: "Near Zeros" are defined as plants with $0 \leq I/K < 0.02$ and are shown in the solid line. Plants with $I/K = 0$ are shown with dashed line.

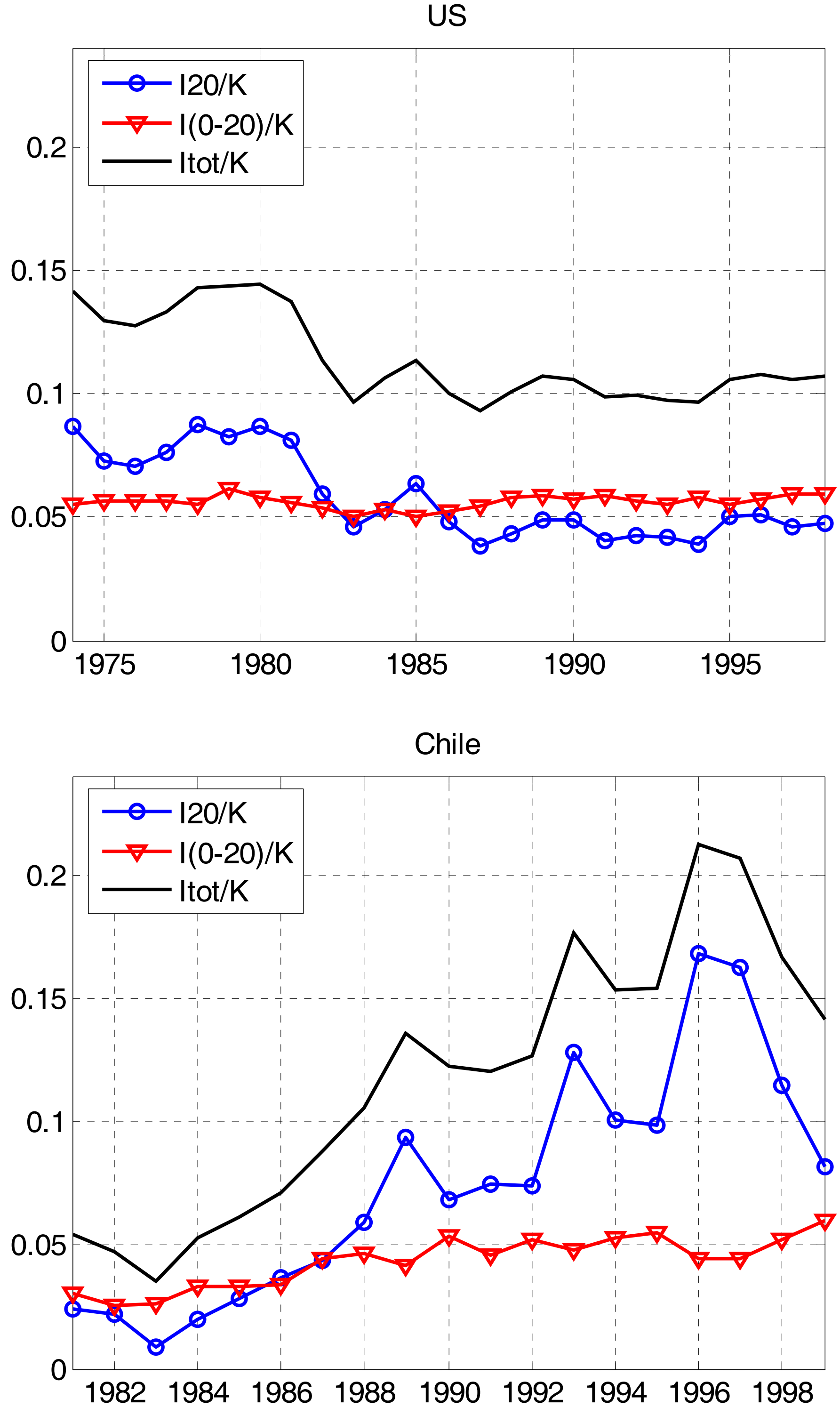
Right panels: Solid line is plants with $I/K > 0.2$. Dashed line is $I/K > 0.35$.
Top-panel is in number of plants, and bottom-panel is capital-weighted.

Figure 3: Cyclicality of Near Zero Investment and Investment Spikes in U.S. and Chilean Manufacturing Plants



