Estimating Firm-Level Risk

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Abstract

There has been much interest recently in models of firm heterogeneity with idiosyncratic productivity shocks. However, there remains substantial disagreement on the persistence of the shocks faced by firms, with estimates ranging from a unit root to a nearly iid component. This paper uses the idea that investment reacts more to a permanent shock than to a transitory shock, to estimate a productivity shock process which has both permanent and transitory components. The methodology is applied to a panel from Compustat using a method of moments estimator. The estimates suggest an important role for permanent shocks. I study the implications of these estimates in a general equilibrium model of firm dynamics. Mistaking permanent shocks for persistent shocks can lead to incorrect inferences regarding, for instance, the effect of a friction on aggregate productivity. As an application of this methodology, I also study the trends and cycles in firm-level volatility.

1 Introduction

Panel data on firms and establishments reveal substantial idiosyncratic volatility.[1] This empirical finding has led to the development of models of firm dynamics with productivity heterogeneity. Productivity heterogeneity is usually derived from idiosyncratic productivity shocks, which are typically assumed to follow an AR(1) process. These models are now common in macroeconomics, industrial organization, trade, corporate finance, and other fields.[2] Two key inputs in these models are the variance and persistence of idiosyncratic shocks. These parameters determine the risk that firms face, their optimal policies for a given structure of adjustment costs, and the benefits of reallocation of inputs across firms.

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[1] Some key facts are: (a) sales, employment and investment are highly volatile; (b) there is a lot of turnover of jobs and firms; (c) productivity heterogeneity is large and persistent. As a result, at a point in time in a given industry, gross entry and exit are both large, even if net entry is small at the industry-level. Similarly, gross job creation and gross job destruction are large, even if net employment growth is small (see Dunne, Roberts and Samuelson (1989), Davis, Haltiwanger and Schuh (1996), and Bartelman and Doms (2000)).

[2] A list which makes no attempt at exhaustivity includes (1) models of factor adjustment costs (e.g., Caballero and Engel (1999) or Cooper and Haltiwanger (2006)); (2) models of entry, exit, and reallocation, (e.g., Hopenhayn (1992) or Hopenhayn and Rogerson (1993)); (3) trade theory (Melitz (2003)); (4) corporate finance (e.g. Gomes (2001), Hennessy and Whited (2005)); (5) public finance (e.g., Gourio and Miao (2008)). While most of these models have been used to study steady-states or balanced growth, recent work incorporates business cycles dynamics.

At the macro level these parameters affect total factor productivity, and may affect business cycle dynamics.

However, despite the importance of these parameters, there is still considerable uncertainty surrounding them, especially the persistence of shocks. For instance, Cooper and Ejarque (2003) or Gilchrist and Sim (2007) estimate a serial correlation around 0.1-0.3, while Caballero and Engel (1999) or Bloom (2007) assume unit roots. Cooper and Haltiwanger (2006), Gomes (2001) or Hennessy and Whited (2005) fall inbetween, with a serial correlation in the 0.7-0.9 range. Given the interest in models of industry dynamics, it seems important to obtain more precise estimates of this important parameter.

Moreover, some facts suggest that the standard AR(1) modeling device, while convenient and realistic, does not capture the entire story. If shocks truly were stationary, we would see firms' sales (or employment) oscillating around a fixed size. There is considerable anecdotal and suggestive evidence that firms are also subject to permanent shocks. This motivates me to introduce permanent shock in my empirical framework.

The key idea of the paper is to introduce a novel procedure to estimate the risk faced by firms. The simple insight is that a firm invests more when it expects its productivity to be high in the future. Hence, investment data *reveal* the firm's expectations and are thus informative on the persistence of productivity. Usinge a simple structural adjustment cost model of investment, I estimate a stochastic process for profitability shocks that includes permanent as well as transitory components. The adjustment cost model shows how to use *jointly* data on productivity (profitability) and investment to infer the dynamic properties of productivity. This procedure leads to a decomposition of productivity shocks into a permanent shock, a transitory shock and an iid shock (i.e., measurement error). By using more data and imposing more economic structure, this procedure should lead to more precise estimates, while taking into account the important measurement error. This is a substantial progress over univariate decompositions based on productivity *alone*.

This insight is implemented through a simulated method of moment estimator. The mapping between some second moments of the data (mostly investment rates and profit rates) and the parameters describing the shock process is relatively transparent. The estimation procedure is run on data drawn from Compustat. Overall, the estimates suggest that permanent shocks are important, with the standard deviation of the innovation estimated to be about .20.[3] Permanent shocks explain a large share of investment, once measurement error is taken out. In contrast, transitory shocks matter relatively more for profits. The estimates also make the model more consistent with several facts, including the size distribution, and the serial correlation of sales (or capital).

A natural concern is that the adjustment cost model is the wrong starting point, because of fixed costs, irreversibility or financial constraints. However, our data is based on large firms, for which investment spikes are less apparent. As argued by Eberly, Rebelo and Vincent (2008), the adjustment cost model is a good, parsimonious model to start with, once we allow for a more general shock process.[4]

[3] This number is for the shock to the profit function (which is larger than the shock to the production function by a factor of about three).

[4] Gilchrist and Himmelberg (1995) also find that the cross-equation restrictions implied by the (constant return) adjustment cost model are not rejected for the large and/or financially unconstrained firms.

Erickson and Whited (2000) similarly argue that Q-theory accounts for a large share of the variation in the data once measurement error is taken into account. Finally, Philippon (2008) and Gilchrist and Zakrajsek (2008) show that Q-theory and the neoclassical model work well using bond prices rather than stock prices to measure Q. Moreover, the basic insight that a firm invests more if it expects a more persistent shock is likely to be relatively robust.

I illustrate the importance of these estimates by embedding my estimated model in a general equilibrium framework. Mistaking permanent shocks for transitory shocks can lead to large errors in predicting the effect of policies.

Finally, as an example of application of the methodology, the procedure is used to measure the changes in the process of idiosyncratic shocks since 1971 in the United States. Did idiosyncratic firm-level risk increase? Is idiosyncratic risk countercyclical? There is an ongoing debate regarding these views. Comin and Philippon (2005) and Davis, Haltiwanger, Jarmin and Miranda (2006) debate whether idiosyncratic risk has increased or decreased in the United States. Eisfeldt and Rampini (2006) and Bloom (2008) document that firm-level idiosyncratic risk is usually countercyclical. My methodology can allow to make some progress on this question.

Organization of the paper

Section 2 reviews the related literature and discusses a simple example which illustrates the importance of the persistence parameter. Section 3 presents an example of the methodology, the model, and the estimation procedure. Section 4 presents the data and results from the estimation. Section 5 studies the implications of the estimates in a general equilibrium model of firm dynamics. Section 6, as an application of the methodology, studies the time variation in idiosyncratic volatility.

2 Literature Review

Productivity heterogeneity has been emphasized in the recent industrial organization and in the trade literature (e.g., Syverson (2004), Melitz (2003)). In the typical four-digit industry, the ratio of the labor productivity of the 25th centile producer to the 75th centile producer is about 2. The ratio of the labor productivity of the 90th centile producer to the 10th centile producer is about 4. Using total factor productivity (TFP) rather than labor productivity, the productivity differentials are somewhat smaller, but still large, respectively 1.4 and 2.[5] Controlling for observables such as vintage or capital intensity does not explain a large share of productivity heterogeneity.

While this heterogeneity is widely accepted, the interpretation in terms of variance and persistence of shocks is more controversial, as noted in the introduction. Many researchers fit models with firms fixed effects, which leads to estimates of relatively low persistence, while some researchers assume a unit root process. The evidence based on univariate decompositions of measured productivity is problematic since measurement error, which is likely to be important in these data, biases the estimates of persistence down. Moreover, productivity is rarely measured directly: it must be inferred as the residual from a production function estimation, which faces the usual endogeneity problem. Some of the estimates are based on Simulated Method of Moments estimations, which are model-dependent. More precisely, the

[5] These numbers are drawn from Syverson (2004), Table 1.

source of identification of the shock variances is sometimes not transparent, since the estimates often try to fit better some other moments of interest. While my procedure suffers from the same limitation, the structure is minimal (adjustment costs and decreasing returns) and the relation between data moments and shocks is more transparent.

My paper is motivated by studies in the investment and corporate finance literature (e.g. Cooper and Haltiwanger (2006), Gomes (2001), Henessy and Whited (2005), Gilchrist and Sim (2007)), which all use univariate AR(1) processes to model productivity shocks. Is this assumption a reasonable description of firm dynamics?

It is interesting that a separate literature, which tries to match the firm size distribution, has emphasized the importance of permanent shocks (e.g. Luttmer 2007, Gabaix 1999; see also Miao (2005)).[6]

There is an important related IO literature, starting from the seminal contribution of Oley and Pakes (1996). These authors show how to estimate productivity from input choices, when the productivity process follows a univariate process. Their method does not apply to my framework since I emphasize multivariate processes, and it is thus not possible to invert the productivity shock from the input choice alone. On the other hand, my estimation method relies on functional form assumptions or a linear approximation, while their procedure is nonparametric. My objectives are more limited than Oley and Pakes, in that I do not wish to measure productivity *for each firm*: I am only after the parameters of the general productivity process.

There is a strong analogy between my proposed methodology and the decomposition of income into permanent and transitory shocks proposed by Blundell and Preston (1998). Blundell and Preston use the permanent income (PIH) model to study consumption and income volatility. Under the PIH, consumption is primarily determined by permanent income, and hence measuring consumption volatility allows to measure the volatility of the shock to permanent income, while the volatility of income is a mix of the volatility of permanent and transitory shocks.[7] My paper is perhaps most closely related to Abbring and Campbell (2006) who employ a similar insight to study firms' exit and learning. Their sample (Texas bars), while adapted to their question, is somewhat less interesting from a macroeconomic perspective than Compustat.

Risk is sometimes measured using stock returns. While stock returns are likely to be a precise measure of risk, they can offer no guidance regarding the persistence of shocks: stock returns are roughly iid, whatever the persistence of the productivity (profitability) process. Moreover, in my model, marginal q differs from average q, which makes it inappropriate to measure Tobin's q from stock market data. Hence incorporating Tobin's q data in the estimation is unattractive.

The persistence parameter also plays a key role in studies of reallocation. For instance, in Gourio and Miao (2008), the productivity and welfare effects of a dividend tax cut depend heavily on this parameter. Another reason why the persistence parameter is important is that it is required to estimate adjustment costs. Many researchers estimating adjustment costs model proceed in two steps, by first measuring and

[6] At a fundamental level, this is based on the fact that a geometric brownian motion with a lower barrier yields a Pareto stationary distribution, as emphasized by Gabaix (1999).

[7] The consumption literature has built on Blundell and Preston (1998) and is now considering more complicated models. See e.g. Guvenen and Smith (2008) for a recent study.

fitting a process to productivity, then estimating the technological or financial frictions (e.g., Cooper and Haltiwanger (2007), Fuentes, Gilchrist and Rysman (2006), or Gilchrist and Sim (2007)). To the extent that the process fitted to productivity does not fully capture the risks faced by firms, this would affect their estimates of adjustment costs.

It seems attractive to use "long-run moments" in the estimation, e.g. the variance ratio emphasized by Cochrane (1988), to better distinguish temporary vs. permanent shocks. The short sample makes these moments hard to use, and they require to balance the panel, which is why I have so far abstracted from this.

Finally, there is a lot of reduced form evidence that permanent shocks may be important. Anecdotally, many large firms that play an important role in the economy today, such as Wal-Mart, Dell, Google, etc., either did not exist, or were very small twenty years ago. Comin and Philippon (2005) document the large amount of turnover in industry leaders. Stationarity test reject the null hypothesis of no unit root, as shown by Franco and Philippon (2007) who also document the importance of permanent shocks at the firm level using a VAR methodology.

2.1 The role of the persistence of idiosyncratic shocks: a simple example

This section illustrates the importance of the persistence of idiosyncratic shocks to productivity by studying a simple example of capital reallocation in general equilibrium. The setup is kept simple so that pencil-and-paper results are feasible.

Consider the following economy. There is a measure one of firms, each of which operates the production function $f(z,k) = zk^{\alpha}$, where z is productivity and k is capital. There is no entry or exit. Firm-level productivity evolves according to the following first-order process:

$$\log z_{t+1} = \rho \log z_t + (1-\rho)\mu + \sigma\varepsilon_{t+1}, \tag{1}$$

where the shock ε_t is independent across firms and time and normally distributed with unit variance. Assume that there are no adjustment costs, but that capital must be chosen one period in advance - the standard time-to-build convention. The firm's objective at time t is to maximize by choice of investment plans $\{i_{t+j}\}_{j=0}^{\infty}$:

$$\begin{aligned} & E_t \sum_{j=0}^{\infty} \frac{1}{(1+r)^j} \left(z_{t+j} k_{t+j}^{\alpha} - i_{t+j} \right), \\ s.t. \quad : \quad & k_{t+j+1} = (1-\delta) k_{t+j} + i_{t+j}, \end{aligned}$$

given an initial condition for k_t. Taking the first-order condition with respect to k_{t+1} yields:

$$\alpha E_t \left(z_{t+1} \right) k_{t+1}^{\alpha-1} = r + \delta,$$

i.e. the optimal decision equates the expected marginal product of capital and the user cost of capital. This can be rewritten as

$$\log k_{t+1} = \frac{1}{1-\alpha} \log E_t z_{t+1} - \frac{1}{1-\alpha} \log \left(\frac{r+\delta}{\alpha} \right), \tag{2}$$

which is the decision rule for k, as a function of the expected z. Given equation (1) we have

$$\log E_t z_{t+1} = \rho \log z_t + (1-\rho)\mu + \frac{\sigma^2}{2},$$

which implies the following decision rule $k'(k,z)$ as a function of the current z :

$$\log k'(k,z) = \frac{1}{1-\alpha}\left(\rho \log z + \frac{\sigma^2}{2} + (1-\rho)\mu\right) - \frac{1}{1-\alpha}\log\left(\frac{r+\delta}{\alpha}\right). \tag{3}$$

We assume that there is a representative household with expected utility and time-separable preferences:

$$E\sum_{t=0}^{\infty}\beta^t U(c_t).$$

There is no aggregate uncertainty: the economy is in a stationary equilibrium, so that aggregates are constant. As a result, the interest rate is $r = \frac{1}{\beta} - 1$. The aggregate resource constraint reads:

$$c + \int\int k'(k,z)d\mu(k,z) \leq \int\int y(k,z)d\mu(k,z) + (1-\delta)\int\int kd\mu(k,z),$$

where μ is the stationary distribution over (k,z) and $k'(k,z)$ is the optimal decision rule obtained by (3). Total output in this economy is

$$Y = \int\int zk^{\alpha}d\mu(k,z),$$

where μ is the cross-sectional distribution of firms over k and z (to be characterized below). The aggregate stock of capital is $K = \int\int kd\mu(k,z)$, and we can define a measure of aggregate TFP, similar to the Solow residual, as:

$$TFP = \frac{Y}{K^{\alpha}}.$$

The distribution μ is obtained as the solution to the equation: for any (measurable) sets A and B,

$$\mu(A\times B) = \int\int \mathbf{1}_{k'(k,z)\in A} Q(z,B)\,\mu(dk,dz),$$

where Q is the transition function of the Markov process (1). The combination of time-to-build and lognormal shocks implies that in this case, the stationary distribution can be computed in closed form. First, note that the unconditional distribution of $\log z$ is $N\left(\mu, \frac{\sigma^2}{1-\rho^2}\right)$, hence given (3) the joint distribution of $(\log k, \log z)$ is normal, and its mean and covariance matrix can be easily computed as:

$$E(\log z) = \mu, \tag{4}$$

$$Var(\log z) = \frac{\sigma^2}{(1-\rho^2)}, \tag{5}$$

$$E(\log k) = \frac{1}{1-\alpha}\left(\mu + \frac{\sigma^2}{2}\right) - \frac{1}{1-\alpha}\log\left(\frac{r+\delta}{\alpha}\right), \tag{6}$$

$$Var(\log k) = \frac{\rho^2\sigma^2}{(1-\alpha)^2(1-\rho^2)}, \tag{7}$$

$$Cov(\log k, \log z) = \frac{\rho^2}{1-\alpha}\frac{\sigma^2}{(1-\rho^2)}. \tag{8}$$

We can now examine how the microeconomic parameters affect aggregates. Simple computations lead to:

$$
\begin{aligned}
\log Y &= \log \int \int z k^{\alpha} d\mu(k,z), \\
&= \log E(\exp(\alpha \log k + \log z)), \\
&= \alpha E \log k + E \log z + \frac{\alpha^2}{2} Var(\log k) + \frac{1}{2} Var(\log z) + \alpha Cov(\log k, \log z),
\end{aligned}
$$

and

$$
\begin{aligned}
\log K &= \log \int \int k d\mu(k,z), \\
&= \log E \exp(\log k), \\
&= E \log k + \frac{1}{2} Var(\log k),
\end{aligned}
$$

hence

$$
\begin{aligned}
\log TFP &= \log Y - \alpha \log K \\
&= E \log z + \frac{1}{2} Var(\log z) + \frac{\alpha^2 - \alpha}{2} Var(\log k) + \alpha Cov(\log k, \log z) \\
&= \log E(z) + \frac{\alpha \rho^2}{1-\alpha} \frac{Var(\log z)}{2},
\end{aligned}
$$

where the last expression comes from using the expressions (4-8). This formula reveals that aggregate TFP is increasing in the square of the micro-persistence parameter ρ.[8] The intuition is straightforward: given the one-period time-to-build, firms are better able to forecast their future capital needs when shocks are more persistent. Hence, the allocation of capital is more efficient (in the static sense) when shocks are more persistent. This is an example where "the micro persistence parameter matters for macroeconomics". By contrast, if there is no time-to-build friction (i.e., firms pick their capital after they have observed their shocks), aggregate TFP is simply given by the formula:

$$
\log TFP = \log E(z) + \frac{\alpha}{1-\alpha} \frac{Var(\log z)}{2},
$$

which shows the standard reallocation effect whereby higher variance in productivity leads to higher TFP, to an extent determined by the amount of decreasing returns to scale. But the micro persistence parameter does not enter this formula.

