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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. Is lumpy investment relevant for the business cycle. Journal of Political Economy, CX 508–534] 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.

JEL classification: E22; E32

Keywords: Adjustment costs; Investment tax credit; Fixed costs; Extensive margin

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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’’.

This paper makes three contributions to this debate. First, it introduces 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’’). The prevalence of spikes in one year also predicts 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.

These empirical results suggest that it is important 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. Therefore, this conclusion is not necessarily overturned by allowing more heterogeneity in the idiosyncratic shocks that firms face.

[1]See among others Becker et al. (2006), Caballero et al. (1995), Cooper et al. (1999), 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, 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.

The conclusion is 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. The second part reviews the Thomas model and explains our calibration. The third part explores 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. The data construction is discussed more completely in Gourio and Kashyap (2007).[2] One important point from that discussion is the method that we use for aggregating the observations. In all of the results reported here, aggregates are constructed by weighting plants by their capital. While there are several good theoretical reasons that motivate this choice, as a practical matter it seems important to make sure that the statistics we analyze are not mechanically driven by the behavior of small firms.

We also refer interested readers to Gourio and Kashyap (2007) for more details on the basic properties of the data (in particular, see their Table 1 and Figs. 1–3). As in all past studies of plant-level data, there are four prominent features of our two samples. First, in both data sets many plants report literally no investment or only tiny investment (e.g. investment of less than 2% of capital) in a given year. We combine these establishments and refer to them as having "near zero" investment. On a capital weighted basis, the near zeros account for over 35% of the plant-years in the Chilean sample and over 15% in the U.S. sample.

Second, there are also many spikes. To facilitate comparisons with most papers in this literature including Cooper et al. (1999), Cooper and Haltiwanger (2006), and Becker et al. (2006), we define spikes to be cases where investment relative to the beginning of period

[2]Importantly, we do not have access to the underlying micro data, but instead have tabulations that group plants according to their current investment rates.

capital is greater than 20%. Using this threshold, 15% and 20%, respectively of the (capital-weighted) plant-years in the Chilean and U.S. samples represent spikes. Importantly, the new facts shown below regarding the importance of the extensive margin also hold when spikes are defined as investments exceeding 35% of capital.

The third and fourth patterns relate to the cyclicality of the share of plants with near-zero investment and the share of plants experiencing spikes. To analyze the cyclical behavior of these series, we remove a linear trend from each series.[3] The de-trended aggregate investment rate is highly positively correlated with the spikes and negatively correlated with the near-zeros. For instance, the correlation between the capital-weighted spikes and the aggregate investment rate (both linearly detrended) is 0.87 for the U.S. sample and 0.96 for the Chile sample; and the correlation between the capital-weighted near zeros and the aggregate investment rate (both linearly detrended) is -0.94 for the U.S. sample and -0.56 for the Chilean sample.

In the remainder of this section we document several new facts regarding the connection between aggregate investment and investment spikes. The aggregate investment rate is calculated by taking the capital weighted average of the establishment level rates and is denoted as $I\text{tot}/K$. (The weighting scheme also means that $I\text{tot}/K$ is the ratio of aggregate investment to aggregate capital in our sample.) Fig. 1 presents a decomposition of 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. $I/K > 20\%$), 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% over total capital, and is shown in the line with inverted triangles.

The relative levels of $I20/K$ and $I\text{tot}/K$ indicate that the spikes account on average for about half of total investment in each country; in other words, $I20/I\text{tot}$ 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 $I\text{tot}/K$ is accounted for by changes in $I20/K$. The share of variance of $I\text{tot}/K$ accounted for by $I20/K$ (as opposed to the residual $I(0–20)/K$)) is 97% for the U.S. sample and 86% 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%. Thus, for the purposes of modeling investment fluctuations it is critical to understand the timing of the investment spikes.[5]

[3]For Chile the sample period corresponds to a remarkable macroeconomic boom (see Hsieh and Parker, 2006; Fuentes et al., 2006) so perhaps the upward trend is not so surprising. For the U.S. there is a modest downward trend. These low frequency movements are outside of the scope of our investigation so we remove the trends. It makes no difference whether we use a linear time trend or Hodrick–Prescott filter to detrend the series.