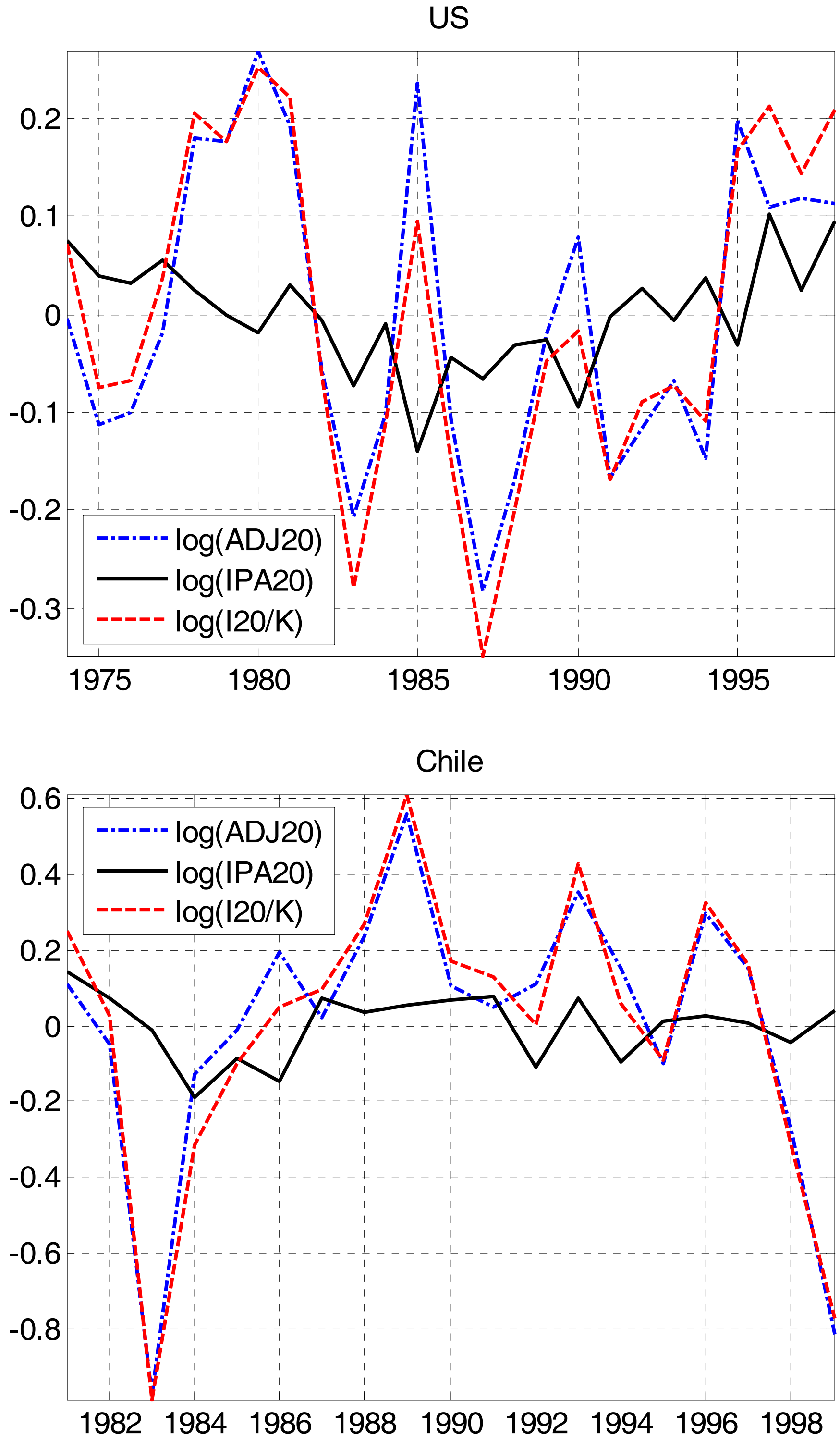

Notes: Itot $\equiv \sum_{\frac{I_{i,t}}{K_{i,t-1}} \geq 0.0} I_{i,t}$, K $\equiv \sum_{\frac{I_{i,t}}{K_{i,t-1}} \geq 0.0} K_{i,t-1}$ , Near zeros is the capital-weighted share of plants with near-zero investment and spikes is the capital-weighted share of plants with a spike. Each series shown in the figure are residuals from a regression that remove a linear time trend.

Figure 4: Decomposition of Aggregate Investment for U.S. and Chilean Manufacturing Plant into Investment Spikes and Remaining Investment.




Notes: $\text{I20} \equiv \sum_{\frac{I_{i,t}}{K_{i,t-1}} > 0.20} I_{i,t}$, $\text{Itot} \equiv \sum_{\frac{I_{i,t}}{K_{i,t-1}} \geq 0.0} I_{i,t}$, $\text{I(0-20)} \equiv \sum_{0.0 \leq \frac{I_{i,t}}{K_{i,t-1}} \leq 0.20} I_{i,t}$, $\text{K} \equiv \sum_{\frac{I_{i,t}}{K_{i,t-1}} \geq 0.0} K_{i,t-1}$

Figure 5: Decomposition of de-trended Aggregate Investment into Intensive and Extensive Adjustment for U.S. and Chilean Manufacturing Plants.




Notes: ADJ20, IPA20 and I20/K are defined in the text. Each series shown in the figure are residuals from a regression that removes a linear time trend.

Figure 6: Cumulative Distribution Function G of Fixed Costs used in Our Calibration.