Hence, these formulas reveal that microeconomic shocks determine the aggregate production function.[9] While much work has emphasized the role of the variance of the shock (e.g. Syverson (2004), Hsieh and Klenow (2008)), persistence is also a key determinant. Of course, in reality time-to-build is not the only friction which slows down reallocation. Physical or financial adjustment costs are likely important as well. In this case, it is not obvious whether highly persistent shocks favor or hinder reallocation and thus aggregate TFP. But in general the micro persistence parameter will affect these quantities.[10]

[8] This is not a Jensen effect; the Jensen effect acts by increasing $E(z)$, the first term. Indeed one can pick μ to offset changes in ρ, this will make the first term $E(z)$ constant as we change ρ.

[9] The analysis of the aggregate production through aggregation over microeconomic production units typically emphasize the variance of productivity shocks (e.g., Houttaker (1956) or Gilchrist and Williams (2000)). This is because of the form of reallocation frictions which is assumed.

[10] See for instance Gourio and Miao (2008) for a quantitative illustration of the role of persistence in determining the macroeconomic effects of a dividend tax cut, in a model with both physical adjustment costs and financial frictions.

3 Model and Estimation Method

Before turning to the full model and estimation method, I illustrate the key idea of the procedure in a simple setup.

3.1 Methodology: a simple example

Consider the baseline quadratic adjustment cost model, with constant returns in profits and in adjustment costs. Hayashi's results imply that average q equals marginal q, and that investment is an affine (linear) function of average q. This allows for closed-form solutions which clarify the intuition for the estimation procedure.

The profit function is $\Pi_{it} = A_{it}K_{it}$ where A_{it} is a measure of profitability (or productivity), i indexes firms, and t indexes time. Assume that profitability is the sum of a persistent component and an iid component:

$$\frac{\Pi_{it}}{K_{it}} = A_{it} = \text{constant} + \underbrace{z_{it}}_{AR(1)} + \underbrace{\varepsilon^M_{it}}_{IID}. \tag{9}$$

Hence, we assume that

$$z_{it} = \rho z_{it-1} + \varepsilon^T_{it},$$

with ε^T_{it} iid across firms and time. The firm problem is to maximize the present discounted value of profits, net of adjustment costs:

$$\max_{\{I_{it},K_{it+1}\}} E_0 \sum_{t=0}^{\infty} \beta^t \left(A_{it}K_{it} - I_{it} - \frac{\psi}{2}\frac{I^2_{it}}{K_{it}} \right), \tag{10}$$

$$s.t. \quad : \quad K_{it+1} = (1-\delta)K_{it} + I_{it}. \tag{11}$$

The first-order condition for investment yields:

$$\frac{I_{it}}{K_{it}} = \text{constant} + \frac{1}{\psi} q_{it}, \tag{12}$$

where ψ is the adjustment cost parameter, and q_{it} is marginal q, the multiplier on the constraint (11). Note that the constant in equations (9) and (12) are independent of i, i.e. there are no time effects. Marginal q is also the expected present discounted value of the marginal product of capital, which is approximately:[11]

$$q_{it} \simeq E_t \sum_{k\geq 1} \beta^k (1-\delta)^{k-1} A_{it+k} = \frac{\beta\rho z_{it}}{1-\beta(1-\delta)\rho}, \tag{13}$$

where ρ is the autocorrelation of z_{it}. This yields the policy function for investment:

$$\frac{I_{it}}{K_{it}} = \text{constant} + \frac{1}{\psi}\,\frac{\beta\rho z_{it}}{1-\beta(1-\delta)\rho}. \tag{14}$$

This policy function reflects that investment does not react to temporary shocks to profitability (i.e. ε^M_{it}), due to the one-period time-to-build assumption. Given this policy function, we can easily compute

[11] The formula below neglects the reduction in future adujstment costs due to investment today.

the second moments implied by the model:[12]

$$\begin{aligned}
Var\left(\frac{\Pi_{it}}{K_{it}}\right) &= \sigma_z^2+\sigma_\varepsilon^2, \\
Var\left(\frac{I_{it}}{K_{it}}\right) &= \frac{\beta^2\rho^2\sigma_z^2}{\psi^2\left(1-\beta(1-\delta)\rho\right)^2}, \\
Cov\left(\frac{I_{it}}{K_{it}},\frac{\Pi_{it}}{K_{it}}\right) &= \frac{1}{\psi}\frac{\beta\rho\sigma_z^2}{1-\beta(1-\delta)\rho}.
\end{aligned}$$

Next, to illustrate the estimation procedure, assume for simplicity that we know the structural parameters β,δ and ψ, but that we ignore the parameters describing the shock processes $\sigma_z^2,\sigma_\varepsilon^2$ and ρ. Then, the three moments allow us to identify these three parameters.

One simple way to solve the system is to find σ_z from the following expression:

$$\sigma_z^2=\frac{Cov\left(\frac{I_{it}}{K_{it}},\frac{\Pi_{it}}{K_{it}}\right)^2}{Var\left(\frac{I_{it}}{K_{it}}\right)},$$

which reflects that a high covariance between investment and profits reveals that transitory shocks are important. Next, we obtain $\sigma_\varepsilon^2=Var\left(\frac{\Pi_{it}}{K_{it}}\right)-\sigma_z^2$, to match the volatility of profit shocks, and finally ρ is deduced from $Var\left(\frac{I_{it}}{K_{it}}\right)$. The identification is driven by the implication of the adjustment cost model that investment does not respond to an iid shock (a cash windfall).

This example illustrates both the benefits and costs of this methodology. On the one hand, the mapping between data moments and parameter estimates is relatively transparent, which is appealing, because it is clear which features of the data drive the estimates. The estimation method brings more data to bear on the question (i.e. both investment and profits instead of profits alone), and exploits the cross-equation restrictions. Of course, if the model is wrong, the estimates might be misleading. In this example, financing constraints imply that investment may react even to an iid shock, which would bias the estimates.

3.2 Model

After the introductory example of the preceding section, I now introduce the full model which I estimate, which is a standard partial-equilibrium adjustment cost model. It is richer than the example of the preceding section in two dimensions: (1) it allows for concavity of the profit function in capital,[13] and (2) the set of shocks that are considered is richer.

Assume the profit function is $\pi(z,K)=zK^\alpha$ where z is productivity (profitability) and K is the current capital stock. This profit function can be derived as the maximized value of profits, when variable factors have been optimized out. As usual, the exponent α reflects decreasing return to scale or curvature in demand.

[12] These moments are both cross-sectional moments and time-series moments, since the model does not incorporate firm fixed effects.

[13] Deviating from constant returns is important because the constant return model does not fit the micro data well (i.e. marginal q is not equal to average q) and, most importantly, because it allows to have a non-stationary process for z while keeping the profit rate stationary.

Productivity shocks are assumed to have the following form:[14]

$$\log z_t = \log z_t^P + \log z_t^T + \varepsilon_t^M,$$

with

$$\log z_t^P = \log z_{t-1}^P + \varepsilon_t^P,$$

and

$$\log z_t^T = \rho \log z_{t-1}^T + \varepsilon_t^T,$$

with $\rho < 1$. Here, $\varepsilon_t^M, \varepsilon_t^T$, and ε_t^P are all *iid* across firms and time, and normally distributed with variances σ_M^2, σ_T^2, and σ_P^2. These shocks are further independent of each other. ε^M can be interpreted as measurement error in profits (or a profit windfall). The two other shocks determine the importance of permanent shocks and of transitory shocks. The only difference between the two is the long-run effect: a permanent shock will lead to a permanent increase in the capital stock and hence, through capital deepening, a further increase in sales and profits. In contrast, a transitory shock has no long-run effect and the firm returns after a while to its initial size (as measured by sales, capital or profit).

The firm's problem is to maximize its value by choice of investment, subject to adjustment costs:

$$\begin{aligned} V(K_0, z_0^P, z_0^T) &= \max_{\{I_t, K_{t+1}\}_{t=0}^{\infty}} E_0 \sum_{t=0}^{\infty} \beta^t \left(z_t K_t^{\alpha} - I_t - K_t c\left(\frac{I_t}{K_t} - \varepsilon_t^{AC}\right)\right), \qquad (15) \\ s.t. &: K_{t+1} = (1-\delta)K_t + I_t, \\ & \quad K_0 \text{ given,} \end{aligned}$$

where c is a convex function satisfying $c(\delta) = c'(\delta) = 0$, and ε_t^{AC} is a shock to the adjustment cost, which is assumed to be *iid* across firms and across time, and normally distributed with variance σ_{AC}^2. Narrowly, the shock ε^{AC} captures variation in the cost of adjusting the capital stock, and more broadly it captures deviation from the smooth adjustment cost model.[15] Finally, the estimation will also allow for classical measurement error in investment.

The Bellman equation is:

$$\begin{aligned} \overline{V}(K, z_p, z_t, \varepsilon_{ac}, \varepsilon_m) &= \max_I \left\{ \begin{array}{c} z_p z_t e^{\varepsilon_m} K^{\alpha} - I - Kc\left(\frac{I}{K} - \varepsilon^{AC}\right) \\ +\beta E_{\varepsilon_p', \varepsilon_t', \varepsilon_{ac}', \varepsilon_m'} \overline{V}(K', z_p', z_t', \varepsilon_{ac}', \varepsilon_m') \end{array} \right\} \\ s.t. &: K' = (1-\delta)K + I, \\ z_p' &= z_p e^{\varepsilon_p'} \text{ and } z_t' = z_t^{\rho} e^{\varepsilon_t'}. \end{aligned}$$

However, given that both ε_m and ε_{ac} are *iid*, this can be rewritten in a simpler way as:

$$\begin{aligned} V(K, z_p, z_t) &= E_{\varepsilon_m}\left(z_p, z_t e^{\varepsilon_m} K^{\alpha}\right) + E_{\varepsilon^{AC}} \max_I \left\{ -I - Kc\left(\frac{I}{K} - \varepsilon_{ac}\right) + \beta E_{\varepsilon_p', \varepsilon_t'} V(K', z_p', z_t') \right\} \\ s.t. &: K' = (1-\delta)K + I, \\ z_p' &= z_p e^{\varepsilon_p'} \text{ and } z_t' = z_t^{\rho} e^{\varepsilon_t'}. \end{aligned}$$

[14] Note that these could be "demand" shocks as well as "supply shocks" (Foster, Haltiwanger, and Syverson (2008)).

[15] However, note that this formulation of adjustment costs does not encompass the foregone profits emphasized by Cooper and Haltiwanger (2006), i.e., the idea that the adjustment cost is proportional to current profits due to a disruption in the production process.

The solution to the Bellman equation leads to the following policy functions:

$$\begin{aligned} I &= I(K, z_p, z_t, \varepsilon_{ac}), \\ K' &= K'(K, z_p, z_t, \varepsilon_{ac}), \\ \pi &= \pi(K, z_p, z_t, \varepsilon_m). \end{aligned}$$

Note how profits are affected by ε_m but not by ε_{ac}, and inversely investment is affected by ε_{ac} but not by ε_m; this is a source of identification of these shocks. Taking first-order condition in (15) yields the standard $q-$theory:

$$q_t = 1 + c'\left(\frac{I_t}{K_t} - \varepsilon_{ac}\right), \tag{16}$$

where q_t is marginal q, i.e. the multiplier on the capital accumulation constraint. Moreover,

$$\begin{aligned} q_t &= \beta(1-\delta)E_t\left(q_{t+1}\right) + \beta\alpha E_t\left(z_{t+1}K_{t+1}^{\alpha-1}\right) \\ &\quad + \beta E_t\left(-c\left(\frac{I_{t+1}}{K_{t+1}} - \varepsilon_{t+1}^{AC}\right) + \frac{I_{t+1}}{K_{t+1}}c'\left(\frac{I_{t+1}}{K_{t+1}} - \varepsilon_{t+1}^{AC}\right)\right), \end{aligned} \tag{17}$$

which shows that marginal q is related to the present discounted value of marginal product of capital, plus terms reflecting changes in adjustment costs. As an illustration, when the adjustment costs terms in (17) can be neglected or cancel out, we have:

$$q_t = \alpha E_t \sum_{j=1}^{\infty} \beta^j (1-\delta)^j z_{t+j} K_{t+j}^{\alpha-1},$$

which clearly shows that marginal q reflects the firm's long-term expectation of its marginal product of capital. Marginal q is unobservable, but the first-order condition (16) shows that investment is related to marginal q.

3.3 Solution method and Impulse Responses

The model has no closed-form solution, hence it is solved numerically. Because the model has several state variables and shocks, and must be solved repeatedly for the estimation, it seems reasonable as a first step to use a linear solution method. This also makes it easy to extend the model to introduce "news shocks" or "long-run shocks".[16]

Because of permanent shocks, the state space is unbounded. The first step in the solution is to note that one can define "trend-adjusted" variables $k_t = K_t / z_{P,t-1}^{\frac{1}{1-\alpha}}$, and $i_t = I_t / z_{P,t-1}^{\frac{1}{1-\alpha}}$, and rewrite the first-order conditions using these detrended variables. It is then easy to find the associated nonstochastic steady-state (i.e. set $\varepsilon^T = \varepsilon^M = \varepsilon^{AC} = 0$) and compute the log-linear approximation to the first-order conditions around the steady-state. This yields a linear rational expectations model which can be easily solved using standard numerical techniques. The details are available in Appendix A. Note that because this is a linear solution, the shock variances do not affect the decisions of the firm (i.e. there is certainty equivalence).

Figure 4 presents the implied impulse response of the capital stock, the profit rate, and the investment rate to each of three shocks: a permanent increase in productivity (ε_p); a transitory shock to productivity

[16] The linear solution also makes it relatively easy to implement a maximum likelihood estimator.

