What Explains the Lagged Investment Effect?[*]

Janice Eberly[†] Sergio Rebelo[‡] and Nicolas Vincent[§]

February 2012

Abstract

The best predictor of current investment at the firm level is lagged investment. This lagged-investment effect is empirically more important than the cash-flow and Q effects combined. We show that the specification of investment adjustment costs proposed by Christiano, Eichenbaum and Evans (2005) predicts the presence of a lagged-investment effect and that a generalized version of their model is consistent with the behavior of firm-level data from Compustat.

J.E.L. Classification: D9, E22.
Keywords: adjustment costs, Tobin's Q.

1. Introduction

Lagged investment is a much better predictor of investment than Tobin's Q and cash flow combined. While this fact has been recognized in empirical work on investment, it has mostly been viewed as an inconvenience. Hayahi's (1982) result that investment should depend only on Tobin's Q placed Q at the center of the empirical investment literature. The potential role of financial frictions or other deviations from Hayashi's framework motivated the subsequent work on the cash-flow effect found in the data.[1] While much progress has been made in understanding the role of Q and cash flow in investment regressions, an important question remains: what explains the lagged-investment effect?

In this paper we first document the importance and robustness of the lagged-investment effect in firm-level Compustat data. We then use these data to estimate the investment adjustment-cost model proposed by Christiano, Eichenbaum, and Evans (2005) (henceforth CEE). This specification was designed to make the impulse response of investment to monetary policy shocks generated by DSGE models consistent with the impulse response estimated using vector auto-regressions. It has since become standard in the DSGE literature.[2]

We show analytically that the CEE model predicts the presence of a lagged-investment effect in addition to cash-flow and Q effects.[3] Moreover, regression coefficients obtained from our model-generated data are similar in magnitude to empirical estimates. We also find that a generalized version of CEE does surprisingly well at explaining the patterns of persistence, volatility, and comovement

---

[1]See Hubbard (1998) for a survey of the empirical literature on investment.

[2]Examples of papers that use this adjustment-cost specification include Fernández-Villaverde and Rubio-Ramírez (2004), Smets and Wouters (2007), Justiniano and Primiceri (2008), Del Negro and Schorfheide (2009), and Gertler and Kiyotaki (2010).

[3]Gilchrist and Himmelberg (1998) raise the possibility that the highly significant lagged-investment effect in their data could be generated by a different adjustment-cost formulation.

observed in firm-level data.

Our paper is organized as follows. In Section 2 we describe the data and document the presence of a lagged-investment effect. In Section 3 we show analytically that a linearized version of the CEE model predicts the presence of a lagged-investment effect. We then discuss a generalized version of the model that we use in our estimation. Section 4 presents our estimation results and discusses the model's implications for investment regressions. Section 5 concludes.

2. The lagged-investment effect

In this section we describe our data set and use it to document the importance of lagged investment as a predictor of current investment. We also summarize some key features of the data.

We use a balanced panel of Compustat firms with annual data for the period 1981-2003. We use a balanced panel because the time dimension of the data is important in identifying the dynamics of the model. The sample includes 776 firms and roughly $14,000$ firm-year observations. We focus our analysis on the large firms in our dataset, defined as those in the top quartile of firms sorted by size of the capital stock in 1981. In the beginning of the sample, the top quartile of firms represents 30 percent of aggregate private non-residential investment and 40 percent of corporate non-residential investment.[4] This focus on large firms coupled with the fact that the balanced panel selects for more stable firms means that we can reasonably abstract from any financing frictions which might be present for smaller firms. We use data for the four variables present in our model: investment in property, plant, and equipment, the physical capital stock, Q, and cash

---

[4]Despite our focus on the largest firms, there remains considerable size heterogeneity within that group: the time-series average of the capital stock ranges from 116 to 239,225 million dollars across the 194 firms.

flow. We exclude from our sample firms that have made a major acquisition in order to definitively focus on investment as purchases of new property, plant, and equipment. We estimate the physical capital stock using the perpetual inventory method, using the book value of capital as the starting value for the capital stock and four-digit industry-specific estimates of the depreciation rate. Q is calculated as the market value of equity plus the book value of debt, divided by the capital stock estimate. Cash flow is measured using the Compustat item for Income before extraordinary items + depreciation and amortization + minor adjustments. We describe the data and sample selection in more detail in Appendix 6.1.