[4]This is measured as Cov $(I20/K, I/K)/\text{Var}(I/K)$. 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: $\text{Var}(I20/K)/\text{Var}(I/K) = 0.964$, $\text{Var}(I(0–20)/K))/\text{Var}(I/K) = 0.024$ and $2\text{Cov}(I20/K, I(0–20)/K)/\text{Var}(I/K) = 0.012$. For Chile, these numbers are $\text{Var}(I20/K)/\text{Var}(I/K) = 0.759$, $\text{Var}(I(0–20)/K))/\text{Var}(I/K) = 0.036$ and $2\text{Cov}(I20/K, I(0–20)/K)/\text{Var}(I/K) = 0.205$.

[5]This fact is also present, to a lesser degree, in Fig. 8 of Cooper et al. (1999). 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.

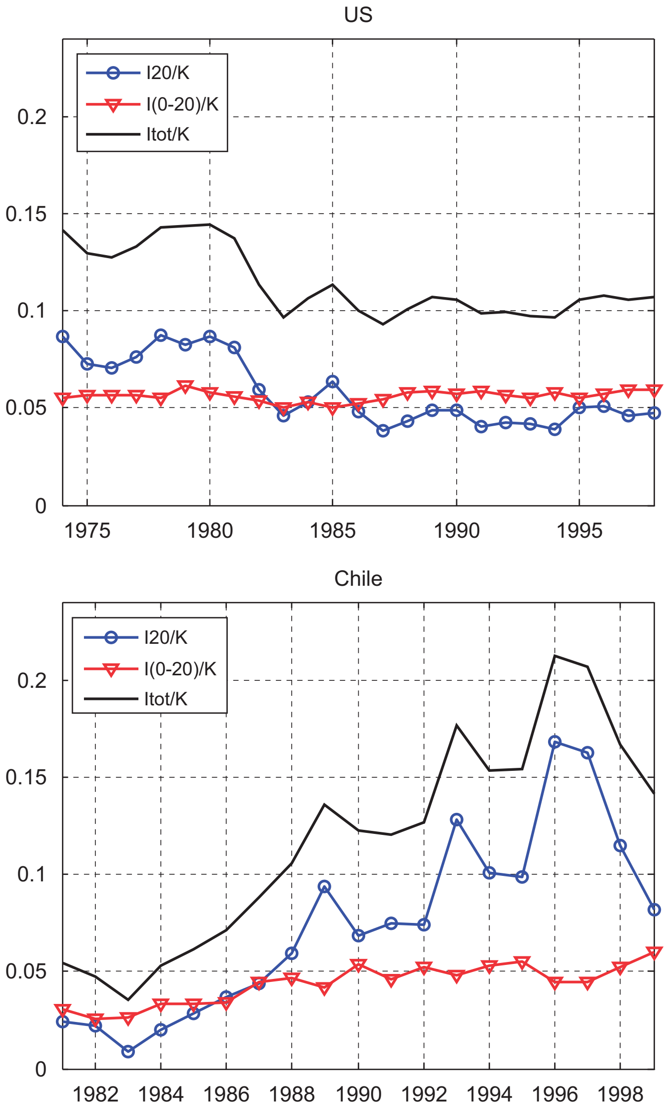

Fig. 1. Decomposition of aggregate investment for U.S. and Chilean manufacturing plant into investment spikes and remaining investment. *Note:* See Table 1 for definitions of the series.