(ε_t) ; and a shock to adjustment costs (ε_{ac}).[17] (Not depicted are the impulse response to measurement error to profit or investment: these shocks obviously have no effect except at time t on measured profits (resp. measured investment).) In response to a permanent shock, investment increases by a large amount, and capital (size) goes up permanently. Profitability jumps initially before reverting to the steady-state. A transitory shock leads to a temporary increase in size which is reverted in the long-run. Finally, an adjustment cost shock affects investment, but not today's profits. Moreover, the profit rate increases due to diminishing returns to capital. Since these movements in investment and profitability are small for this last shock, the adjustment shock is very similar to measurement error in investment.

3.4 Estimation method

The model is estimated using the simulated method of moments (SMM): parameters are picked to minimize the discrepancy between data moments and model moments.[18] As is well known, this estimation method works well when the moments are sensitive to parameter values.

The parameters to estimates are the curvature of the profit function α and the depreciation rate δ, the adjustment cost curvature $\eta = \delta c''(\delta)$, the four parameters describing the profitability shock process ($\sigma_m, \sigma_p, \sigma_t$ and ρ) and the variance of the shock to adjustment costs σ_{ac} as well as the measurement error in investment σ_{mi}, for a total of 9 parameters. The only remaining parameter is β, which is not estimated. Given that it is typically hard to identify and there are reasonable priors regarding its value, I set $\beta = .95$ and will check later that the results are not too sensitive to this assumption.

Of course, given that this richer model has more parameters than the example above, we need to add more moments for the estimation, on top of the variances and covariance of investment and profit rates which were used in the example.

First, we need to add moments which are informative regarding the parameters α, δ and η. This leads me to incorporate the means of the investment and profit rates in the estimation. It is easy to see analytically that the nonstochastic steady-state of the model is pined down by δ, α and β (see Appendix A). As we will see, the monte carlo experiments and numerical results suggest that the mapping between these means and δ, α is fairly direct. Regarding η, note that it will have a clear effect on the variance of the investment rate, which is already included.

Second, we need to introduce moments which capture the dynamics of investment and profitability, and help measure the share of permanent, transitory and iid shocks: hence we also include the first three autocovariances of the investment and profit rates. I also incorporate the covariance between the profit rate and capital growth over the next three years. This attempts to distinguish highly persistent shocks: the lone feature which distinguishes permanent and transitory shocks is that the size of the firm is affected "in the long run" by a permanent shock.

To summarize, the twelve moments used are:

[17] For these figures, the parameters are set as follows: $\eta = 1.48$, $\delta = 0.167, \alpha = 0.64$, $\beta = .95, \rho = 0.55$.

[18] See Cooper and Haltiwanger (2006) and Henessy and Whited (2005) for related recent applications of this methodology.

$$
\begin{aligned}
&E\left(\frac{I_{it}}{K_{it}}\right), E\left(\frac{\pi_{it}}{K_{it}}\right),\\
&Var\left(\frac{I_{it}}{K_{it}}\right), Var\left(\frac{\pi_{it}}{K_{it}}\right), Cov\left(\frac{I_{it}}{K_{it}}, \frac{\pi_{it}}{K_{it}}\right),\\
&Cov\left(\frac{I_{it}}{K_{it}}, \frac{I_{it-1}}{K_{it-1}}\right), Cov\left(\frac{I_{it}}{K_{it}}, \frac{I_{it-2}}{K_{it-2}}\right), Cov\left(\frac{I_{it}}{K_{it}}, \frac{I_{it-3}}{K_{it-3}}\right),\\
&Cov\left(\frac{\pi_{it}}{K_{it}}, \frac{\pi_{it-1}}{K_{it-1}}\right), Cov\left(\frac{\pi_{it}}{K_{it}}, \frac{\pi_{it-2}}{K_{it-2}}\right), Cov\left(\frac{\pi_{it}}{K_{it}}, \frac{\pi_{it-3}}{K_{it-3}}\right),\\
&Cov\left(\log\frac{K_{it}}{K_{it-3}}, \frac{\pi_{it-3}}{K_{it-3}}\right).
\end{aligned}
$$

While the three periods that we use may sound too small to distinguish permanent and transitory shocks, the trade-off is that considering longer lags lead to considerable attrition and sample selection.[19] The standard errors can be computed using the SMM formula.[20]

The intuition for the identification is similar to the example above. The shock ε_t^M captures changes in profits that are uncorrelated with current (and future) investment. When there is no measurement error in investment ($\sigma_{mi} = 0$), the shock ε_t^{AC} captures changes in investment that are (approximately) uncorrelated with current or future profits. As noted above, the shock to adjustment cost and the measurement error in investment have fairly similar implications, hence it is hard to identify them when both are present.

The shocks ε_t^T and ε_t^P affect both profits and investment, ε_t^P however has more persistent effect and is the only one to affect the firm size even in the long run. This suggests that in order to estimate the variance of these shocks as well as ρ, it is necessary to use either a long-run measure of firm size. Given the other parameters, the adjustment cost parameter η is identified off the variance of investment rates and covariance between investment and profit rates.

3.5 Evaluation of the Estimator: Monte-Carlo Evidence

Before applying the estimator to the dataset, it is useful to verify if it is well-behaved. One may worry that the estimator does not allow to identify all the parameters of the productivity shock process, namely $\sigma_p, \sigma_t, \rho,$ and σ_m. If $\rho = 0$, σ_t and σ_m are not separately identified, and if $\rho = 1$, σ_t and σ_p are not separately identified. Hence, for ρ close to zero (resp. close to one), it will be very hard to distinguish the transitory shock from the i.i.d. shock (resp. the permanent shock).[21]

To assess the performance of the estimator, I use a monte-carlo method. I simulate 100 panels

[19] It should be clear that we are not attempting here to distinguish the case of a unit root and the case of an AR(1) with persistence .999. Rather, as discussed in the literature review, the question is whether the typical estimate of $\rho = .8$ that are used in applied studies capture an important share of firms dynamics.

[20] Usually, the model moments are obtained by simulating the model; but here given that the paper uses a linear approximation and the delta method to obtain model moments, they can actually be computed "exactly".

[21] There is a related numerical issue, which is that minimizing the criterion jointly over σ_p, σ_t, ρ, and σ_m is not completely straigthforward. I solve this by doing a two-stage minimization: fix ρ, then pick the other parameters to minimize the criterion; then repeat this by trying many different values of ρ. One may restrict the search to an interval $\rho \in [\underline{\rho}, \overline{\rho}]$. In most simulations, and in all the data estimations, finding an interior solution for ρ is easy (the criterion appears to be a well behaved function of ρ).

of artificial data from the model.[22] Using these artificial data, the estimator finds the best-fitting parameters, which can then be compared to the true parameters. Table 1 presents the mean and standard deviation of estimates, compared to the true values. The first three rows show the performance of the estimator when $\sigma_t = 0$, so that productivity shocks are only iid or permanent. The next three rows study the case when $\sigma_p = 0$: there are only iid or AR(1) productivity shocks. Finally, the last three rows presents the results for the general model. Each model is further estimated with measurement error in investment ($\sigma_{mi} > 0$) or shocks to adjustment costs ($\sigma_{ac} > 0$).

Overall the estimator seems to work well. In all cases, the mean estimate is close to the truth. The standard deviation of the estimates around this mean is rather low for almost all parameters. The exceptions are the adjustment cost parameter η, and in specifications 3a-3b the parameter ρ.Clearly, identification of ρ is nontrivial. However, even though ρ (and to a lower extent η) is hard to estimate precisely, this does not contaminate the other estimates ($\sigma_m, \sigma_p, \sigma_t$) which appear to be quite accurate. This is important since the main goal of the paper is to estimate this decomposition of shocks.

Monte carlo experiments reveal, unsurprisingly, that allowing for both σ_{mi} and σ_{ac} to be positive does not affect the results, except that σ_{ac} and σ_{mi} are imprecisely estimated. The impulse response function shown above indeed suggests that disentangling these two shocks is difficult. The estimation results will assume that either $\sigma_{ac} > 0$ or $\sigma_{mi} > 0$; the results will be insensitive to which shock is assumed; having both shocks also yields similar results.

To conclude, note that it may well be possible to improve the performance of the estimator by adding or selecting more the moments. Alternatively, maximum likelihood is feasible using the Kalman filter, at least for the linear model.

4 Empirical Results

First I present the data sources, the moments used in the estimation, and some simple summary statistics. Next, I present the results from the SMM estimation.

4.1 Data

The data used in this study are two panels drawn from Compustat, which is the standard source for most studies of investment. The first dataset is an unbalanced panel with $N = 18309$ and $T = 35$ (1971-2006); the total number of firm-year observations is 131448. The second dataset is a balanced panel of firms (1981-2006), which is more comparable to the existing literature ($N = 128$, $T = 26$). Comparing these two datasets also allows me to check how entry and exit (which are not modeled) might affect the results. The details of data construction are in Appendix B.

The moments thus computed, which will be used in the estimation, are reported in Table 2. (Table 2 reports the standard deviations and correlations rather than the variances and covariances, since they are easier to understand.) These estimates pool the time-series and cross-section data, and assume no

[22] These are balanced panels with $N = 128$ and $T = 27$. (Add results with unbalanced panels.) There are actually only 50 panels for specifications 2a-2b and 3a-3b. (Add more.)

fixed effects.[23] The table reports the moments for five different constructions: balanced vs. unbalanced panel, with and without time effects, and the unbalanced panel with industry (2-digit SIC code) fixed effects.[24]

These moments capture some well-known feature of the data: profitability is fairly volatile and persistent. Investment is both less volatile and less persistent. The moments are somewhat different between the two panels: unsurprisingly, the unbalanced panel has more volatility, and it also has lower persistence both in investment and profitability. This likely reflects an important selection in the balanced panel towards stable firms, which are more likely to survive an extended period of time. Note also that the correlation between investment and profits is somewhat higher in the balanced panel.

Removing time effect has little effect on most of the moments, except for a noticeable increase in the persistence of investment, and to a lesser extent of profitability. Removing industry effects has smaller effects than removing time effects, though there is some increase in the persistence of investment.

Figures 1, 2, 3 and 5 present some simple features of the data: first, the distribution of investment rates and profit rates has a large variance, and some positive skewness (around 2). Second, the correlogram of investment rates and profit rates (for the balanced and unbalanced panel) show that profits are always more persistent than investment, and both variables are significantly less persistent when firm fixed effects have been taken out. The cross-correlogram shows that profits tend to lead investment by a year in the balanced panel, whereas in the unbalanced panel there is no such effect.

4.2 Main Results

I first present the estimates, then look at the fit of the model, and finally turn to some robustness exercises.

4.2.1 Estimates

Table 3 reports the parameter estimates for the six main specifications of the model, using the unbalanced panel. These correspond to two possibilities for the shocks to adjustment costs and measurement error in investment (a) $\sigma_{ac} = 0$, (b) $\sigma_{mi} = 0$; and three possibilities for the productivity shock process: (1) permanent shocks but no AR(1) shocks, i.e. $\rho = \sigma_t = 0$; (2) no permanent shocks, i.e $\sigma_p = 0$, (3) the full model with both kind of shocks. Note that in all the reported results I used the identity matrix to weight the moments.[25]

Consider first the estimates for the adjustment cost parameter η, which range from 1.12 and 1.94, depending on the specification. This number is the elasticity of Tobin's q to investment, and is equal to $\delta c''(\delta)$.[26] To contrast this number to other estimates found in the literature, note that if the adjustment cost is assumed to be quadratic, i.e. $c(x) = \frac{\psi}{2}(x-\delta)^2$, we have $\eta = \delta\psi$. Typical estimates for ψ range

[23] The data standard errors were computed by GMM using the pooled data (i.e. the large NT asymptotics), allowing for arbitrary time series correlation within each firm, arbitrary heteroskedasticity, but assuming zero correlation between firms. See Appendix C for details.

[24] There are not enough firms in the balanced panel to estimate industry fixed effects.

[25] The second-stage estimates, using as weighting matrix the inverse of the covariance of the moments, appear to be unstable, which is why they have not been incorporated yet.

[26] We have $\widehat{q_t} = \eta\,\widehat{i_t/k_t} - \frac{\eta}{\delta}\varepsilon_t^{AC}$ (see appendix A).

from 4 (e.g., Gilchrist and Himmelberg (1995)) to values as high as 20 or more, which translates into elasticities of about .75 to 4. Hence, my estimates are in the middle of this range of estimates.[27]

Regarding the shock process, we see that when there are only permanent shocks (i.e. case (i)), they are estimated to be fairly large, around 24% per year. The iid shocks to profit and to investment (or to adjustment costs) are quite large, reflecting either important measurement error, important highly transitory components, or model misspecification. In interpreting this table, recall that the units of σ_p, σ_t and σ_m are percentage shocks to profits, the units of σ_{mi} are percentage shocks to investment, but the shock ε_{ac} is multiplied by $c''(\delta) = \eta/\delta \simeq 7 - 12$ in its effect on q (see footnote 26). Also, note that these are the shocks to profitability; if the profit function comes from maximizing over labor, i.e.

$$\pi(z, K) = \max_N \{zK^\alpha N^\upsilon - wN\}$$

then $\pi(z, K) = z^{\frac{1}{1-\upsilon}} K^{\frac{\alpha}{1-u}} \times$ constant, so that shocks are amplified by a factor $\frac{1}{1-\upsilon} \simeq 3$ if the labor share is $\frac{2}{3}$. Hence, the standard deviation of fundamental shocks to sales (output) is about 8% for the permanent shock.

Turning to the specification (2) for the shock process, i.e. no permanent shocks and only persistent shocks, we see that ρ is estimated to be fairly high, around .78. This result is similar to what other papers in the investment literature have found (e.g., Cooper and Haltiwanger (2006), Gomes (2001), Hennessy and Whited (2005)). The transitory shock has a very large variance, around .89 which translates into a 30% standard deviation for the shock to output.

The third specification (3) allows for both a permanent and an AR(1) component. In this cae, we find that both are significant, but the AR(1) component becomes fairly transient ($\rho = .55$). As a result, this AR(1) component becomes quite similar to the iid profit shock, and the two variances σ_m and σ_t become hard to distinguish; the estimator in some cases reduces the measurement error to zero or close. But in all specifications the permanent shock remains important and precisely estimated.

The estimates for the adjustment cost parameter η and the profitability shock $(\sigma_p, \rho, \sigma_t)$ are not substantially affected by the specification of the adjustment cost shock, i.e. specification (a) or (b) lead to the same results.[28] These two specifications are essentially equivalent.

Finally, remark that the parameter estimates α and δ are very stable across specifications. This reflects that they are essentially pined down by the means of profit rates and investment rates respectively (see Appendix A).

4.2.2 Fit of the model and Implications

To evaluate the fit of the model and the various specifications, it is useful first to note that the model matches most of the moments reasonably well: it fits the mean and variances almost exactly, and matches reasonably well the "long-run moment" $Cov(\log \frac{K}{K_{-3}}, \frac{\pi_{-3}}{K_{-3}})$, and it matches the shape of the autocovariance on average, even though it cannot . The main drawback seems to be that the model over-

[27] This is in spite of the fact that other researchers have used different estimation techniques and different estimating equations, e.g. based on using market data and Hayashi's theorem to measure marginal q as average q.

[28] Having both adjustment cost shocks and measurement error in investment also leads to similar estimates. But as expected, the standard errors reveal that it is hard to disentangle the two shocks σ_{ac} and σ_{mi} in this specification.

predicts significantly the correlation between current investment and profits. I suspect that information, planning and gestation lags can account for some of this.

The model makes several interesting predictions. Table 7 gives a variance decomposition of investment and profits into the various shocks. Measurement error (iid shocks) appear to be important both for profits and for investment.[29] Interestingly, in the case of specification 3, investment appears to be largely driven by permanent shocks (and measurement error), while profits are largely driven by transitory shocks. This suggests that using profits to deduce the amount of shocks faced by firms may lead to incorrect conclusions, since profits are buffeted by many transient shocks which do not appear to affect investment.