2.1. Key empirical features

In Table 1 we report summary statistics for both the 1981-2003 period and for two sub-periods, 1981-1992 and 1993-2003. These estimates are similar to those reported in other studies that use Compustat data. Bootstrap standard errors are indicated in parenthesis. We report the median across firms of selected time-series moments. An alternative would have been to compute moments for the average across firms of the variables of interest. However, this procedure would eliminate the idiosyncratic variability associated with individual firms. Henceforth, to simplify the exposition we use I/K and CF/K to refer to the investment-capital ratio and the cash–flow–to-capital ratio, respectively.

The most striking features of the data are the important differences across sub-samples. In particular, the mean and standard deviation of Q and CF/K in the second sub-sample are significantly higher than in the earlier period. All variables exhibit positive skewness, and there is more skewness in the full sample than in each of the two sub-samples. Finally, Q exhibits strong persistence, while the persistence in I/K and CF/K is more moderate.

2.2. Investment regressions

The three panels of Figure 1 provide scatter plots of pooled time-series-cross-section data that are useful to visualize the relation between I/K and the three variables of interest: Q, CF/K and lagged I/K.

We use $\log(Q)$ and $\log(CF/K)$ in our investment regression because, as discussed in Abel and Eberly (2002), this specification provides a better fit owing to skewness in the firm-level data. Similarly, the log specification makes our parameter estimates less sensitive to a small number of very high Q values observed in the data.[5]

We now describe results from regressing I/K on different combinations of three variables: $\log(Q)$, $\log(CF/K)$, and lagged I/K.

In Panel A of Table 2 we report estimates from pooled, time-series-cross-section regressions. Comparing columns 1 and 2 we see that Q and CF/K individually have similar explanatory power. Regressing I/K on either of these variables generates an R^2 of 30 percent. When both Q and CF/K are included in the regression (column 4), the goodness-of-fit rises slightly to 0.34. We obtain a much higher R^2 (0.57) when we use lagged I/K as the sole explanatory variable. When all three regressors are present, the coefficient on lagged I/K remains large (0.6253) and very highly significant, while the coefficients on Q and CF/K are significant but small in magnitude (0.0126 and 0.017, respectively).

To investigate the robustness of the lagged-investment effect we run panel versions of these regressions with firm fixed effects. The results, reported in Panel B of Table 2, lead to similar conclusions. The explanatory power of lagged investment is much greater than that of Q and CF/K together (R^2 of 0.57 versus 0.30).

---

[5]When we run linear regressions, the coefficient on Q is small but significant, and the coefficient on CF/K is larger and also statistically significant. These results accord with the investment regression results reported in the literature. In addition, the lagged investment coefficient is roughly unaffected.

When all three variables are included as regressors the coefficient on lagged I/K is large (0.4462) and significant. The coefficient on Q is small and significant, while the coefficient on CF/K is marginally significant.

Since lagged investment is by definition correlated with the panel-level effects, we re-run the panel regressions using Arellano and Bond's (1991) consistent GMM estimator. The results are reported in Panel C of Table 2. The results obtained with this estimator are very similar to those reported in Panel B. In addition, the lagged-investment effect continues to be highly significant even when we include year dummies (column 3). Columns 4 and 5 of Panel C show that the lagged-investment effect is present in both subsamples (1981-1992 and 1993-2003). We also find that including lags of both Q and CF/K has a negligible impact on the size and significance of the lagged-investment coefficient. We use the estimates in the second column of the Panel C of Table 2 (displayed in bold) as the benchmark estimates that we later compare with the implications of the model.