To go further and understand how spikes matter for business cycles, we start from the following identity $I20/K \equiv I20/K20 \cdot K20/K \equiv \mathrm{IPA20} \cdot \mathrm{ADJ20}$. This implies:

$$\mathrm{Log}\left(\frac{I20}{K}\right) \equiv \log(\mathrm{IPA20}) + \log(\mathrm{ADJ20}), \tag{1}$$

$$I20 \equiv \sum_{(I_{i,t}/K_{i,t-1})>0.20} I_{i,t}, \quad K20 \equiv \sum_{(I_{i,t}/K_{i,t-1})>0.20} K_{i,t-1}, \quad K \equiv \sum_{(I_{i,t}/K_{i,t-1})\geqslant 0} K_{i,t-1}.$$

In words, Eq. (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 Kryvtsov (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.

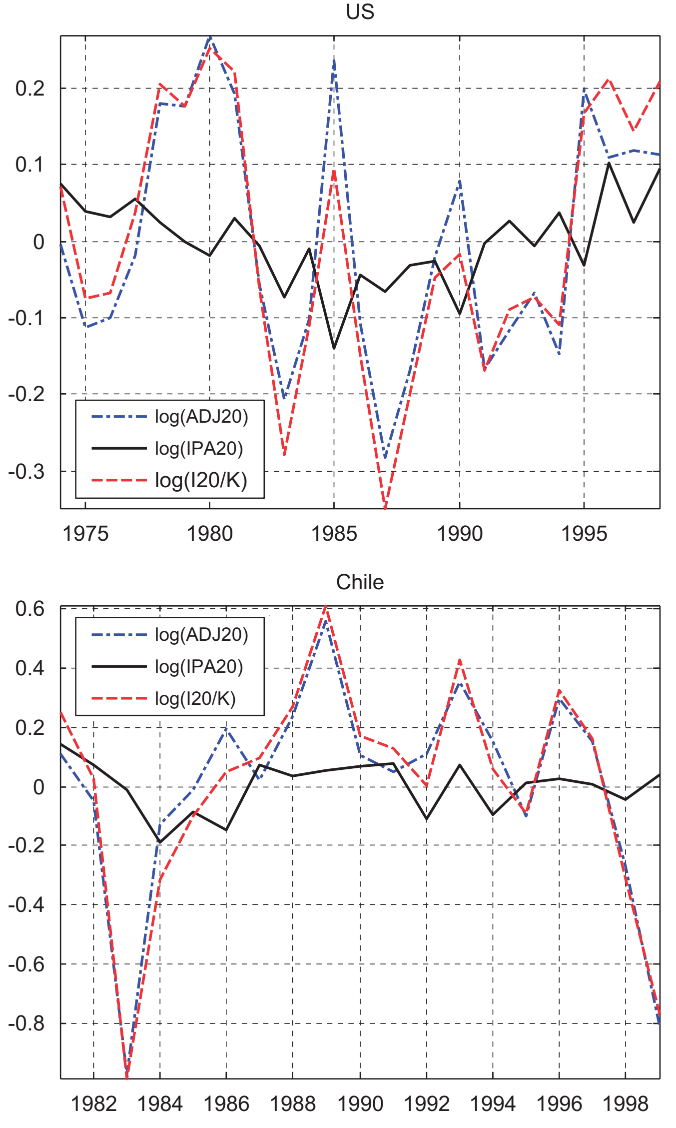

Fig. 2. Decomposition of de-trended aggregate investment into intensive and extensive adjustment for U.S. and Chilean manufacturing plants. *Note:* ADJ20, IPA20 and $I20/K$ are defined in the text. Each series shown in the figure are residuals from a regression that removes a linear time trend.