Figures 5, 6 and 7 compare the correlogram of size (log capital) in the data, in specification 2, and in specification 3. The correlogram of log capital can be computed by taking fixed effects (which is equivalent to computing the correlation for each firm, then averaging) or without fixed effects. In the data, these two procedures are not equivalent: taking fixed effects reduces substantially the correlation. Without fixed effects, the correlation is extremely high. The model with only AR(1) shock (specification 2) unsurprisingly generates too little persistence for both measures. Adding fixed effects in the model will move up the blue (circles) line but will not affect the red (crosses) lines. In contrast, the model with permanent shocks (specification 3) matches well the two correlograms, with and without fixed effects. (It overpredicts somewhat the persistence obtained using no fixed effects.) This is, of course, in spite of the fact that the model does not have fixed effects. These pictures suggest that (a) the AR(1) model does not generate enough persistence for the data and (b) the model with permanent shocks, which is fairly parsimonious, replicates well the persistence in the data. Point (a) is not too surprising since with moderately persistent AR(1) shocks, mean reversion is much stronger in the model than in the data.

Finally, figures 8 and **??** show the correlogram of investment, profit (with and without fixed effects), and the cross-correlogram implied by the model. (These figures can be compared to the data: figures 2 and 3.) The model does reasonably well in matching the panel correlogram (which is essentially the moments targeted) but does less well at matching the average correlogram (i.e. with fixed effects). As noted above, the model overpredicts the contemporaneous correlation of investment and profits, but the last panel shows that it overpredicts this correlation at all horizons.

4.3 Robustness

4.3.1 Balanced Panel

Table 6 shows the results for a balanced panel. Even though sample selection may seem important, the estimates are not very different than in the unbalanced panel: the adjustment cost parameter is a bit smaller, the persistence parameter a bit higher, both reflecting the higher persistence in the balanced panel. Since there is less volatility in the balanced panel, all the shocks become smaller, but the permanent shock remains important, around 16%.

[29] This is consistent with Erickson and Whited (2000) who use stock market data.

4.3.2 Time Effects and Industry Effects

Table 8 presents the results of the estimation when a time effect is removed from all the series.[30] For simplicity, I present here only the results with measurement error (i.e. $\sigma_{ac} = 0$ and $\sigma_{mi} > 0$) and for the unbalanced panel. The three sets of results refer to the three specifications for productivity shocks (1), (2) and (3). Since the mean is removed from the moments, I remove the mean from the moments that are matched, and I set $\alpha = .64$ and $\delta = .167$ as suggested by the previous estimation results. Comparing table 8 with table 3, we see that the estimates are not significantly affected by the inclusion of time effects: the estimates for the permanent shocks or for adjustment costs are not substantially different. For instance with specification (3), measurement error and the permanent shock volatility are largely unchanged. As the moments show somewhat more persistence once time effects are taken into account, it is not surprising that ρ is somewhat higher (.82 vs .78). The adjustment cost is somewhat lower at 1.31 (vs. 1.48), probably due to the difference in the contemporaneous correlation of investment and profits. Table 9 shows the fit of the moments.

Next, I investigate the consequences of removing an industry fixed effect from the series. The motivation for introducing industry fixed effects is that measurement error in investment and capital may be industry-specific.[31] This subsection thus removes an industry (2-digit SIC) fixed effects from the moments before estimating the model. As with time effects, $\alpha = .64$, $\delta = .167$. The estimates are in Table 10 and the moments matched in Table 11. In this case too, the estimates appear to be robust: the values of ρ and η are slightly affected, and the shock variances are only mildly affected.

4.3.3 Set of Parameters Estimated vs. Calibrated

The discount factor β was not estimated. As an illustration of the effect of changing β, Table 12 shows how the results for the estimation of one baseline specification model (both permanent and transitory shocks, no measurement error) is altered when β takes fairly extreme values: $\beta = .88$ or $\beta = .98$. We observe that the estimates for ρ, η, σ_t,$\delta, \sigma_m, \sigma_{mi}$ are essentially unaffected by these changes, while the value of α is smaller (as expected since α is pined down from the mean profit rate, the mean investment rate and β) . Most importantly, as β becomes larger the estimate of σ_p becomes substantially larger. This appears to be driven by the lower α; rationalizing the change in size observed in the data (i.e. the last moment, $Cov(K/K_{-3}, \pi_{-3}/K_{-3})$) requires larger permanent shocks given a higher curvature of the profit function.

The estimation results are also robust to two other variations: (a) estimating α and δ vs.calibrating them using the steady-state; (b) having both adjustment cost shocks and measurement error in investment. In that case, the relative importance of these two shocks is not precisely estimated, but the other parameter estimates are largely unaffected.

[30] More precisely, before computing the data moments, we fit a regression $x_{it} = \delta_t + \varepsilon_{it}$, for $x = I/K, \pi/K$, and K/K_{-3}. The data moments so calculated are reported in section XXX.

[31] There may also be differences in technologies. The estimation imposes that the parameters α, δ and η are the same for all firms.

5 Implications of permanent shocks in general equilibrium

In this section, I embed the partial equilibrium adjustment cost model estimated in the previous section in a general equilibrium framework, and use the estimates to study the effects of physical adjustment costs on reallocation, aggregate output and capital accumulation, and aggregate TFP. The model is similar to Hopenhayn and Rogerson (1993), Gomes (2001), Veracierto (2002) and Gourio and Miao (2008): firms are ex-ante identical but ex-post heterogeneous due to productivity shocks. In contrast to these papers however, the model incorporates permanent shocks.[32] An advantage of this framework is that it is easy to add richer physical or financial frictions to assess the robustness of the results.

This framework is used to contrast the predictions implied by a model with permanent shocks to a model with standard AR(1) shocks. The model allows me to conduct the following experiment: assume that the estimates of Section 4 are correct, but that the economist falsely fits a model without permanent shocks, and then uses his results to assess the effect of removing a friction. By how much will his answers be wrong?

5.1 Model setup

Time is discrete. There is a continuum of firms and a representative household. The representative household has preferences

$$E\sum_{t=0}^{\infty}\beta^t U(c_t),$$

where U is an increasing and concave function. Labor supply is inelastic, equal to $\overline{N}$. The model features no aggregate shocks. By a law of large numbers, idiosyncratic shocks wash out, and aggregate quantities and prices are constant over time. Hence, in a stationary steady-state, firms discount future payoffs at rate β.

Each firm operates a Cobb-Douglas technology with decreasing return to scale:

$$Y = zK^{\alpha}N^{\upsilon},$$

where z is the idiosyncratic productivity of the firm. The firm can adjust labor each period labor in a frictionless market, however investment in capital goods is subject to adjustment costs. It is assumed that the productivity $\log z$ is the sum of two components:

$$\log z = \log z_p + \log z_t,$$

where $\log z_t$ follows a stationary Markov process with transition function Q, and $\log z_p$ follows a normal unit root process:

$$\log z_p' = \log z_p + \sigma_p\varepsilon_p',$$

where a prime ($'$) denotes next period value, and ε_p is *iid* across firms and time and $N(0,\sigma_p^2)$. This is of course the process estimated in Section 4, assuming that z_m is purely measurement error.

The value W of a firm with current capital K, and current productivity values z_p, z_t is given by the following Bellman equation:

[32] Unlike Luttmer (2007), the model does not have aggregate growth.

$$
\begin{aligned}
W(K,z_p,z_t;w) &= \max_{N,I}\left\{z_p z_t K^\alpha N^\upsilon - wN - I - \frac{\psi}{2}\left(\frac{I}{K}-\delta\right)^2 K + \beta(1-\eta)EW(K',z_p',z_t';w) + \beta\eta K\right\}, \\
s.t. &: K' = (1-\delta)K + I, \\
& \quad z_t \text{ Markov with transition function } Q(.,.); \\
z_p \text{ satisfies:} & \quad \log z_p' = \log z_p + \sigma_p \varepsilon_p', \text{ with } \varepsilon_p' \text{ iid } N(0,1).
\end{aligned}
$$

The only difference with the model estimated in section 4 is that there is an exogenous rate of exit η. We need to introduce exit since otherwise, in the presence of permanent shocks, there is no stationary distribution of firms. While it would be interesting to model exit as an economic decision, this equations assumes for simplicity a constant rate of exit. If the firm exits, it can sell its capital. (This assumption is not critical.) Entry takes the following form: upon paying an entry cost c_{in}, the firm enters with some capital K_{in} and productivities (z_p, z_t) which are drawn according to a distribution υ.

Note that there are no shocks to adjustment costs; the interpretation here is again that there is measurement error in investment, as in section 4, but it has no relation to real investment.

We can now compute optimal labor demand, output supply and profit function by maximizing out labor:

$$
N = N(z_p,z_t,K;w) = \left(\frac{z_p z_t K^\alpha \upsilon}{w}\right)^{\frac{1}{1-\upsilon}},
$$

$$
Y = Y(z_p,z_t,K;w) = A_1 \times (z_p z_t)^{\frac{1}{1-\upsilon}} \times K^{\frac{\alpha}{1-\upsilon}},
$$

$$
\Pi = \Pi(z_p,z_t,K;w) = A_2 \times (z_p z_t)^{\frac{1}{1-\upsilon}} \times K^{\frac{\alpha}{1-\upsilon}},
$$

where $A_1 = \left(\frac{\upsilon}{w}\right)^{\frac{\upsilon}{1-\upsilon}}$ and $A_2 = A_1(1-\upsilon)$. This is of the form used in the estimation in Section 5, up to a redefinition of α and of z.

We now can rewrite the Bellman equation as:

$$
\begin{aligned}
W(K,z_p,z_t;w) &= \max_{I}\left\{(z_p z_t)^{\frac{1}{1-\upsilon}} K^{\frac{\alpha}{1-\upsilon}} A_2(w) - I - \frac{\psi}{2}\left(\frac{I}{K}-\delta\right)^2 + \beta(1-\eta)EW(K',z_p',z_t';w) + \beta\eta K\right\}, \\
s.t. \quad : \quad & K' = (1-\delta)K + I.
\end{aligned} \tag{18}
$$

The optimal solution yields the policy functions:

$$
\begin{aligned}
K' &= g(K,z_p,z_t;w), \\
I &= h(K,z_p,z_t;w).
\end{aligned} \tag{19}
$$

This can be further simplified using the homogeneity of the objective function. More precisely, define $k = \frac{K}{z_p^{\frac{1}{1-\alpha-\upsilon}}}$, and the investment rate $\iota = \frac{I}{K}$, then it is easy to verify the following guess:

$$
W(K,z_p,z_t;w) = z_p^{\frac{1}{1-\alpha-\upsilon}} j(k,z_t;w),
$$

where j satisfies the following functional equation:

$$\begin{aligned}
j(k,z_t;w) &= A_2(w) z_t^{\frac{1}{1-\upsilon}} k^{\frac{\alpha}{1-\upsilon}} \\
&\quad + \max_{\iota} \left\{ -\left(\iota + \frac{\psi}{2}(\iota-\delta)^2\right) k + \beta(1-\eta) E\left[e^{\frac{\sigma_p \varepsilon_p'}{1-\alpha-\upsilon}} j(k', z_t'; w)\right] + \beta\eta k \right\} \qquad (20) \\
s.t. &: \\
k' &= \frac{K'}{z_p'^{\frac{1}{1-\alpha-\upsilon}}} = \frac{K'}{K} \frac{K}{z_p^{\frac{1}{1-\alpha-\upsilon}}} \frac{z_p^{\frac{1}{1-\alpha-\upsilon}}}{z_p'^{\frac{1}{1-\alpha-\upsilon}}} = (1-\delta+\iota) k e^{\frac{-\sigma_p \varepsilon_p'}{1-\alpha-\upsilon}}.
\end{aligned}$$

This is a substantial improvement over the previous equation because (1) the state variables are now bounded (while before z_p and K were unbounded) and (2) there are only two states instead of three. We have now a dynamic programing problem with two states which can be solved using standard numerical techniques. (See Appendix D for details on the numerical solution.)

To find aggregates, we need to keep track of the measure of firms with state K, z_p, z_t. This measure satisfies the following law of motion: for any (measurable) sets A, B, C,

$$\begin{aligned}
& \mu'(A \times B \times C) \\
= \; & (1-\eta) \int 1_{g(K,z_p,z_t) \in A} \times \Pr(z_p \exp(\sigma_p \varepsilon_p') \in B) \times Q(z_t, C) \times \mu(dK, dz_p, dz_t) \\
& + M \times \upsilon(z_p, z_t) 1_{K_{in} \in A}, \qquad (21)
\end{aligned}$$

where M is the mass of new entrant each period, g is the policy function from (19), υ is the distribution of entrants over the two shocks z_p and z_t, and K_{in} is the initial capital of entrants.[33]

A stationary equilibrium is defined as a value function W and policy function g, a distribution μ, mass of entrant M, and wage w such that:

(1) the value function W and policy function g solve (18);

(2) the distribution μ is self-preserving, i.e. $\mu' = \mu$ in equation (21);

(3) the labor market clears:

$$\int\int\int n(K, z_p, z_t; w) \mu(dK, dz_p, dz_t) = \overline{N};$$

(4) the free entry condition holds:

$$\int\int W(K_{in}, z_p, z_t) d\upsilon(z_p, z_t) = c_{in}.$$

As a result, the goods market clears:

$$\begin{aligned}
& C + \int\int\int \left(I(K, z_p, z_t; w) + \frac{\psi}{2} \left(I(K, z_p, z_t; w), K \right) \right) \mu(dK, dz_p, dz_t) + M \left(c_{in} + K_{in} \right) \\
= \; & \int\int\int Y(K, z_p, z_t; w) \mu(dK, dz_p, dz_t). \qquad (22)
\end{aligned}$$

To solve for the equilibrium, we follow Hopenhayn and Rogerson (1993) and Gomes (2001): first, we find a wage such that the free entry condition holds; next, we find the equilibrium number of entrants which is consistent with labor market clearing. The goods market clearing condition then defines the equilibrium consumption C.

[33] Because we will assume that the adjustment cost is a function of the I/K ratio, we cannot assume that firms start with zero initial capital.

5.2 Model Calibration and Experiments

The calibration of the model is based on the estimates of section 4 (whenever possible). As in the estimation, $\beta = .95$ a priori. We set $\upsilon = .66$ to match the labor share; the parameter α is then picked to replicate the curvature of profit, estimated to be .64.[34] The shock process is the one estimated:[35] $\sigma_p = .07, \sigma_t = .32, \rho = .55$. The iid shocks to profits and investment are assumed to be pure measurement error. The exit rate is set equal to 5%. The entry cost is normalized to 1. The initial capital is assumed to be the nonstochastic steady-state, and firms enter with $z_p = 1$ and z_t uniformly distributed. Note that we do not need to specify the utility function U. The adjustment cost parameter is taken to be 8.98, corresponding to $\psi = \eta/\delta$ with $\eta = 1.5$ and $\delta = .167$.

The policy function is depicted in figure **??**. The investment rate $\iota = I/K$ is decreasing in k, and is increasing in z_t. This reflects the adjustment of capital towards its desired value, which is not instantaneous due to the adjustment cost. Note that a positive permanent shock has the effect of lowering k, since K is a state variable, which increases investment. Because of permanent shocks, the size distribution is very skewed.

We now consider some experiments with this model. The key point is that the predictions implied by the model regarding macroeconomic aggregates are sensitive to the assumptions made regarding the shock process. This was illustrated analytically in section 2. We now make the point quantitatively.

Consider first the following experiment. Assume that the model is the truth, and that we are trying to predict the effect of a "reform" which reduces adjustment costs down to zero. With our knowledge of parameters, it is straightforward to compute the equilibrium of the model for the original value of ψ, and for $\psi = 0$. Comparing macroeconomic aggregates shows that such a reform (were it possible) would increase aggregate output by 14.1%, aggregate capital by 29.4% and aggregate TFP by 8.05%. Clearly, such a reform increases productivity by increasing entry and speeding reallocation of factors across firms.