In sum, we find that lagged I/K is a better predictor of current I/K than Q and CF/K, even when combined. The coefficient on lagged I/K is roughly 0.40. This lagged-investment effect is robust across specifications. Q has a small but robust and significant effect on I/K. In contrast, the cash-flow effect is weak and not robust in our sample, becoming insignificant or negative in some of the regression specifications.

3. The CEE model

The firm's problem is given by the following Bellman equation, where y' denotes next period's value of variable y:

$$V(K, I_{-1}, z) = \max_{I, K'} zK - I + \beta \int V(K', I, z')F(dz', z), \qquad (3.1)$$

subject to:

$$K' = I - I\phi(I/I_{-1}) + (1 - \delta)K. \qquad (3.2)$$

The firm's output is given by zK, where K denotes the stock of capital and z is a stochastic variable governed by the distribution $F(\cdot)$. This variable represents a shock to productivity or to the price of the firm's output. We can interpret the production function as requiring a single productive factor, capital. Alternatively, we can think of output as being produced with capital, labor, and other variable factors, with labor and variable factors being costlessly adjustable. In this case, zK represents output net of labor and other variable costs. Under this interpretation, which we adopt throughout the paper, the variable z can also incorporate shocks to the real wage or to the price of other variable factors.

Investment, denoted by I, is subject to adjustment costs according to the CEE specification which is given by equation (3.2), where $\phi''(.) > 0$.

Matsuyama (1984) provides an interpretation of the CEE adjustment cost formulation based on the idea that firms have to learn how to implement a given rate of investment. Lucca (2007) provides micro-foundations for the CEE formulation by assuming that investment projects are imperfect substitutes and have an uncertain duration. He shows that the linearized first-order condition implied by his model is the same as that implied by the CEE model.

To study the properties of the model, it is convenient to assume that in a deterministic steady state with constant z there are no adjustment costs. This property requires that:

$$\phi(1) = \phi'(1) = 0. \qquad (3.3)$$

The function $V(K, I_{-1}, z)$ represents the value of a firm with capital stock K, lagged investment, I_{-1}, and total factor productivity, z. Lagged investment is a state variable for the firm because it enters the adjustment cost specification given

6

by equation (3.2). We denote the discount factor by β. Capital depreciates at rate δ.

The optimal solution to the firm's problem is characterized by the first-order conditions for K' and I:

$$\lambda = \beta \int V_1(K', I, z') F(dz', z), \tag{3.4}$$

$$1 = \lambda - \lambda\phi(I/I_{-1}) - \lambda(I/I_{-1})\phi'(I/I_{-1}) + \beta \int V_2(K', I, z') F(dz', z), \tag{3.5}$$

and two envelope conditions:

$$V_1(K, I_{-1}, z) = z + \lambda(1 - \delta), \tag{3.6}$$

$$V_2(K, I_{-1}, z) = \lambda\phi(I/I_{-1})\left(I/I_{-1}\right)^{-2}. \tag{3.7}$$

The variable λ denotes the Lagrange multiplier associated with equation (3.2).

To study the properties of this problem we linearize the first-order conditions around a deterministic steady state. Equations (3.5) and (3.7), together with the requirement of no adjustment costs in the steady state (equation (3.3)), imply that the steady state value of λ is equal to one. Equations (3.2) and (3.3) imply that the steady state level of investment is: $I = \delta K$.

We assume that the steady state value of z satisfies the following equation:

$$1/\beta - 1 = z - \delta. \tag{3.8}$$

The left-hand side of this equation is the real interest rate faced by the firm. The right-hand side is the marginal product of capital net of depreciation.