Fig. 2 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:

$$\text{Share ADJ20} \equiv \frac{\text{covariance}(\log(\text{ADJ20}),\ \log(I20/K))}{\text{variance}(\log(I20/K))} \quad \text{and}$$

$$\text{Share IPA20} \equiv \frac{\text{covariance}(\log(\text{IPA20}),\ \log(I20/K))}{\text{variance}(\log(I20/K))}.$$

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% instead of 20%. 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:

$$\frac{I\text{tot}_t}{K_{t-1}} = \alpha + \beta \text{Trend}_t + \gamma \frac{I\text{tot}_{t-1}}{K_{t-2}} + \phi \frac{\text{Sales}_{t-1}}{\text{K}_{t-2}} + \sum_{h=1}^{H} \omega_h \text{ADJ20}_{t-h}. \tag{2}$$

The novelty is that the addition of the (capital-weighted) share of adjusters to an otherwise standard accelerator type investment equation. This type of accelerator style equation has repeatedly been shown to be an effective forecasting equation in horse-races of different specifications (Bernanke et al., 1988; Oliner et al., 1995).

Table 1 shows estimates of Eq. (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

[6] Our decomposition splits a (small) covariance term equally between Share ADJ20 and Share IPA20. If instead we use an exact three way decomposition, the results for the U.S. (Chile) are as follows: Var(log ADJ20)/Var(log $I20/K$) $= 0.850$ (0.903), Var(log IPA20)/Var(log $I20/K$) $= 0.114$ (0.052) and Cov(log ADJ20,log IPA20)/Var(log $I20/K$) $= 0.036$ (0.044).

Table 1
Forecasting of aggregate investment by share of plants undergoing investment spikes

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

Dependent variable is $I\text{tot}_t/K_{t-1}$, 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 $I\text{tot}_{t-1}/K_{t-2}$. Rows of the table show regressions with different right hand side variables. $\text{Sales}_{t-1}/K_{t-2}$ is the (lag of) total plant-level shipments divided by the (lag of) 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 1974–1998. For the Chilean sample the time period is 1981–1999. The standard errors are computing using the Newey and West (1987) correction with three lags.
ADJ20 is defined from the decomposition:

$$\frac{I20}{K} \equiv \frac{I20}{K20} \cdot \frac{K20}{K} \equiv \text{IPA20} \cdot \text{ADJ20},$$

$$\text{where } I20 \equiv \sum_{(I_{i,t}/K_{i,t-1})>0.20} I_{i,t}, \quad K20 \equiv \sum_{(I_{i,t}/K_{i,t-1})>0.20} K_{i,t-1}, \quad K \equiv \sum_{(I_{i,t}/K_{i,t-1})\geqslant 0} K_{i,t-1}.$$

significant.[7] 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 $I20/I\text{tot}$ 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

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

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 concentrate especially on matching the fact that ShareADJ20 is large.

3. A DSGE model with fixed costs of adjusting capital

We first present the Thomas model and then discuss our calibration.

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 DSGE framework.[8]

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 ξ 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 δ. Therefore,

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

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:

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

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.

[8]The setup is similar to the sticky price model of Dotsey et al. (1999).

Table 2
Parameters in 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 ($\psi+v$)	0.905	0.60
Share of capital in production function ψ	0.325	0.2155
Share of capital in output $\psi/\psi+v$	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 $H(x) = (F(x)\text{-}F(0))/(F(1)\text{-}F(0))$, with $F(x) = 1/(2\pi)*(\arctan(\sigma_1(x-1/2))+\arctan(\sigma_2(x-1)))$. We set $\sigma_1 = 150$ and $\sigma_2 = 33.3$.

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

$$A_t = \Theta_{\mathrm{A}}^t z_t, \quad \log z_t = \rho \log z_{t-1} + \varepsilon_t,$$

where ε_t is distributed independently $\mathrm{N}(0,\sigma^2)$.

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 (θ_j).

Thomas shows that firm's investment decisions follow a cutoff rule: for any given vintage 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. The proportion of firms which are below the threshold (and so choose to adjust) is denoted α_j. 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% of plants raise their real capital stocks by 30% or more; (ii) these plants account for 25% of aggregate investment.

The rest of the model is intentionally chosen to follow the 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 2, are very standard.[9] 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.