Now suppose that an economist is trying to predict the effect of this reform. The economist knows the model and the parameter values but he ignores the correct shock process. The economist fits, as is standard in the literature, a model with fixed effects and an AR(1) shock. For instance, assumes that he uses a balanced panel to estimate:

$$\log \Pi_{it} = \alpha_i + b \log K_{it} + z_{it}, \tag{23}$$

$$z_{it} = \rho z_{it-1} + \sigma \varepsilon_{it}. \tag{24}$$

For simplicity, we assume that the economist knows the correct curvature parameter $b = \frac{\alpha}{1-\upsilon}$. (Not knowing b raises additional issues.) Simulations reveal that this economist would estimate $\rho \simeq .807$ and $\sigma \simeq 1.173$ (These numbers are found by simulating data from the 'true' model and estimating **??**-24 as the economist would do.) With these numbers in hand, the economist would predict that eliminating

[34] Implicitely, we assume that pure profits (which equal to the entry cost in present value) are counted as capital income in the NIPA.

[35] As explained in section 4, we need to multiply the estimates by a factor $\frac{1}{1-\upsilon}$ to obtain the shock to the production function.

adjustment costs would increase output by 10.3%, capital by 4.1%, and TFP by 9.4%. These numbers are markedly different from the truth. Hence, not knowing the correct process for productivity shocks would lead to a significant error, even if the economist knew exactly the rest of the structure of the economy.

6 Application: the evolution of idiosyncratic volatility

As an example of application of the methodology, this section studies the variation of idiosyncratic risk over the past 35 years in the United States. This exercise is interesting in light of two debates. First, some authors argue that idiosyncratic volatility has increased over time (Comin and Philippon, 2005). This is true in the Compustat sample but does not appear to be true in larger Census universes (Davis, Haltiwanger, and Miranda, 2006). Second, several authors have recently documented that firm-level idiosyncratic risk is somewhat countercyclical (Bloom 2008, Eisfeldt and Rampini 2007).[36]

The procedure that we used before by pooling cross-section and time-series data can be applied year-by-year, using only cross-sectional moments. Under the assumption that firms realize the shock process that they face, we can use these cross-sectional moments to identify the variance of each of the shocks hitting these firms, in any given year. Note that under the linear approximation, shock variances do not enter the decision rules. Hence, it is irrelevant for this exercise when firms learn their shock variances.[37]

I present the results only for the simple specification with permanent and iid shocks (specification 1). Here the issue is not to distinguish permanent and highly persistent shocks but to see which of the iid shocks or highly persistent shocks have contributed to the increase and countercyclicality of volatility.

Figure 10 displays the cross-sectional moments that we use to estimate the model. The evolution of the shock process that we will find is directly due to the evolution of these moments: the variance of profit rates has almost steadily increased, while the variance of investment rates increased in the 1970s before falling back.[38] Interestingly, several of these moments show sharp variations in some of the recession years (1981, 2001 in particular). Table 13 presents results from regression of each moment on a time trend, and from regressions of each HP-filtered moment on HP-filtered GDP, with a smoothing parameter of 100. The results confirm that some moments are significantly countercyclical, esp. the long-run moment $Cov(\log \frac{K}{K_{-3}}, \frac{\pi_{-3}}{K_{-3}})$.[39]

These time-varying moments lead to time-varying parameters. Figure 11 presents the implied parameters, with the two standard error bands. Clearly the iid shock to profits has increased over the sample, but has fallen since 2000. The iid shocks to investment has increased then decreased. The permanent shock has increased, but has shown some important fluctuations, which are negatively correlated

[36] Here too, there is a parallel with the consumption literature, which also argues that income volatility has gone up, and is countercyclical.

[37] More precisely, the shock variances could be deterministic variables, or stochastic variables which are revealed over time. The only important condition is that at time t, firms know the variance of the shock that just hit them. Importantly, I fix the parameters α, δ and η in this estimation; otherwise the firm would react to predictable variation in these parameters.

[38] The serial correlation of investment has increased slightly, while the serial correlation of profit is mostly trendless.

[39] Note that this moment is actually computed in a forward looking way: i.e. at time t we compute $Cov(\log \frac{K_{t+3}}{K_t}, \frac{\pi_t}{K_t})$.

with GDP (-0.51). Figure 12 shows the HP-filtered parameters and HP-filtered GDP. The conclusion is that the two iid shocks are only weakly correlated with GDP, but permanent shocks appear to be countercyclical. This corroborates the view of Bloom (2008), and Eisfeldt and Rampini (2007), that idiosyncratic shocks are countercyclical.

Comparing figures 10 and 11 shows that the graph for the estimate for σ_p is very similar-looking to the graph of the moment $Cov(\log \frac{K}{K_{-3}}, \frac{\pi_{-3}}{K_{-3}})$. This suggests strongly that the long-run moment identifies the share of permanent shocks. The countercylicality of σ_p is a direct consequence of the countercyclicality of the long-run moment.[40] While the t-stats are small, the magnitude of the slope is relatively large (-0.33).

Overall, this application of our methodology confirm that in this sample, volatility has increased, and we can trace it down to an increase in the volatility of both iid and (most importantly) permanent shocks. These permanent shocks appear to be larger in recessions.

7 Conclusions and Work in Progress

The shock process is an important, and rather understudied, input into models of firm heterogeneity. The procedure proposed in this paper allows to use investment decisions to infer the persistence of the shock process. The estimates suggest that permanent shocks are important. It would be interesting to use alternative estimators (e.g., maximum likelihood) to estimate this decomposition. Allowing for exit may be interesting.

The importance of permanent shocks calls for more theoretical and quantitative work incorporating these shocks into the models, and possibly modeling their sources. In particular, there is little work which integrates the firm size distribution and investment dynamics.

This study has proceeded under the assumption that the firm observes all the components of its productivity at any point in time and can instantaneously distinguish permanent and transitory components. An alternative assumption, which would be interesting, is that the firm faces a signal extraction problem and needs to learn its productivity over time. Contrasting the implications of these two models seems interesting.

[40] One may worry that this countercylical moment reflects financing constraints which are more binding in recessions, leading to a higher covariance of current profits with future growth. This is certainly a possibility (and the correlation between current investment and profits is also somewhat countercyclical), but note that this simple correlation may not be a good proxy for financial constraints, as argued by many authors.

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8 Appendix A: Solution method

The equations characterizing the solution are:

$$q_t = \beta(1-\delta)E_t\left(q_{t+1}\right)+\beta\alpha E_t\left(z_{t+1}K_{t+1}^{\alpha-1}\right)+\beta E_t\left(-c\left(\frac{I_{t+1}}{K_{t+1}}-\varepsilon_{t+1}^{AC}\right)+\frac{I_{t+1}}{K_{t+1}}c'\left(\frac{I_{t+1}}{K_{t+1}}-\varepsilon_{t+1}^{AC}\right)\right), \quad (25)$$

$$q_t = 1+c'\left(\frac{I_t}{K_t}-\varepsilon_t^{AC}\right) \quad (26)$$

$$K_{t+1} = (1-\delta)K_t + I_t, \quad (27)$$

$$\Pi_t = z_t K_t^{\alpha}, \quad (28)$$

$$\log z_t = \log z_t^P + \log z_t^T + \varepsilon_t^M, \quad (29)$$

$$\log z_t^P = \log z_{t-1}^P + \varepsilon_t^P + x_t^{(0)}, \quad (30)$$

$$\begin{aligned} x_t^{(j)} &= x_{t-1}^{(j+1)}, j = 0...J-1 & (31)\\ x_t^{(J)} &= \varepsilon_t^N. & (32)\end{aligned}$$

$$\log z_t^T = \rho \log z_{t-1}^T + \varepsilon_t^T. \quad (33)$$

I use a log-linear method to approximate this solution. Here $x_t^{(j)}$ captures advance information (aka "news shocks"), or, if it is correlated with the current ε's, can capture "long-run shock" i.e. positive autocorrelation of the growth rate of profitability.

8.1 Stationarity

Define the "detrended" capital $k_t = K_t/z_{P,t-1}^{\frac{1}{1-\alpha}}$, and investment $i_t = I_t/z_{P,t-1}^{\frac{1}{1-\alpha}}$.Then the FOC for investment reads:

$$q_t = 1+c'\left(\frac{i_t}{k_t}-\varepsilon_t^{AC}\right).$$

The capital accumulation law of motion is:

$$\begin{aligned} k_{t+1} &= \left(\frac{z_{P,t}}{z_{P,t-1}}\right)^{\frac{1}{\alpha-1}}((1-\delta)k_t+i_t)\\ &= \exp\left(\frac{1}{\alpha-1}\left(\mu+\varepsilon_t^P+x_t^{(0)}\right)\right)((1-\delta)k_t+i_t)\end{aligned}$$

The series q_t, k_t, i_t fluctuate around a stationary steady-state characterized by:

$$\begin{aligned} \frac{i^*}{k^*} &= \exp\left(\frac{\mu}{1-\alpha}\right)-1+\delta = \widetilde{\delta}, & (34)\\ q^* &= 1+c'\left(\frac{i^*}{k^*}\right), & (35)\end{aligned}$$

and the last equation is:

$$q^*(1-\beta(1-\delta)) = \beta\alpha e^{\mu}k^{\alpha-1}+\beta\left(-c\left(\widetilde{\delta}\right)+\widetilde{\delta}c'\left(\widetilde{\delta}\right)\right),$$

Assuming $c\left(\widetilde{\delta}\right)=0$ and $c'\left(\widetilde{\delta}\right)=0$, we have:

$$q^* = \frac{\beta\alpha e^{\mu}}{1-\beta(1-\delta)}k^{*\alpha-1}. \quad (36)$$

Equations (34-36) can be solved for the steady-state: $\frac{i^*}{k^*} = \widetilde{\delta}$, $q^* = 1$, and k^* is given by (36).

I now linearize the model around this steady-state. Note that all firms will have the same steady-state for detrended variables, but since they experience different histories of shocks they will have different scaling z^P_{t-1}. Note that there are no fixed effects here.

It will be useful to define detrended profits as:

$$\pi_t = \frac{\Pi_t}{z_{P,t-1}^{\frac{1}{1-\alpha}}} = \frac{z_t}{z_{P,t-1}} \left(\frac{K_t}{z_{P,t-1}^{\frac{1}{1-\alpha}}} \right)^{\alpha} = z_t^T \exp\left(\mu + \varepsilon_t^P + x_t^{(0)}\right) \varepsilon_t^M k_t^{\alpha}.$$

8.2 Log-Linearization

To obtain the first log-linearized equation, we use 26. Let $\eta = \widetilde{\delta} c''(\widetilde{\delta})$, and denote $\widehat{x}_t = \frac{x_t - x^*}{x^*}$ for any variable x. Then:

$$\begin{aligned}
q_t &= 1 + c'(i_t/k_t - \varepsilon_t^{AC}) \\
q^* &= 1 + c'(i^*/k^*) = 1. \\
\frac{q_t - q^*}{q^*} &= c'(i_t/k_t - \varepsilon_t^{AC}) \\
&= \underbrace{c'(i^*/k^*)}_{0} + c''(i^*/k^*)\left(i_t/k_t - \varepsilon_t^{AC} - i^*/k^*\right) \\
\widehat{q}_t &= \eta \times \widehat{i_t/k_t} - c''(i^*/k^*)\varepsilon_t^{AC}
\end{aligned}$$

leading to the first equation:

$$\widehat{q}_t = \eta\left(\widehat{i}_t - \widehat{k}_t\right) + \eta_2 \varepsilon_t^{AC}. \tag{37}$$

The second equation is obtained from 27:

$$\widehat{k}_{t+1} = -\frac{1}{1-\alpha}\left(\varepsilon_t^P + x_t^{(0)}\right) + \left(\omega \widehat{k}_t + (1-\omega)\widehat{i}_t\right), \tag{38}$$

where $\omega = \frac{(1-\delta)k^*}{(1-\delta)k^* + i^*}$. To linearize the third equation,we use **??**:

$$q_t = \beta(1-\delta)E_t\left(q_{t+1}\right) + \beta\alpha e^{\mu} E_t\left(z_{t+1}^T e^{\varepsilon_{t+1}^P + x_{t+1}^{(0)}} e^{\varepsilon_{t+1}^M} k_{t+1}^{\alpha-1}\right) + \beta E_t\left(-c\left(\frac{i_{t+1}}{k_{t+1}} - \varepsilon_{t+1}^{AC}\right) + \frac{i_{t+1}}{k_{t+1}} c'\left(\frac{i_{t+1}}{k_{t+1}} - \varepsilon_{t+1}^{AC}\right)\right),$$

which yields:

$$\widehat{q}_t = \beta(1-\delta)E_t\left(\widehat{q}_{t+1}\right) + (1 - \beta(1-\delta)) \times E_t\left(\log z_{t+1}^T + \varepsilon_{t+1}^P + x_{t+1}^{(0)} + (\alpha-1)\widehat{k}_{t+1}\right). \tag{39}$$

since the rest is 0 in steady-state. In the case where there are no news shocks, it is easy to solve this model by the method of undetermined coefficients. In general, it is easier to use a linear equation solver.

9 Appendix B: Data Construction

I use the Compustat industrial annual data from 1971 to 2006 and use the following standard criteria to drop data. First, I delete observations of firms whose primary SIC classification is between 6000 and 6999 or between 4900 and 4999, since the model may not be appropriate for regulated or financial firms. Second, we delete observations of firms with negative or zero values of book value of capital (item 8), sales (item 12), or assets (item 6). Investment is defined as data30. (Changing the definition to net out capital sales (item 107) does not affect the results significantly.) We measure earnings using item 13 (operating income). Observations with a merger flag in year t are removed from the sample in years $t-1$, t and $t+1$. To diminish the effect of extreme observations, I drop outliers, i.e. firms which have in a given year a profit rate above 4 or less than $-.5$, or an investment rate above 1.5. Finally, the moments are computed based on all the firm-years points for which data is available for four consecutive years (since the moments require four consecutive years of data).

10 Appendix C: Computation of the moment standard errors

The standard errors of the moments measured in the data is used to compute the standard error of the estimates (and to find the optimal weighting matrix giving the second-stage estimates). The covariance matrix is obtained by stacking the moments that we need to measure, using GMM to obtain the standard errors, and then using the delta method to obtain the covariance matrix of the moments of interest.

To simplify the notation, I assume a balanced panel in what follows. Let $x_{it}^{(k)}$, $i = 1...N$ and $t = 1...T$, where $k = 1...K$ indexes the time series; so $x_{it}^{(1)} = I_{it}/K_{it}$, $x_{it}^{(2)} = \pi_{it}/K_{it}$, $x_{it}^{(3)} = I_{it}^2/K_{it}^2$, etc. The moments we try to estimate are the $\mu^{(k)}$ defined as $E(x_{it}^{(k)} - \mu^{(k)}) = 0,\ k = 1...K$, which can be regarded as a just-identified GMM system. The estimates are the sample counterparts,

$$\widehat{\mu}^{(k)} = \frac{1}{NT} \sum_{i,t} x_{it}^{(k)}.$$

The covariance matrix of the vector of estimates $\widehat{\mu}^{(k)}$can be computed using the GMM formula in the case of perfect identification:

$$Var(\widehat{\mu}) = \frac{S}{NT},$$

where S is estimated as

$$\widehat{S} = \frac{1}{NT} \sum_{t,l=1}^{T} \sum_{i=1}^{N} (x_{it} - \mu)(x_{il} - \mu)',$$

where I have denoted $\mu = (\mu^{(1)}, ..., \mu^{(K)})'$ and $x_{it} = (x_{it}^{(1)}, ..., x_{it}^{(K)})'$. This formula allows for arbitrary correlation across time within each firm. (Note that in contrast to time series estimation, there is no Newey-West downweighting of higher order terms.) For instance, if $x_{it} = x_i$, $\widehat{S} = T\Sigma$, and $Var(\widehat{\mu}) = \frac{\Sigma}{N}$, reflecting that there are only N observations. This formula assumes, however, that observations are not correlated in the cross-section. This assumption is correct when time effects are removed but is incorrect in general (though it is clearly much more appropriate to rule out cross-sectional than time-series correlation). The difference between the estimated standard errors of the estimates with and without time effects suggest that the difference is not crucial.

11 Appendix D: Numerical solution for the general equilibrium model

This appendix sketches the solution method used to solve the general equilibrium model.

(1) Pick the parameters. The process for z_t is approximated by a Markov chain using Tauchen's method. (I used 6 points.) The (normal) process for ε_p is approximated with a finite distribution. (I used 5 points.) We pick a grid for k. (I used 100 equally spaced points.) Finally we pick a grid for ι, the investment rate. (I used 100 points.)