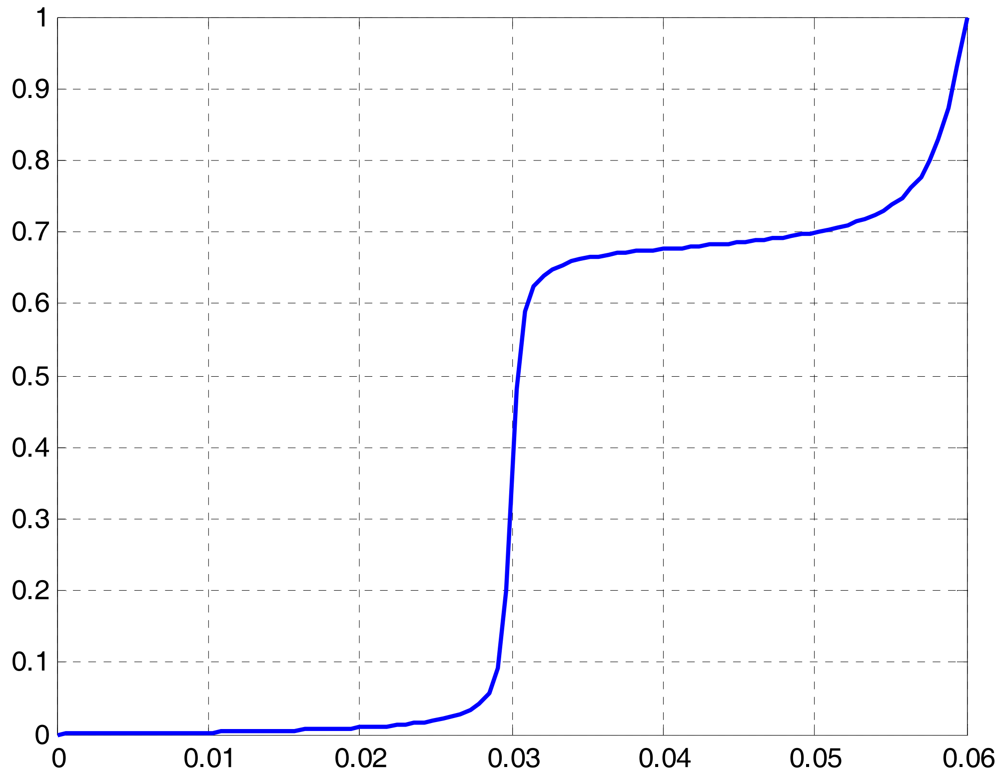


Figure 7: Cumulative Distribution Function G of Fixed Costs used