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

Table 3
Steady-state and business cycle lumpiness statistics for various calibrations

Row		J	Total adjustment costs/total I %	Mean % plants $I/K>0.20$	Mean $I20/I\text{tot}$	% Variance of $I\text{tot}/K$ due to $I20/K$	Share ADJ 20
1	Data U.S.	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

Note: Results from simulations of the model (500 simulations of 200 periods each). Model series are filtered with a Hodrick–Prescott filter with smoothing parameter 100. See the text for the full characteristics of the alternative calibrations and the definition of ShareADJ20.

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 θ_j's and the k_j's).[10]

3.2. Calibration of the model

The first three rows of Table 3 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% of the total variance of investment and the extensive margin accounts for only 51% of the variance of spikes; in the data both these percentages are roughly 90%.

Gourio and Kashyap (2007) describe several comparative static exercises that help provide intuition for why the extensive margin is not very important in the Thomas calibration. These experiments focus on three key parameters: 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).

These experiments suggest that the key determinant of the extensive–intensive 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 Fig. 3. This particular CDF implies that the fixed costs for most firms bunch around B and $B/2$, but as we show in Gourio and Kashyap (2007), all of our results also obtain if there is bunching only around one level of fixed cost and there is considerable

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

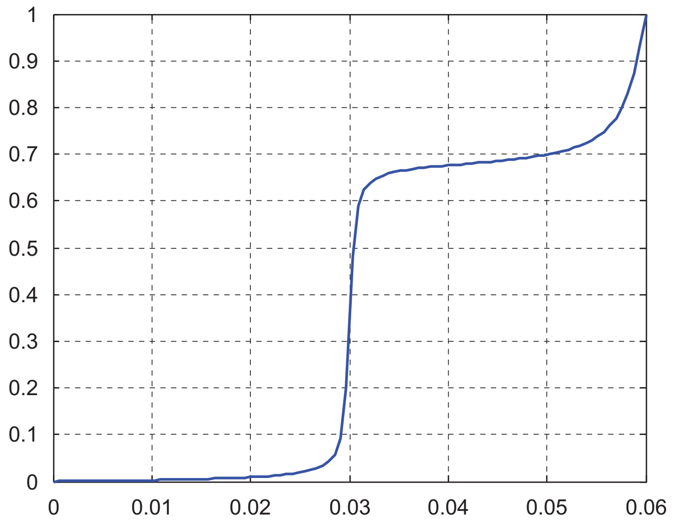

Fig. 3. Cumulative distribution function G of fixed costs used in our calibration.

heterogeneity in the rest of the distribution.[11] Hence, what matters for us is the "compression" and not the lack of heterogeneity.

Before turning to the results, we note one other observation regarding the original Thomas calibration. As reported in the fourth column of Table 3, total expenditure due to adjustment costs is roughly $\frac{1}{5}$ of 1% of total investment spending. This cost seems small on an anecdotal basis, considering 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% during investment spikes. They simulate the model and find that on average spending on adjustment costs is equal to 0.91% of capital. Given that investment for their sample is about 12.2% of capital, this implies that adjustment costs average roughly 7.5% 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

[11]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 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 $\sigma_2 = 33.3$.

(between 1.1% and 9.7% of investment). So Table 3 also reports the variation in total adjustment costs paid relative to investment for each of the calibrations. 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 Fig. 3 for the uniform distribution.[12] 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 3. With these changes the extensive margin in the model rises to 92.6% and the variance of $I\text{tot}/K$ due to $I20/K$ rises to 99.9%. 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 1% 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. 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 2% 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 B is increased further, to $B = 0.06$, then $J = 45$ and the expenditure on adjustment costs rises to just over 3% of investment. In this case, roughly 96% 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, 2006; Fuentes et al., 2006; Hennessy and Whited, 2005). Thus, there are both empirical and theoretical reasons to consider calibrations with more curvature.