(2) Guess a wage w.

(3) Iterate until convergence on the Bellman equation, which now has a discrete state and action space:

$$\begin{aligned} j(k, z_t) &= A_2(w) z_t^{\frac{1}{1-\upsilon}} k^{\frac{\alpha}{1-\upsilon}} \\ &+ \max_{\iota} \left\{ -\left(\iota + \frac{\psi}{2} (\iota - \delta)^2 \right) k + \beta(1-\eta) \sum_{z_t'} Q(z_t, z_t') \sum_{\varepsilon_p'} \pi(\varepsilon_p') \left[e^{\frac{\sigma_p \varepsilon_p'}{1-\alpha-\upsilon}} j\left((1-\delta+\iota)\, k e^{\frac{-\sigma_p \varepsilon_p'}{1-\alpha-\upsilon}}, z_t' \right) \right] + \beta\eta k \right\}. \end{aligned}$$

(4) Check the free entry condition:

$$\sum_{z_t, z_p} \upsilon(z_t, z_p) z_p^{\frac{1}{1-\alpha-\upsilon}} j(k_{in}, z_t) = c_{in}.$$

If it does not hold with the required precision, adjust the wage w and go back to (3).

(5) Compute the policy function $\iota(k, z_t)$.

(6) Simulate a large panel of firms, assuming N firms, with δN randomly picked disappearing each period and replaced by δN new firms. Compute the aggregate labor demand of these firms.

(7) Pick the number of firms in the economy M to scale the labor demand to $\overline{N}$.

Specification		η	σ_p	σ_t	ρ	σ_m	σ_{ac}	σ_{mi}	α	δ
1a	Truth	1	.15	–	–	.3	.15	–	.64	.17
	Mean Est.	1.005	.1482	–	–	.301	.1482	–	.6400	.1701
	SD Est.	.0647	.0081	–	–	.0185	.0084	–	.0126	.0047
1b	Truth	1	.15	–	–	.3	–	.6	.64	.17
	Mean Est.	1.001	.1482	–	–	.302	–	.6016	.6412	.17
	SD Est.	.0376	.0084	–	–	.0169	–	.0242	.0118	.0057
2a	Truth	1	–	.4	.93	.3	.15	–	.65.	.16
	Mean Est.	1.003	–	.3990	.9336	.3001	.1495	–	.6397	.1600
	SD Est.	.0074	–	.0306	.0118	.0252	.0026	–	.0242	.0047
2b	Truth	1	–	.4	.93	.3	–	.6	.64	.16
	Mean Est.	.9966	–	.4022	.9338	.3039	–	.673	.6414	.1584
	SD Est.	.0671	–	.0283	.0129	.0237	–	.0210	.0210	.005
3a	Truth	1	.15	.35	.7	.3	.15	–	.64	.16
	Mean Est.	.9957	.1442	.3559	.6954	.2911	.1505	–	.6429	.1612
	SD Est.	.0850	.0162	.0354	.1081	.4110	.0023	–	.0175	.0055
3b	Truth	1	.15	.35	.7	.3	–	.6	.64	.16
	Mean Est.	.9839	.1452	.3604	.6960	.2925	–	.6005	.6407	.1599
	SD Est.	.0882	.0153	.311	.0862	.0330	–	.0204	.0175	.0055

Table 1: Test of the estimator by Monte-Carlo simulations. For each of six specifications, I simulate 100 balanced panels of artificial data (N=128, T=27). The SMM estimator is then used to estimate the structural parameters given the panel. The table report the mean and standard deviation, across the 100 panels, of the estimates, as well as the true parameters. The six specifications are indicated as follows: (a) model with adjusment cost shock; (b) model with measurement error in invesment ; and (1) model with only permanent shocks ; (2) model with only AR(1) shocks; (3) model with both permanent and AR(1) shocks.

	Ei	$E\pi$	σ_i	σ_π	$\rho_{i\pi}$	ρ_{1i}	ρ_{2i}	ρ_{3i}	$\rho_{1\pi}$	$\rho_{2\pi}$	$\rho_{3\pi}$	$\rho(\log \frac{K}{K_{-3}}, \frac{\pi_{-3}}{K_{-3}})$
UB	.1676	.3471	.1503	.4833	.1864	.4319	.1871	.0329	.6922	.4931	.3795	.3079
s.e.	.0014	.0056	.0016	.0078	.0089	.0072	.0081	.0085	.0074	.0108	.0120	.0086
Bal.	.1269	.3165	.0878	.2817	.2906	.5242	.2693	.1196	.7900	.6572	.5541	.3416
s.e.	.0042	.0182	.0052	.0237	.0477	.0386	.0545	.0555	.0350	.0395	.0474	.0421
UB+TE	–	–	.1489	.4833	.1842	.5015	.3311	.2423	.7086	.5290	.4336	.2989
s.e.	–	–	.0015	.0079	.0089	.0066	.0067	.0066	.0070	.0099	.0107	.0086
Bal.+ TE	–	–	.0843	.2793	.2758	.5713	.4006	.2893	.8234	.7103	.6153	.3331
s.e.	–	–	.0051	.0238	.0490	.0367	.0477	.0486	.0300	.0341	.0426	.0421
UB+IE	–	–	.1470	.4653	.1872	.4870	.3077	.2146	.6882	.4986	.3988	.3017
s.e.	–	–	.0015	.0074	.0086	.0065	.0067	.0064	.0071	.0100	.0108	.0084

Table 2: Data Moments. The table reports the means, standard deviations and autocorrelations of the investment rate and the profit rate, and the correlation between capital growth over the past three years with the profit rate three years ago. The five rows refer to the different samples: (1) unbalanced panel; (2) balanced panel; (3) unbalanced panel with time effects (TE), (4) balanced panel with time effects, and (5) unbalanced panel with industry fixed effects (IE). Standard errors are computed using GMM and the delta method, by stacking all the moments and using the NT asymptotics. See appendix C for details.

Specification		ρ	η	σ_m	σ_{ac}	σ_t	σ_p	α	δ	σ_{mi}
1a	Estimate	–	1.9428	0.9623	–	–	0.2446	0.6368	0.1671	0.7894
	s.e.	–	0.0744	0.0148	–	–	0.0046	0.0097	0.0012	0.0106
1b	Estimate	–	1.9382	0.9623	0.1357	–	0.2402	0.6368	0.1671	–
	s.e.	–	0.0743	0.0148	0.0019	–	0.0046	0.0097	0.0012	–
2a	Estimate	0.7800	1.1233	0.4651	–	0.8898	–	0.6468	0.1692	0.7882
	s.e.	0.0069	0.0551	0.0177	–	0.0164	–	0.0098	0.0013	0.0104
2b	Estimate	0.7800	1.1401	0.4813	0.1387	0.8790	–	0.6464	0.1691	–
	s.e.	0.0069	0.0560	0.0167	0.0018	0.0164	–	0.0098	0.0013	–
3a	Estimate	0.5500	1.4857	0.0298	–	1.0045	0.2073	0.6454	0.1689	0.7734
	s.e.	0.0205	0.0680	0.6282	–	0.0257	0.0056	0.0098	0.0013	0.0112
3b	Estimate	0.5500	1.4813	0.0009	0.1353	1.0049	0.2023	0.6454	0.1688	–
	s.e.	0.0202	0.0682	14.7255	0.0019	0.0254	0.0056	0.0098	0.0013	–

Table 3: Parameters estimates and standard errors from SMM estimation. Unbalanced panel. Six specifications: (a) measurement error in investment, no shock to adjustment costs, (b) no measurement error in investment, shock to adjustment costs; (1) permanent shocks only; (2) AR(1) shocks only; (3) both permanent and AR(1) shocks. Moments are weighted using the identity matrix.

	$E(i)$	$E(\pi)$	σ_i^2	σ_π^2	$\gamma(i,\pi)$	$\gamma_1(i)$	$\gamma_1(\pi)$	$\gamma_2(i)$	$\gamma_2(\pi)$	$\gamma_3(i)$	$\gamma_3(\pi)$	$\gamma\left(\log\frac{K}{K_{-3}}, \frac{\pi_{-3}}{k_{-3}}\right)$
Data	.1690	.3432	.0237	.2416	.0135	.0101	.1661	.0042	.1178	.0004	.0885	.0870
Models:												
1a	.1671	.3451	.0237	.2416	.0288	.0062	.1277	.0060	.1242	.0058	.1208	.0841
1b	.1671	.3451	.0238	.2416	.0289	.0057	.1277	.0055	.1242	.0054	.1207	.0843
2a	.1692	.3430	.0237	.2416	.0349	.0044	.1628	.0032	.1215	.0023	.0895	.0778
2b	.1691	.3431	.0236	.2416	.0348	.0038	.1621	.0027	.1217	.0018	.0903	.0781
3a	.1689	.3432	.0237	.2426	.0316	.0061	.1627	.0058	.1178	.0055	.0921	.0794
3b	.1688	.3432	.0238	.2426	.0317	.0056	.1627	.0052	.1178	.0049	.0921	.0796

Table 4: Data moments and model moments from the SMM estimation. Unbalanced panel. Six specifications: (a) measurement error in investment, no shock to adjustment costs, (b) no measurement error in investment, shock to adjustment costs; (1) permanent shocks only; (2) AR(1) shocks only; (3) both permanent and AR(1) shocks. Gamma stands for covariance.

		σ_p	σ_t	σ_{ac}	σ_m	σ_{mi}	Total
Model 1a	i	26.4	0	0	0	73.6	100
	π	54.0	0	0	46.0	0	100
Model 1b	i	26.0	0	74.0	0	0	100
	π	52.9	0	2.0	45.1	0	100
Model 2a	i	0	24.1	0	0	75.9	100
	π	0	88.6	0	11.4	0	100
Model 2b	i	0	23.5	76.5	0	0	100
	π	0	87.5	1.3	11.2	0	100
Model 3a	i	25.3	2.8	0	0	71.8	100
	π	30.6	69.3	0	0.1	0	100
Model 3b	i	23.6	2.8	73.6	0	0	100
	π	29.2	69.3	1.6	0.0	0	100

Table 5: Variance decomposition of the investment rate i and the profit rate pi implied by the estimated model. The table shows the share of each variable (i or pi) due to each shock, for each of six specifications: (a) measurement error in investment, no shock to adjustment costs, (b) no measurement error in investment, shock to adjustment costs; (1) permanent shocks only; (2) AR(1) shocks only; (3) both permanent and AR(1) shocks. Results based on the unbalanced panel.

		ρ	η	σ_m	σ_{ac}	σ_t	σ_p	α	δ	σ_{mi}
Model 1a	Estimate	–	1.6679	0.4822	–	–	0.1761	0.5663	0.1267	0.5775
	s.e.	–	0.3137	0.0414	–	–	0.0153	0.0299	0.0042	0.0327
Model 1b	Estimate	–	1.6650	0.4822	0.0751	–	0.1734	0.5663	0.1267	–
	s.e.	–	0.3133	0.0414	0.0043	–	0.0154	0.0299	0.0042	–
Model 2a	Estimate	.8900	1.0795	0.2751	–	0.4332	–	0.5671	0.1269	0.5752
	s.e.	.0192	0.2203	0.0535	–	0.0465	–	0.0299	0.0042	0.0343
Model 2b	Estimate	.8800	1.0593	0.2524	0.0757	0.4466	–	0.5672	0.1269	–
	s.e.	.0194	0.2176	0.0580	0.0044	0.0456	–	0.0299	0.0042	–
Model 3a	Estimate	.6000	1.3882	0.0000	–	0.4991	0.1633	0.5671	0.1269	0.5690
	s.e.	.1055	0.2516	732.6605	–	0.0530	0.0168	0.0299	0.0042	0.0343
Model 3b	Estimate	.6000	1.3854	0.0000	0.0744	0.4991	0.1604	0.5671	0.1269	–
	s.e.	.1038	0.2526	263.7063	0.0044	0.0526	0.0170	0.0299	0.0042	–

Table 6: Parameter estimates and standard errors from SMM estimation. Balanced panel. Six specifications: (a) measurement error in investment, no shock to adjustment costs, (b) no measurement error in investment, shock to adjustment costs; (1) permanent shocks only; (2) AR(1) shocks only; (3) both permanent and AR(1) shocks. Moments are weighted using the identity matrix.

	$E(i)$	$E(\pi)$	σ_i^2	σ_π^2	$\gamma(i,\pi)$	$\gamma 1(i)$	$\gamma 1(\pi)$	$\gamma 2(i)$	$\gamma 2(\pi)$	$\gamma 3(i)$	$\gamma 3(\pi)$	$\gamma\left(\log \frac{K}{K_{-3}}, \frac{I_{-3}}{K_{-3}}\right)$
Data	.1269	.3165	.0077	.0794	.0072	0.0040	0.0627	0.0021	.0522	.0009	.0440	.0343
Model 1a	.1267	.3167	.0077	.0794	.0115	0.0023	0.0545	0.0022	.0529	.0022	.0514	.0335
Model 1b	.1269	.3165	.0077	.0794	.0128	0.0020	0.0616	0.0017	.0527	.0014	.0448	.0323
Model 2a	.1269	.3165	.0077	.0795	.0120	0.0024	0.0624	0.0023	.0517	.0022	.0448	.0325
Model 2b	.1267	.3167	.0077	.0794	.0115	0.0021	0.0545	0.0021	.0529	.0020	.0514	.0336
Model 3a	.1269	.3165	.0077	.0794	.0128	0.0018	0.0621	0.0015	.0526	.0012	.0443	.0323
Model 3b	.1269	.3165	.0077	.0795	.0120	0.0022	0.0624	0.0021	.0517	.0020	.0448	.0326

Table 7: Data moments and model moments from the SMM estimation. Balanced panel. Six specifications: (a) measurement error in investment, no shock to adjustment costs, (b) no measurement error in investment, shock to adjustment costs; (1) permanent shocks only; (2) AR(1) shocks only; (3) both permanent and AR(1) shocks. Gamma stands for covariance.

		ρ	η	σ_m	σ_t	σ_p	σ_{mi}
Model 1	Estimates	–	2.1417	0.9271	–	0.2422	0.7927
	s.e.	–	0.0788	0.0135	–	0.0039	0.0112
Model 2	Estimates	0.8200	1.3076	0.5186	0.8095	–	0.7999
	s.e.	0.0052	0.0605	0.0138	0.0151	–	0.0112
Model 3	Estimates	0.5250	1.7278	0.0000	0.9593	0.2179	0.7867
	s.e.	0.0224	0.0718	264.094	0.0274	0.0044	0.0116

Table 8: Parameter estimates and standard errors from SMM estimation. Unbalanced panel with time effects. Alpha and delta are set equal to .64 and .167. Three specifications: (1) permanent shocks only; (2) AR(1) shocks only; (3) both permanent and AR(1) shocks. Model with measurement error in investment and no adjustment cost shock.

	σ_i^2	σ_π^2	$\gamma_1(i,\pi)$	$\gamma_1(i)$	$\gamma_1(\pi)$	$\gamma_2(i)$	$\gamma_2(\pi)$	$\gamma_3(i)$	$\gamma_3(\pi)$	$\gamma\left(\log\frac{K}{K_{-3}}, \frac{\pi_{-3}}{K_{-3}}\right)$
Data	.0233	.2412	.0132	0.0116	0.1698	0.0075	0.1266	0.0054	0.1031	0.0847
Model 1	.0233	.2412	.0283	0.0056	0.1365	0.0054	0.1330	0.0053	0.1297	0.0829
Model 2	.0233	.2417	.0302	0.0056	0.1674	0.0054	0.1271	0.0052	0.1048	0.0792
Model 3	.0233	.2412	.0329	0.0042	0.1663	0.0033	0.1312	0.0025	0.1025	0.0774

Table 9: Data moments and model moments from the SMM estimation. Unbalanced panel with time effects. Alpha and delta are set equal to .64 and .167. Three specifications: (1) permanent shocks only; (2) AR(1) shocks only; (3) both permanent and AR(1) shocks. Model with measurement error in investment, and no shocks to adjustment costs. Gamma stands for covariance.