as robustness checks.

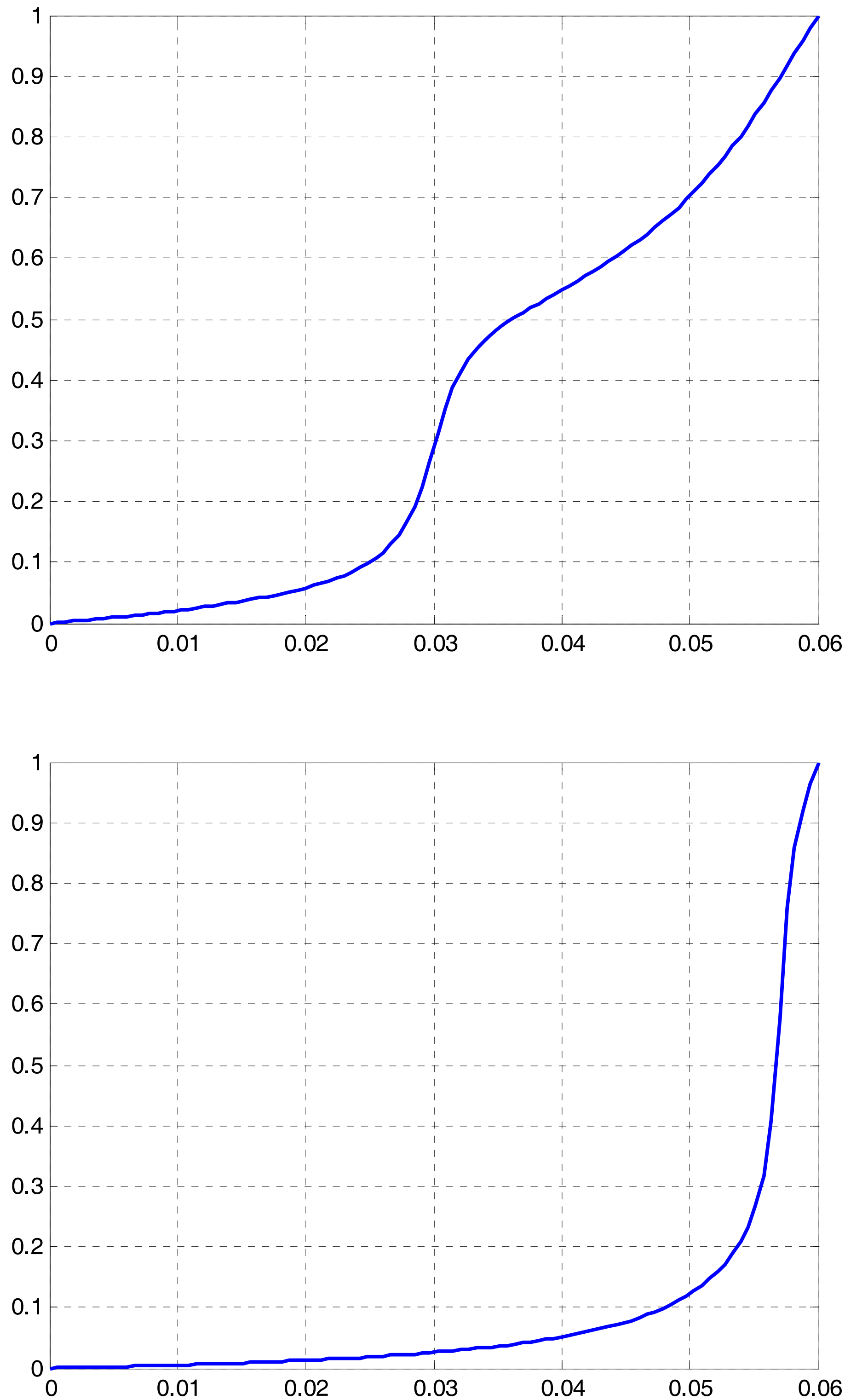
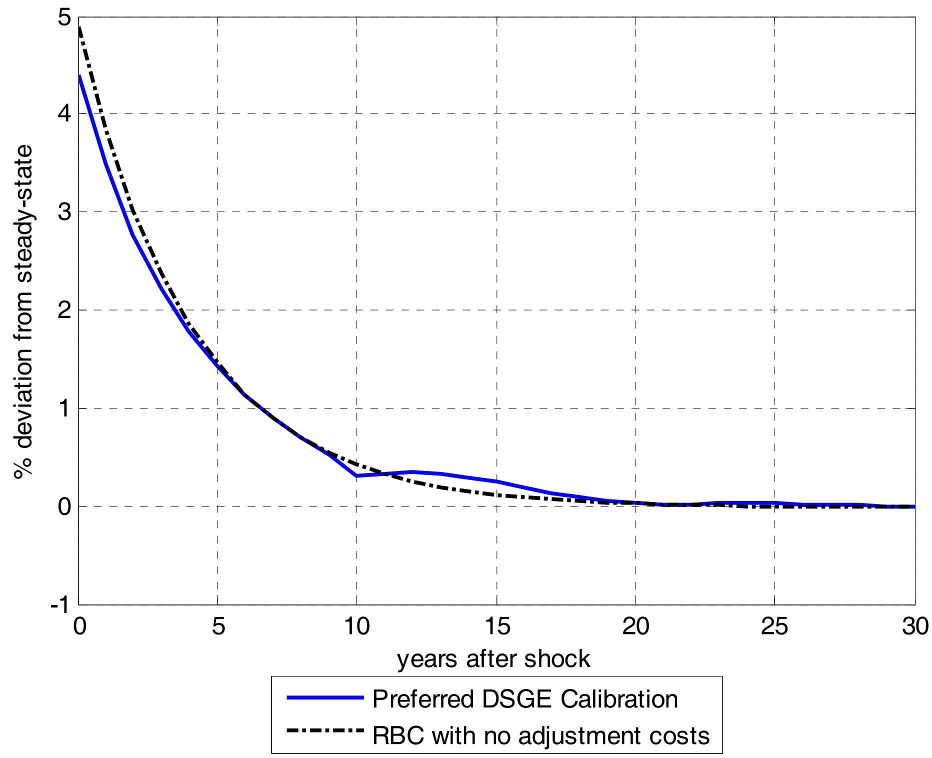