Comparing rows 6 and 7 show 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

[12]Recall that the uniform CDF is linear and hence has no compression.

[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.

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 2 and the resulting moments are shown in the last row of Table 3. For these parameter values, the extensive margin is dominant and 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 it is possible to match the moments more closely. But 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 there is no maintenance motive for investing. Gourio and Kashyap (2007) show that adding maintenance improves the ability of the model to match the cross-sectional distribution of investment rates, by generating small investments, without affecting the other results noticeably.[14]

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 (2005) 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 non-linearities. 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 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 et al. (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

[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).

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; Rogerson, 1988). Since the dispute is about whether general equilibrium offsets are central to this debate, this seems to be the appropriate place to start. Second, we focus on the shape of the distribution of fixed costs while they emphasize the role of sectors.[15] 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 the 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. Gourio and Kashyap (2007) replicate this comparison of the impulse response of the two models to the productivity shock.[16] 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% 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% 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. There is no theoretical reason why *all* the effects of fixed costs

[15] Another recent paper on the topic is Sveen and Weinke (2007). 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.

[16] 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.

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 smoothing and investment lumpiness will go one way or the other. Consistent with this intuition, the results below show 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*

Fig. 4 displays 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% 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

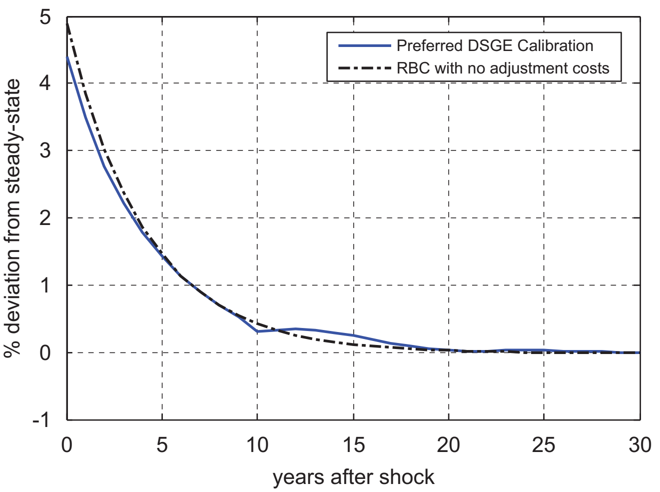

Fig. 4. Impulse response of aggregate investment to an aggregate productivity shock for our preferred calibration of the DSGE model with fixed costs.