Specification		ρ	η	σ_m	σ_t	σ_p	σ_{mi}
1	Estimates	–	1.8986	0.9204	–	0.2410	0.7663
	s.e.	–	0.0716	0.0135	–	0.0036	0.0114
2	Estimates	0.8100	1.1294	0.5283	0.7944	–	0.7732
	s.e.	0.0055	0.0532	0.0134	0.0153	–	0.0118
3	Estimates	0.5125	1.5067	0.0000	0.9526	0.2156	0.7586
	s.e.	0.0225	0.0639	330.728	0.0276	0.0043	0.0119

Table 10: Parameter estimates and standard errors from SMM estimation. Unbalanced panel with Industry effects. Alpha and delta are set equal to .64 and .167. Three specifications: (1) permanent shocks only; (2) AR(1) shocks only; (3) both permanent and AR(1) shocks. Model with measurement error in investment and no adjustment cost shock.

Specification	σ_i^2	σ_π^2	$\gamma_1(i,\pi)$	$\gamma_1(i)$	$\gamma_1(\pi)$	$\gamma_2(i)$	$\gamma_2(\pi)$	$\gamma_3(i)$	$\gamma_3(\pi)$	$\gamma\left(\log\frac{K}{K_{-3}}, \frac{\pi_{-3}}{K_{-3}}\right)$
data	.0227	.2243	.0128	.0110	.1535	.0068	.1113	.0047	.0885	.0842
1	.0227	.2243	.0281	.0061	.1211	.0060	.1177	.0058	.1144	.0819
2	.0227	.2248	.0302	.0062	.1509	.0059	.1118	.0056	.0906	.0781
3	.0227	.2243	.0332	.0046	.1495	.0035	.1159	.0026	.0888	.0764

Table 11: Data moments and model moments from the SMM estimation. Unbalanced panel with industry effects. Alpha and delta are set equal to .64 and .167. Three specifications: (1) permanent shocks only; (2) AR(1) shocks only; (3) both permanent and AR(1) shocks. Model with measurement error in investment, and no shocks to adjustment costs. Gamma stands for covariance.

β		ρ	η	σ_m	σ_t	σ_p	α	δ	σ_{mi}
.88	Estimates	0.5800	1.6061	0.0103	1.0186	0.1055	0.8895	0.1689	0.7816
	s.e.	0.0170	0.0718	1.6368	0.0234	0.0079	0.0133	0.0013	0.0104
.93	Estimates	0.5600	1.5220	0.0229	1.0084	0.1827	0.7114	0.1689	0.7756
	s.e.	0.0195	0.0691	0.7883	0.0249	0.0059	0.0107	0.0013	0.0108
.98	Estimates	0.5500	1.3990	0.0001	0.9969	0.2370	0.5515	0.1689	0.7707
	s.e.	0.0216	0.0655	309.3158	0.0262	0.0058	0.0085	0.0013	0.0110

Table 12: Parameter estimates and standard errors from SMM estimation, for various values of beta. Unbalanced panel. Specification with both transitory and permanent shocks and measurement error in investment (i.e. sigma ac=0).

		σ_i	σ_π	$\rho(i,\pi)$	$\rho_1(i)$	$\rho_1(\pi)$	$Cov\left(\log\frac{K}{K_{-3}}, \frac{\pi_{-3}}{K_{-3}}\right)$
Regression of moment	coeff	-0.000	0.007	0.001	0.001	0.001	0.001
on time trend	t-stat	-0.064	1.768	0.317	0.185	0.101	0.306
	R2	0.006	0.745	0.072	0.009	0.004	0.114
Regression of hp-filtered	coeff	0.003	0.014	-0.396	-1.965	-0.897	-0.330
moment on hp-filtered GDP	t-stat	0.003	0.010	-0.273	-0.682	-0.385	-0.341
	R2	0.000	0.000	0.086	0.128	0.067	0.246

Table 13: This table reports estimates of regressions of various cross-sectional moments (computed in section 6) on either a time trend or hp-filtered gdp, with the OLS t-stats and R2. For the regression on hp-filtered gdp, the moment is also hp-filtered.

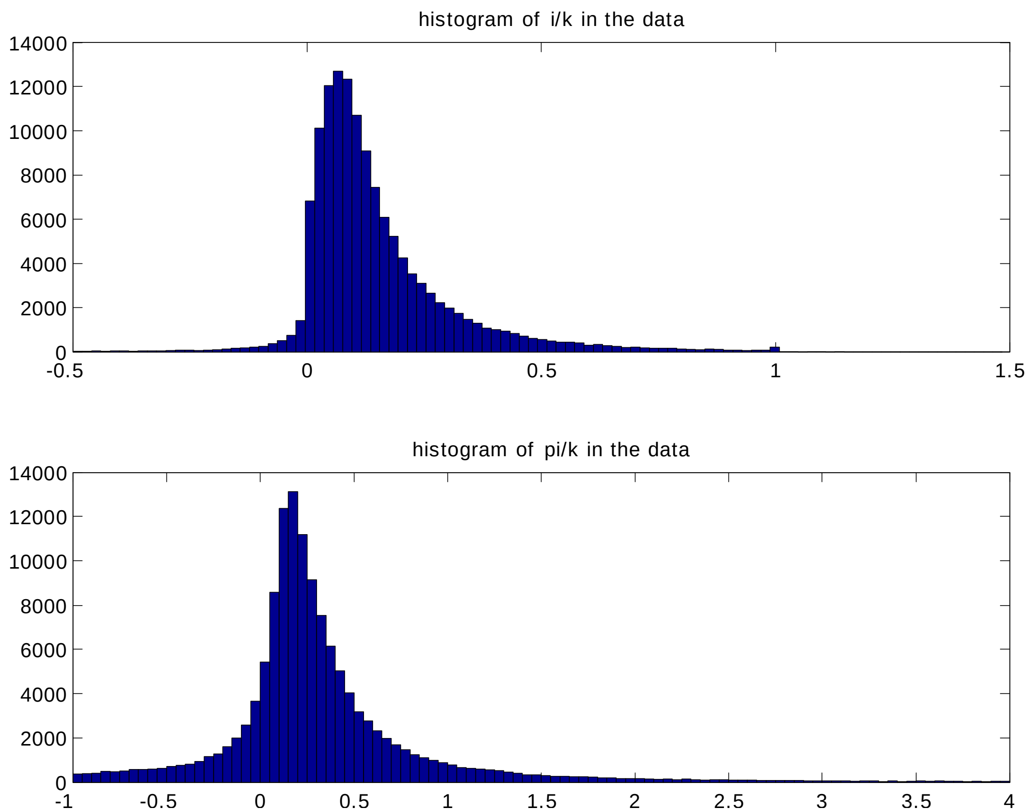

Figure 1: Histogram of all observations of profit rates and investment rates.

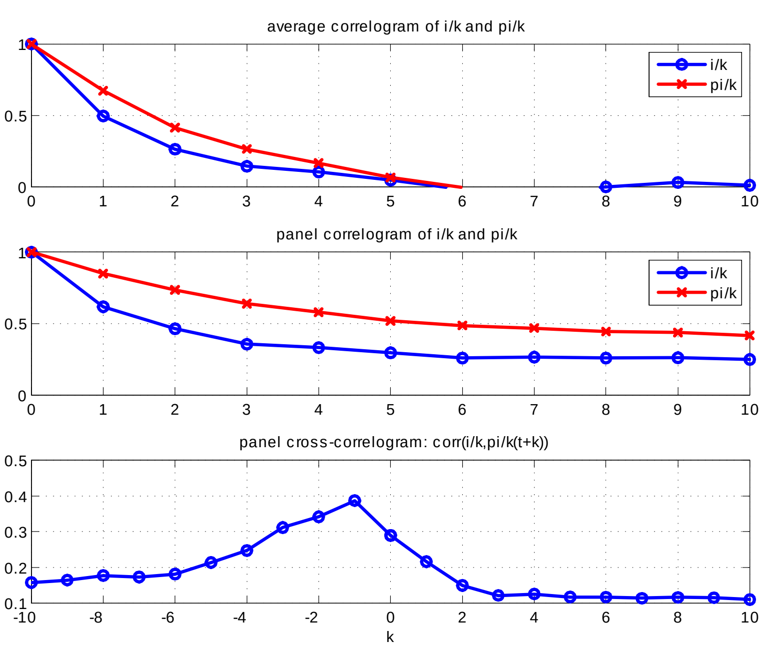

Figure 2: Correlogram of investment rate and profit rate in the balanced panel. Top panel: average of correlogram computed for each firm (i.e. with fixed effect). Middle panel: correlogram of pooled data. Bottom panel: cross-correlogram of pooled data.

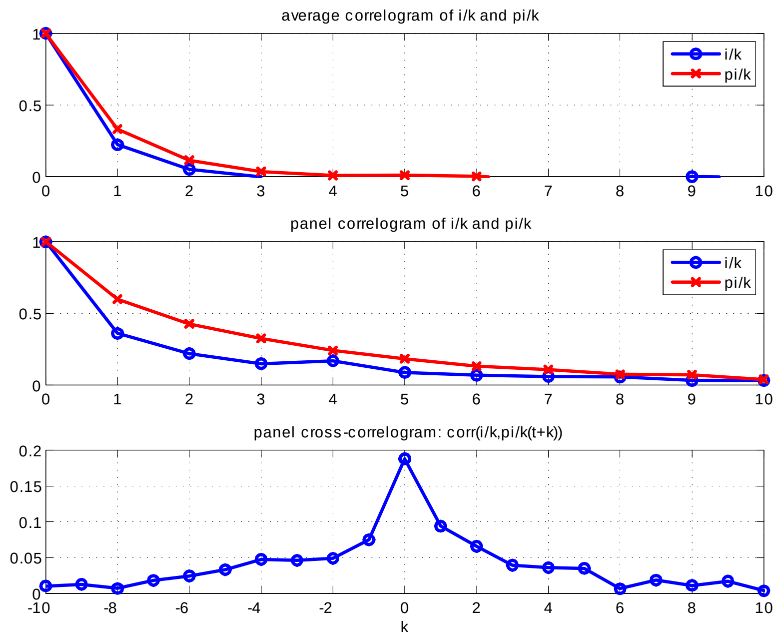

Figure 3: Correlogram of investment rate and profit rate in the unbalanced panel. Top panel: average of correlogram computed for each firm (i.e. with fixed effect). Middle panel: correlogram of pooled data. Bottom panel: cross-correlogram of pooled data.

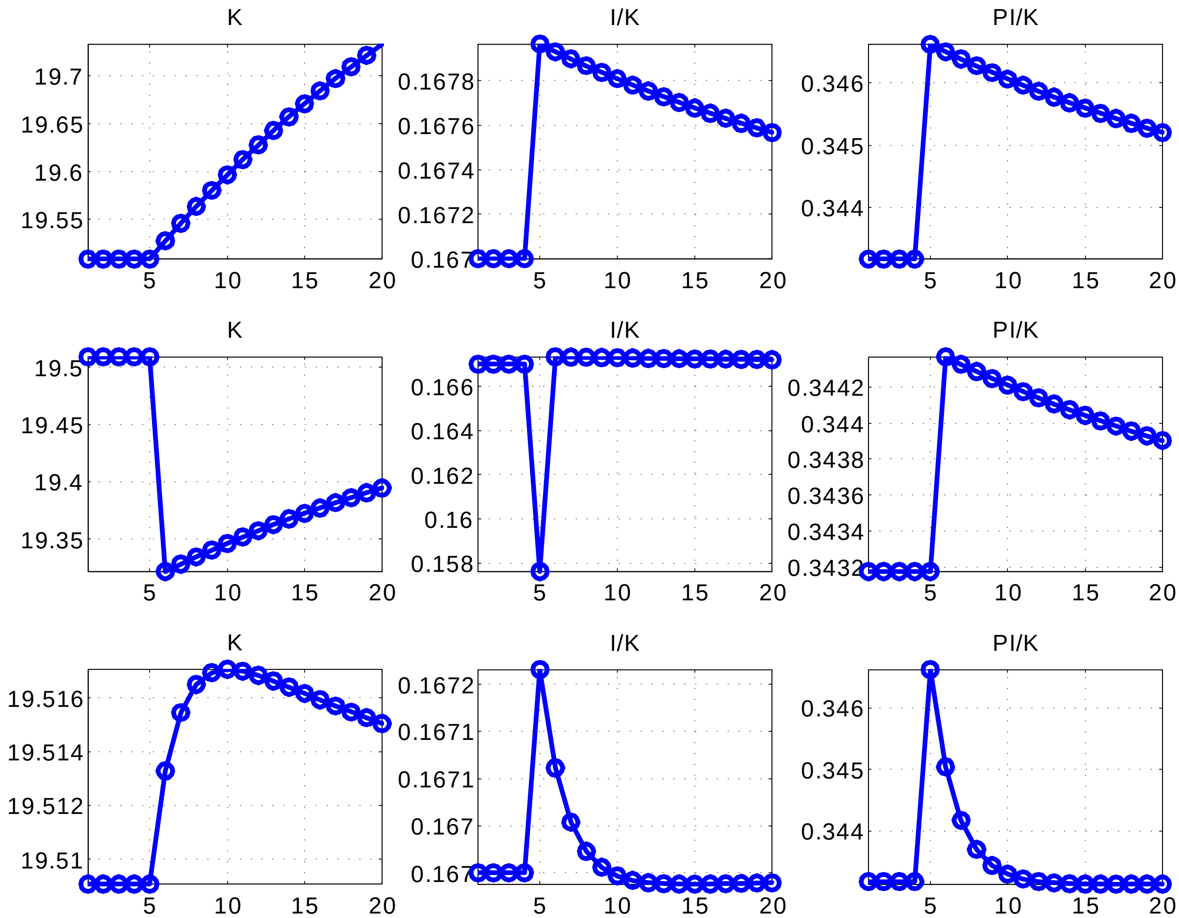

Figure 4: Impulse responses to three shocks. The first (resp. third) row depicts the response to an unexpected permanent (resp. transitory) shock to productivity at time $t = 5$. The second row depicts the responses to an adjustment cost shock ε^{AC}.

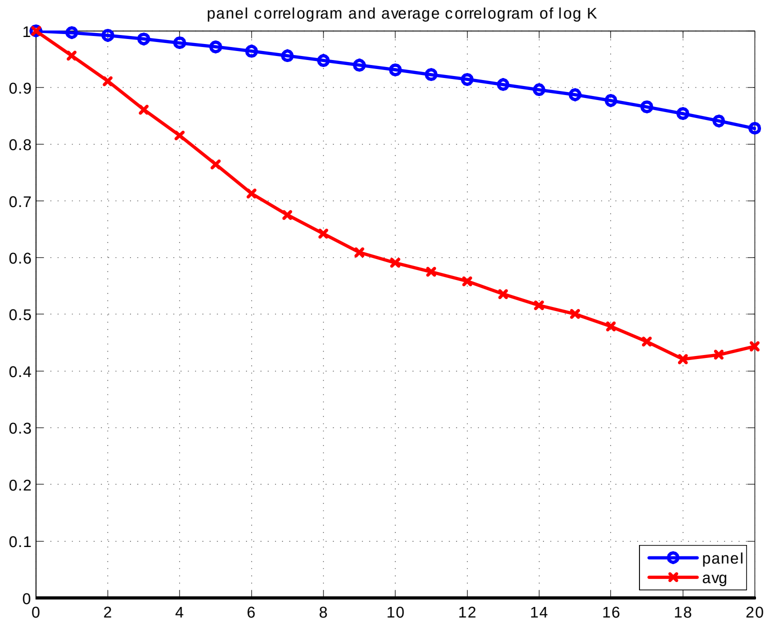

Figure 5: Correlogram of log capital in the data; (a) with fixed effects (i.e. average of correlograms computed for each firm separately) and (b) without fixed effects (i.e. panel correlogram). Balanced panel.