Figure 8: Impulse Response of Aggregate Investment to an Aggregate Productivity Shock for our Preferred Calibration of the DSGE Model with Fixed Costs (Top Panel) and for the Original Thomas Calibration (Bottom Panel).



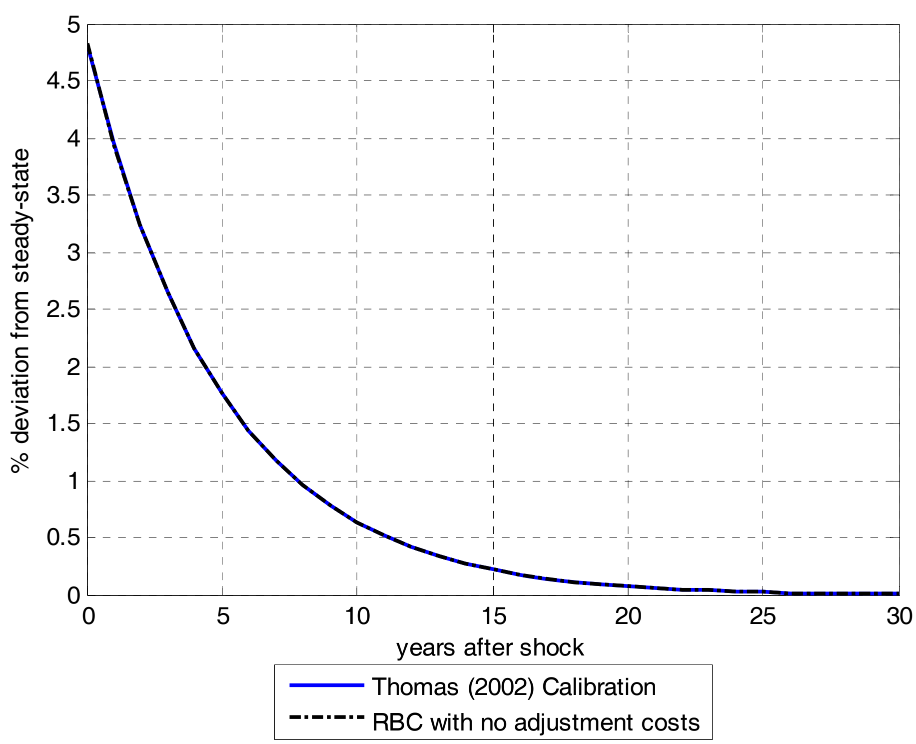
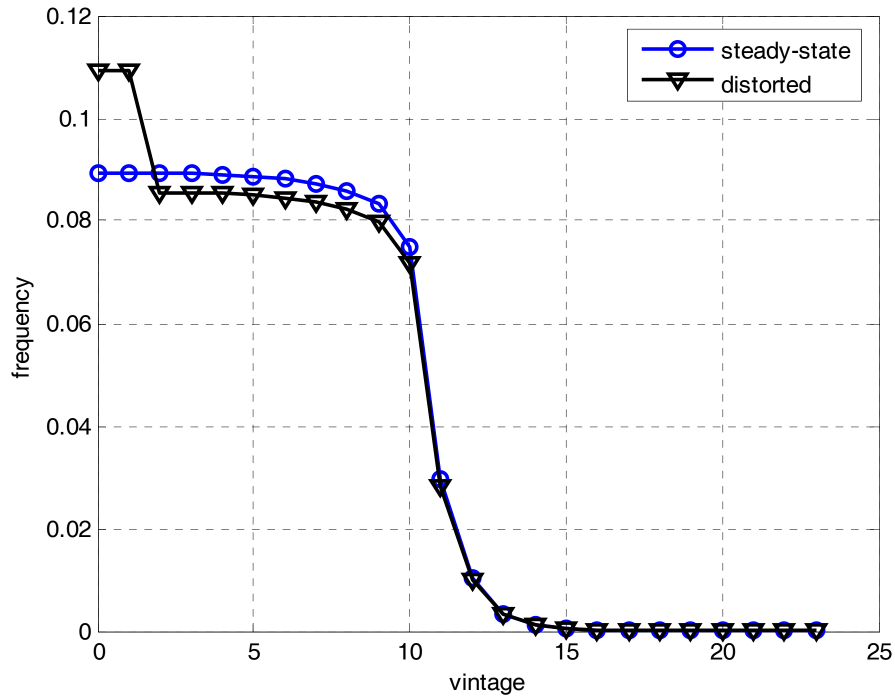
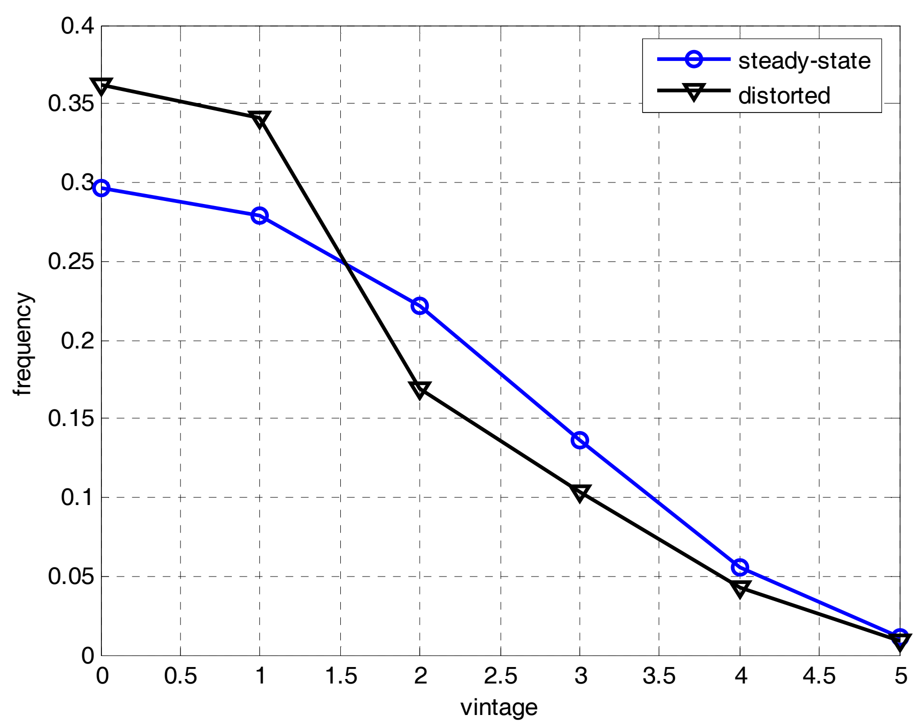



Figure 9: Initial Cross-Sectional Distribution for the experiment of Section 4.3 in our Preferred Calibration (Top Panel) and in the Thomas Calibration.




Notes: In both cases the first two vintages are up by 20% each and the other vintages are reduced equally.

Figure 10: Dynamic Path for Aggregate Investment When the Initial Distribution of Capital is Distorted in the Our Calibration of the DSGE Model with Fixed Costs (Top Panel) and in the Thomas Calibration (Bottom Panel).