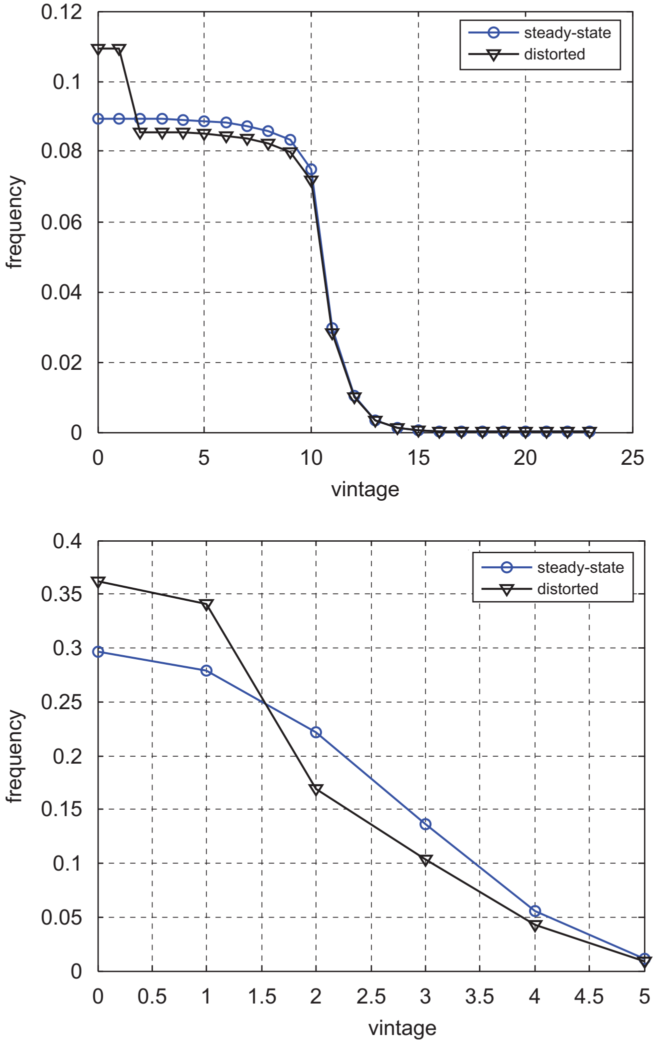

Fig. 5. Initial cross-sectional distribution for the experiment of Section 4.3 in our preferred calibration (top panel) and in the Thomas calibration. In both cases the first two vintages are up by 20% each and the other vintages are reduced equally.

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.[17]

[17]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.

4.3. The dynamic effects of a shift in the cross-sectional distribution

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 it would 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. Gourio and Kashyap (2007), 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).

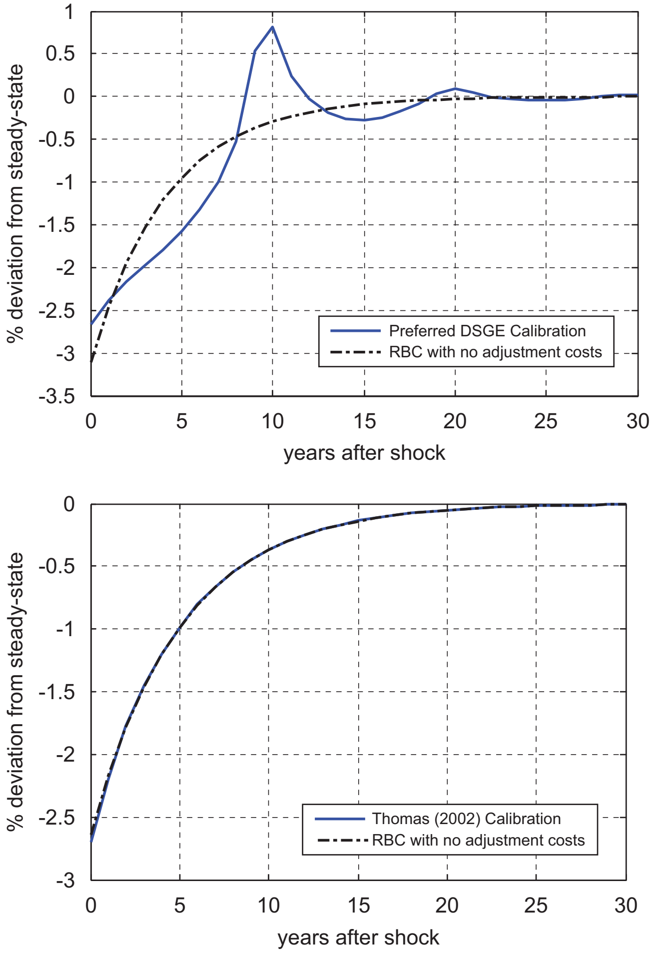

Fig. 6. Dynamic path for aggregate investment when the initial distribution of capital is distorted in our calibration of the DSGE model with fixed costs (top panel) and in the Thomas calibration (bottom panel).

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. Fig. 5 presents the exact perturbations that we consider and Fig. 6 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, there is a magnified ''echo effect'' when firms which had invested recently finally re-invest after 8–11 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.

Importantly, all of these results are obtained with log utility. As a point of reference the bottom panel of Fig. 6 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 suggests strongly 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

This paper makes 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, 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 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.

The 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.

The 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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