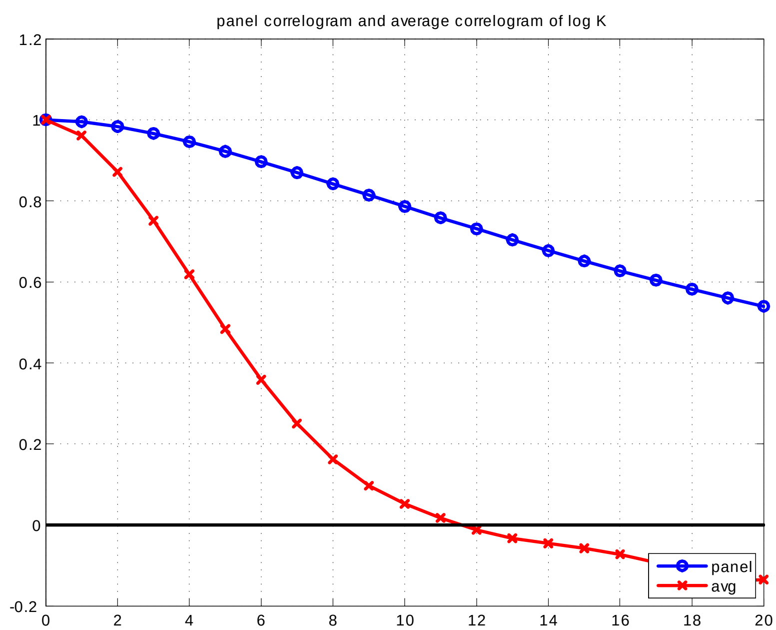

Figure 6: Correlogram of log capital implied by the model with only AR(1) shocks; (a) with fixed effects (i.e. average of correlograms computed for each firm separately) and (b) without fixed effects (i.e. panel correlogram). Based on simulations using the SMM estimates.

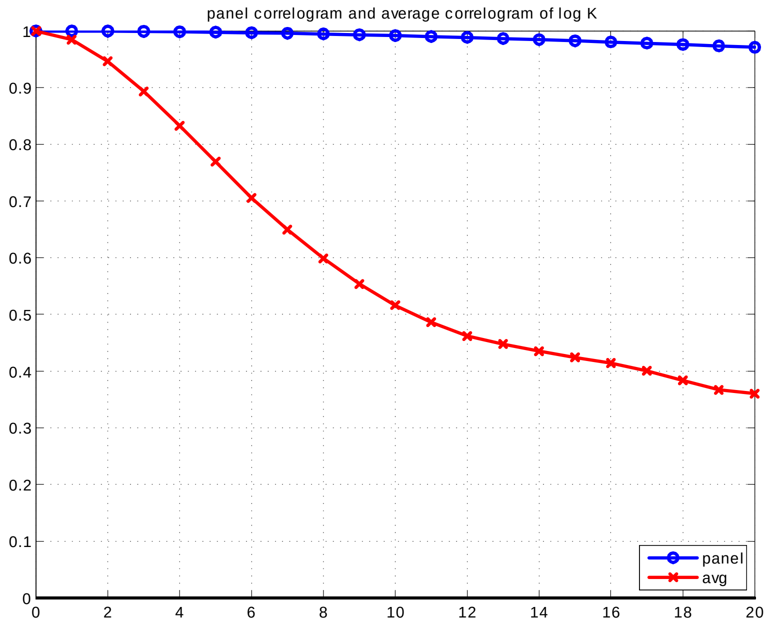

Figure 7: Correlogram of log capital implied by the model with permanent and transitory shocks; (a) with fixed effects (i.e. average of correlograms computed for each firm separately) and (b) without fixed effects (i.e. panel correlogram). Based on simulations using the SMM estimates.

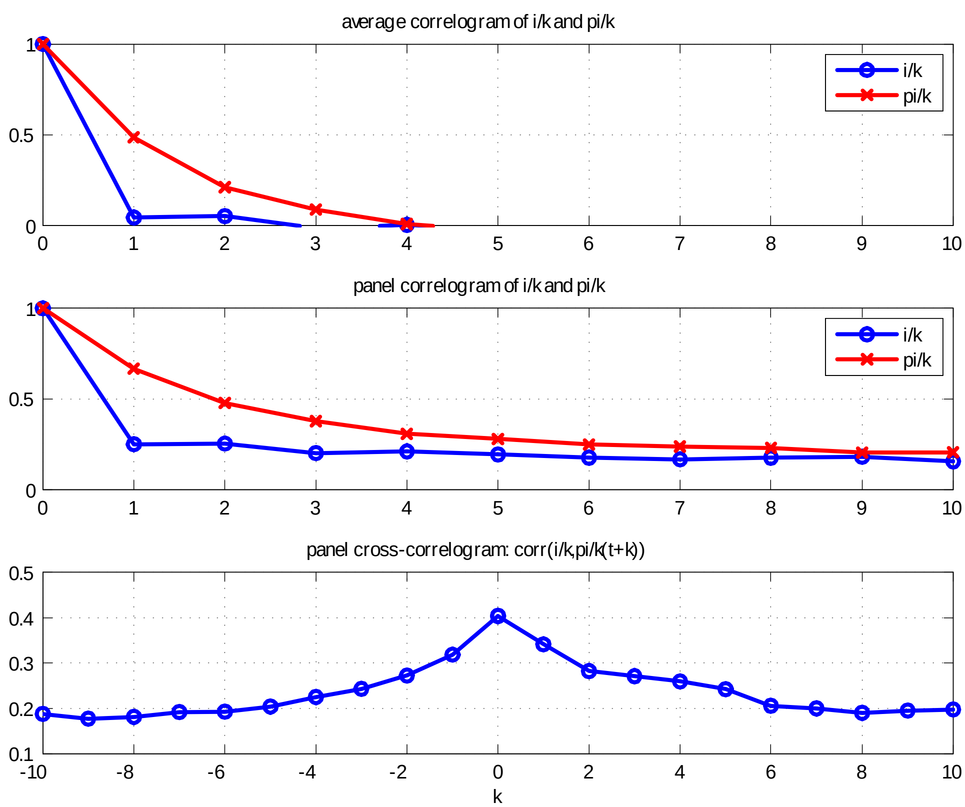

Figure 8: Correlogram of investment rate and profit rate in the model (permanent+transitory shocks). Top panel: average of correlogram computed for each firm (i.e. with fixed effect). Middle panel: correlogram of pooled data. Bottom panel: cross-correlogram of pooled data.

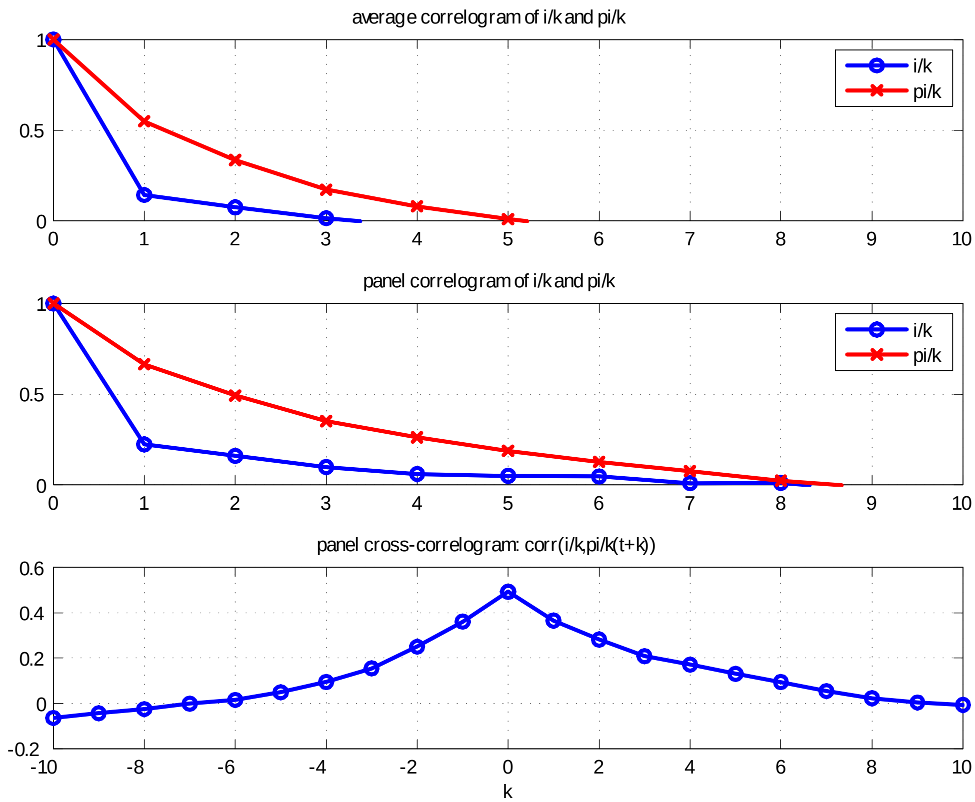

Figure 9: Correlogram of investment rate and profit rate in the model (Ar1 estimates). Top panel: average of correlogram computed for each firm (i.e. with fixed effect). Middle panel: correlogram of pooled data. Bottom panel: cross-correlogram of pooled data.

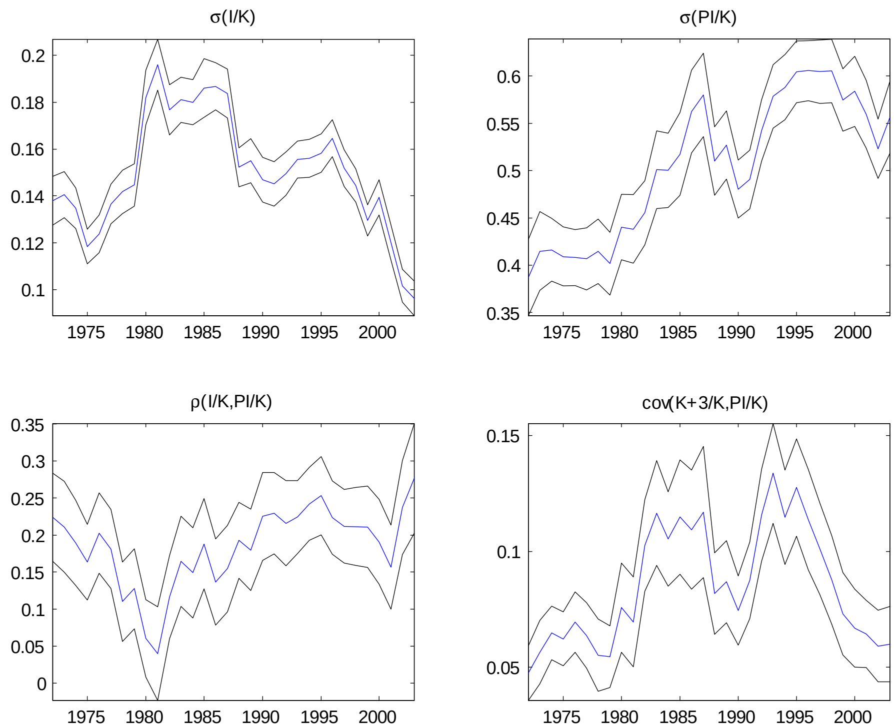

Figure 10: This figure plots, for each year (1971 to 2002) the estimated standard deviation of investment rate, of profit rate, the correlation between the investment rate and the profit rate, and the correlation between the current profit rate and the next 3y growth rate of capital. Two-standard error bands on each side are computed using .GMM. (See appendix C.)

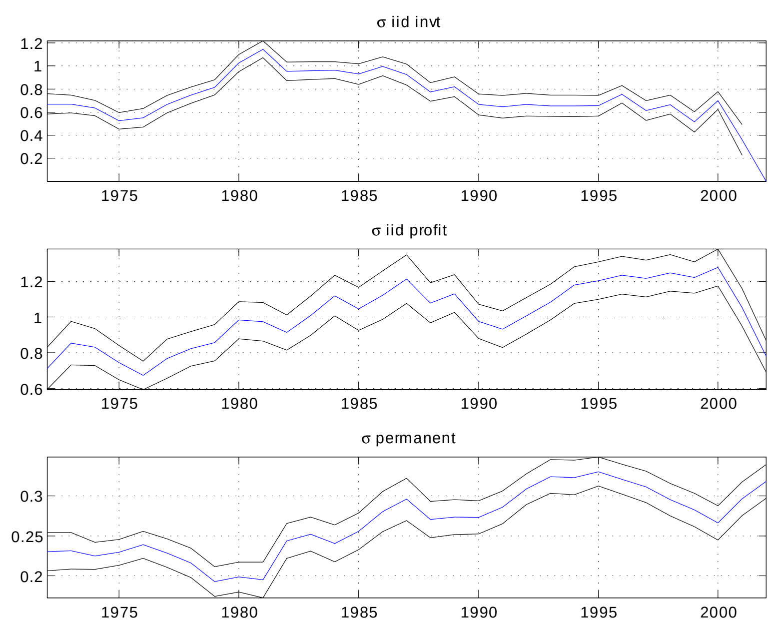

Figure 11: This figure plots, for each year (1971 to 2002) the estimated parameters of the model: standard deviation of iid shock to investment (top panel), iid shock to profit (middle panel), and permanent shock to profitability (bottom panel), with the +/- two standard error bands. Estimates from SMM using cross-sectional data in each year.

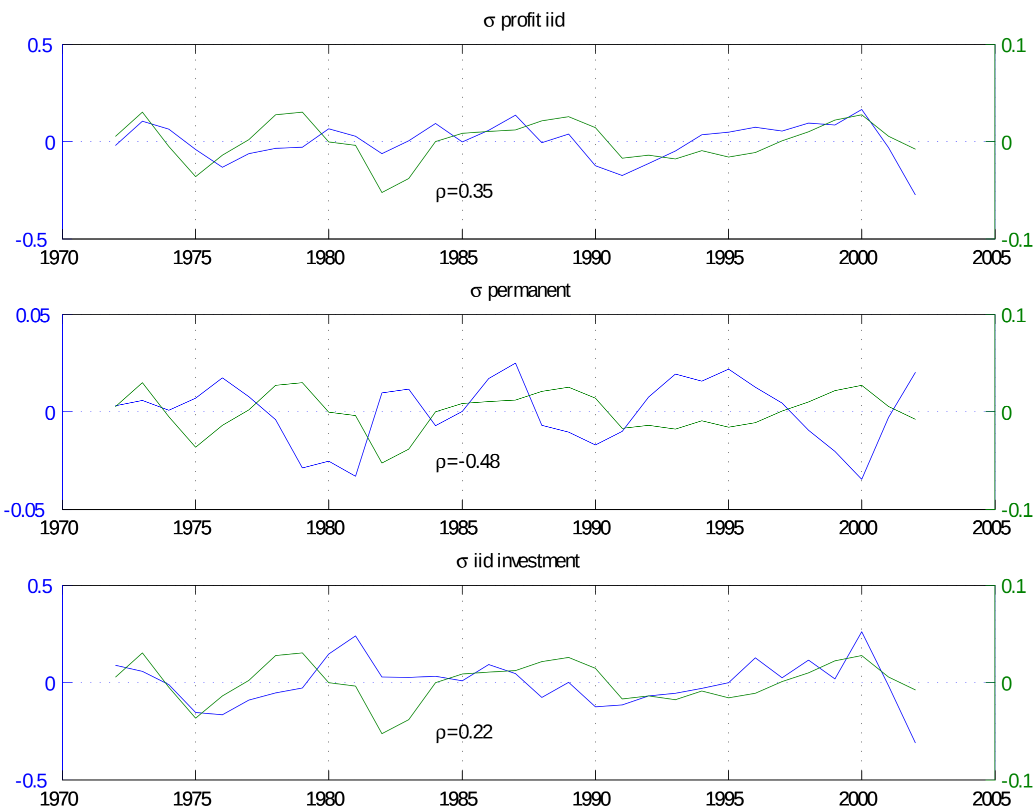

Figure 12: This figure plots, for each year (1971 to 2002) the HP-filtered estimated parameters of the model: standard deviation of iid shock to investment (top panel), iid shock to profit (middle panel), and permanent shock to profit (bottom panel), with the HP-filtered GDP (right-scale) Estimates from SMM using cross-sectional data in each year.