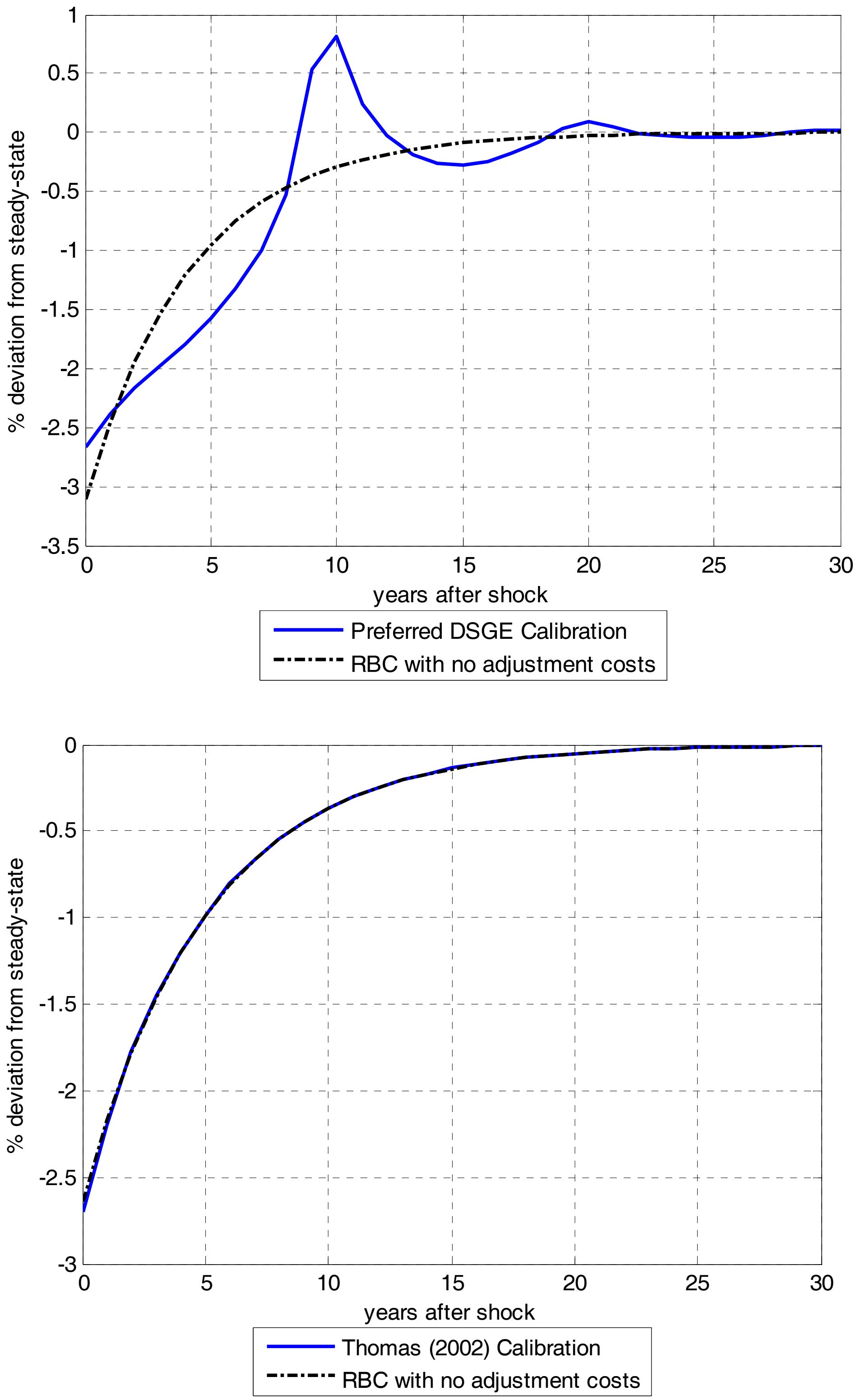
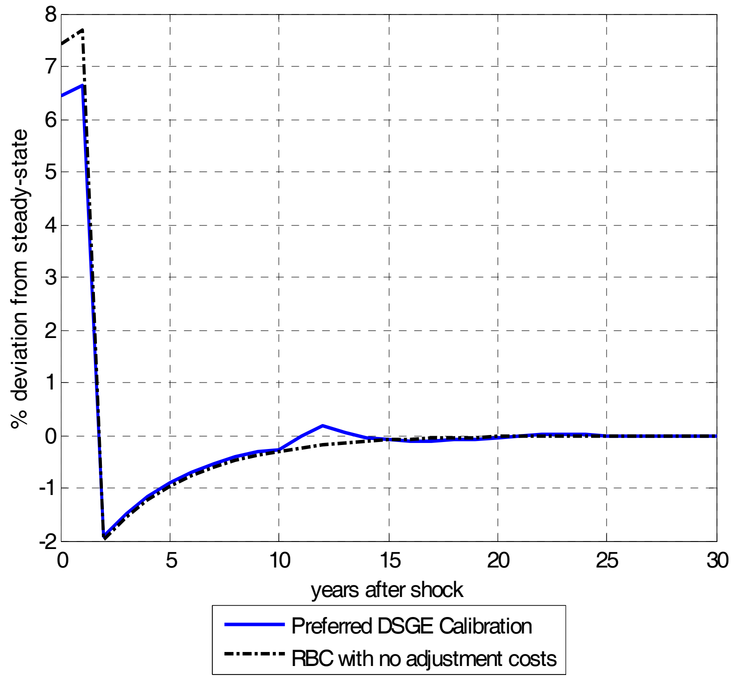
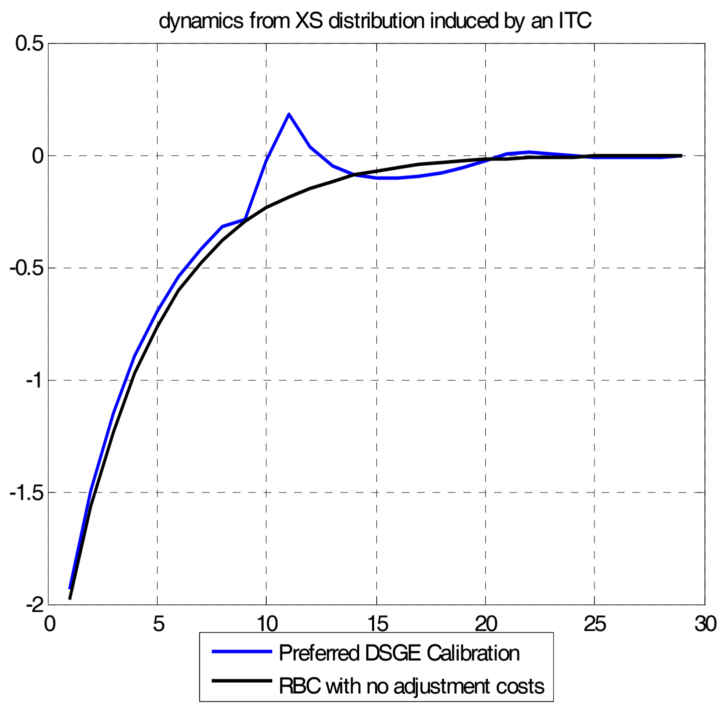


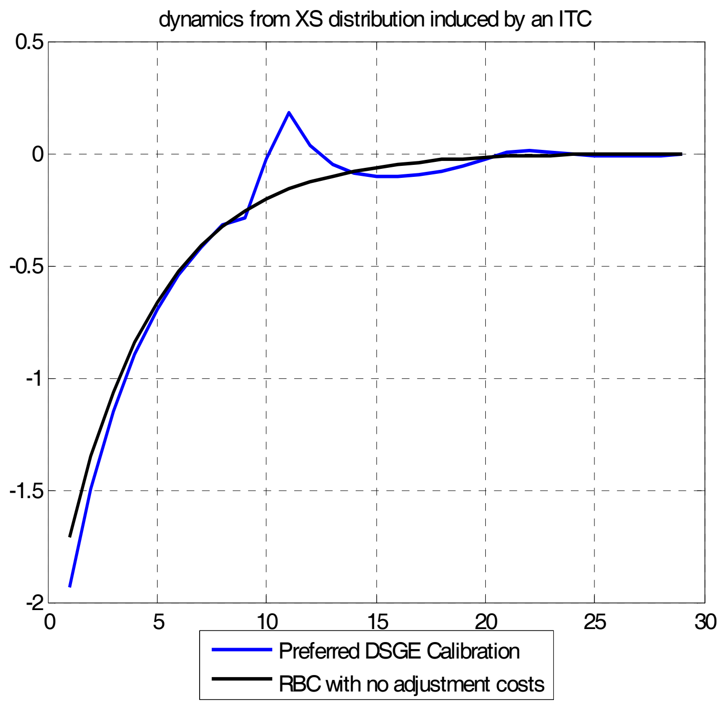
Figure A-1: Comparison of an ITC for our Preferred Calibration and the RBC model
Panel 1: Impulse Response to an unexpected 1% ITC lasting two years




Panel 2: Impulse Response to an unexpected 1% ITC lasting two years, period 3 onward



Panel 3: Panel 2 rescaled so that both models begin period 3 with identical levels of capital




Panel 4: Difference between the responses in panel 3 for a 10 percent ITC

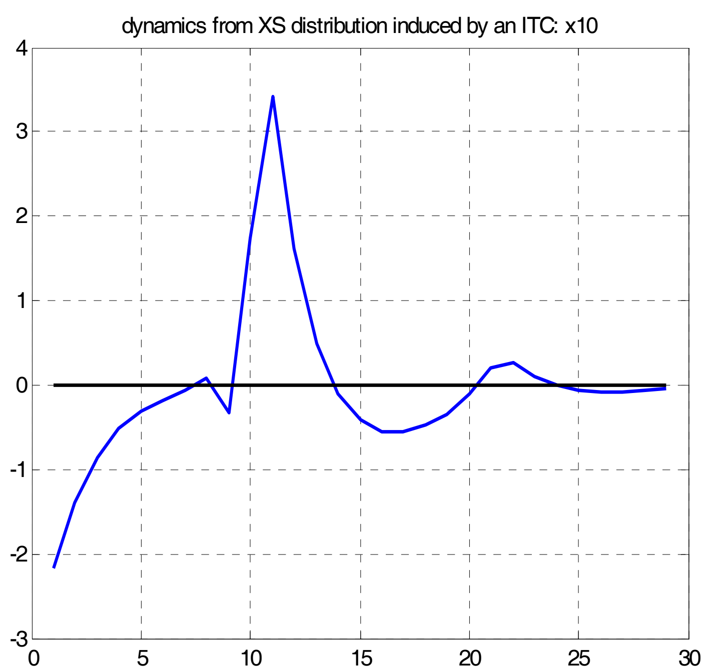
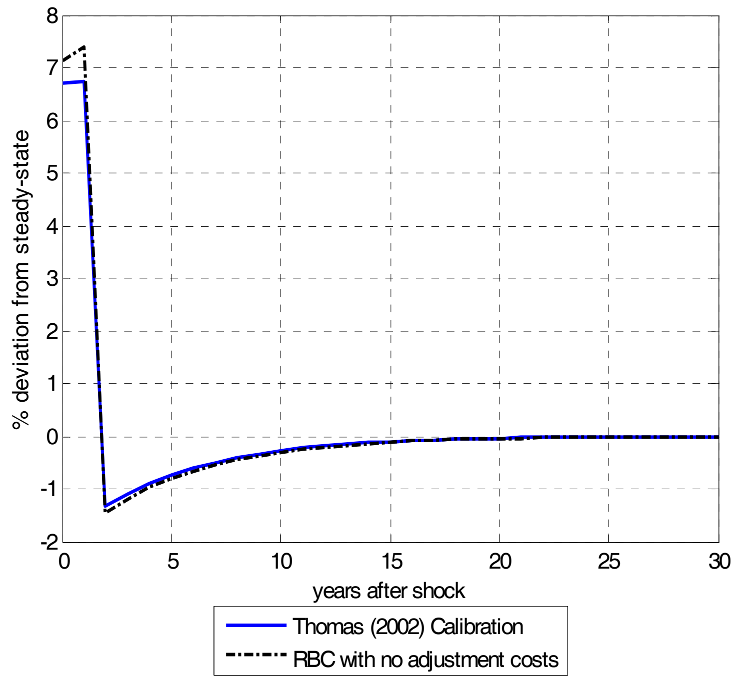
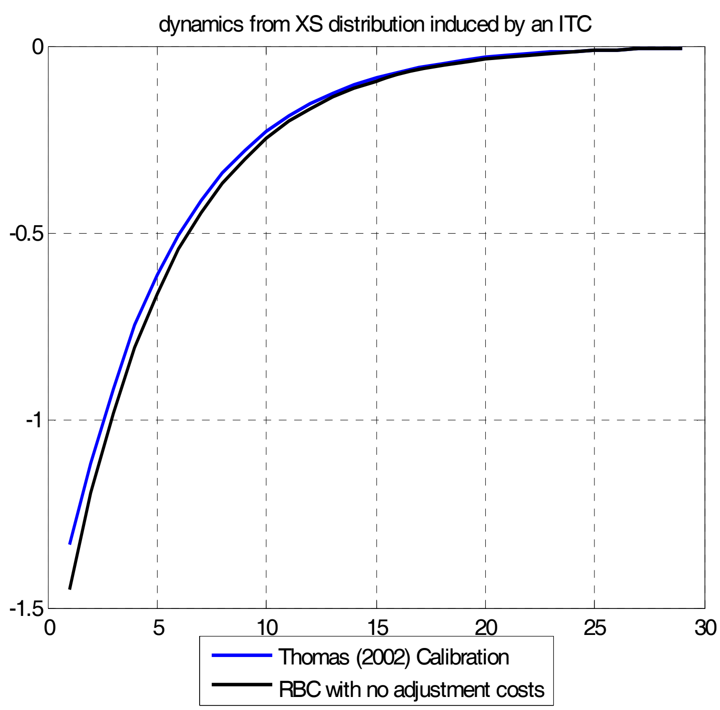


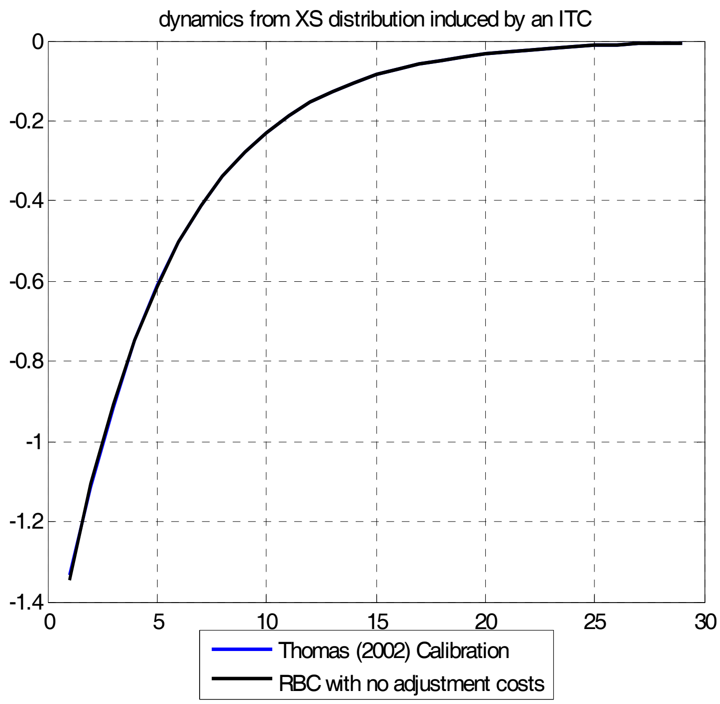
Figure A-2 Comparison of an ITC for the Thomas (2002) model and the RBC model
Panel 1: Impulse Response to an unexpected 1% ITC lasting two years




Panel 2: Impulse Response to an unexpected 1% ITC lasting two years, period 3 onward



Panel 3: Panel 2 rescaled so that both models begin period 3 with identical levels of capital




Panel 4: Difference between the responses in panel 3 for a 10 percent ITC