Equation (3.1) and condition (3.8) imply that the steady state value of the firm is given by:

$$V = K/\beta.$$

Tobin's (average) q is defined as:[6]

$$Q = V/K = 1/\beta.$$

Linearizing equation (3.2) around the steady state we obtain:

$$\hat{K}_{t+1} = \delta \hat{I}_t + (1 - \delta)\hat{K}_t, \tag{3.9}$$

where

$$\chi = \phi''(1) > 0.$$

Combining equations (3.4)-(3.7) and linearizing the resulting conditions we obtain:

$$\hat{\lambda}_t/\beta = E_t \left[z\hat{z}_{t+1} + (1 - \delta)\hat{\lambda}_{t+1} \right], \tag{3.10}$$

$$0 = \hat{\lambda}_t - \chi \left(\hat{I}_t - \hat{I}_{t-1} \right) + \beta \chi \left(\hat{I}_{t+1} - \hat{I}_t \right). \tag{3.11}$$

To study the properties of the investment regressions implied by the linearized version of the model we assume that $\hat{z}_t$ follows an AR(1) process with first-order serial correlation ρ. The resulting solution to the firm's problem takes the form:

$$\hat{I}_t = \pi_{ii}\hat{I}_{t-1} + \pi_{iz}\hat{z}_t + \pi_{ik}\hat{K}_t. \tag{3.12}$$

Solving for coefficients π_{ii}, π_{iA}, and π_{ik} using the method of undetermined coefficients we obtain:

$$\hat{I}_t = \hat{I}_{t-1} + \frac{\beta\rho}{1 - \beta\rho} \frac{z/\chi}{1 - (1 - \delta)\beta\rho} \hat{z}_t. \tag{3.13}$$

The properties of this solution are as follows. The higher the degree of adjustment costs, χ, the smaller the response of investment to a given shock. The higher the

---

[6]The steady-state value of Q is different from one because this version of Tobin's Q is based on the value of the firm in the beginning of the period. The value of Q computed using the end of period value of the firm (after cash flow has been received and investment expenditures have been incurred) is equal to one. This effect of timing on the value of Q is common in discrete time models.

degree of shock persistence, ρ, the stronger the response of investment to shocks. When shocks are i.i.d. ($\rho = 0$) investment is constant over time.

It is useful to use this linearized solution to compute Tobin's Q. Combining the equation for the value of the firm and the linearized laws of motion for investment and capital yields:

$$\hat{V}_t = \frac{z}{1/\beta - \rho} \hat{z}_t + \hat{K}_t. \tag{3.14}$$

In general $\hat{V}_t$ should be a function of the state variables $\hat{K}_t$, $\hat{I}_{t-1}$ and the shock, $\hat{z}_t$. The fact that $\hat{V}_t$ does not depend on $\hat{I}_t$ results from adjustment costs being zero in steady state. Equation (3.14) implies that $\hat{Q}_t$ is given by:

$$\hat{Q}_t = \hat{V}_t - \hat{K}_t = \frac{\beta z}{1 - \beta \rho} \hat{z}_t. \tag{3.15}$$

We can now use equation (3.13) to study the model's implications for the form of the investment regression equation. We denote the investment-capital ratio by $i_t = I_t/K_t$.

Using the policy function for investment and the linearized law of motion for the capital stock we obtain the following expression for $\hat{\imath}_t$:

$$\hat{\imath}_t = (1 - \delta)\hat{\imath}_{t-1} + \frac{\beta \rho}{1 - \beta \rho} \frac{z/\chi}{1 - (1 - \delta)\beta \rho} \hat{z}_t. \tag{3.16}$$

The investment-capital ratio is a linear function of its own lag and the shock, $\hat{z}_t$. Since cash-flow/capital in deviation from its steady state value is equal to $\hat{z}_t$ ($\hat{C}_t - \hat{K}_t = \hat{z}_t$), it enters significantly in a regression of $\hat{\imath}_t$ on $\hat{\imath}_{t-1}$. Equations (3.15) and (3.16) imply that if $\hat{Q}$ is included in the regression instead of cash-flow, we obtain a positive regression coefficient given by $z/\{\chi[1 - (1 - \delta)\beta \rho]\}$.

In sum, this model predicts the presence of a lagged-investment effect as well as a role for cash-flow or Q. A simple modification of the model allowing both a cash-flow and Q effect in addition to the lagged investment effect involves assuming that the production function has decreasing returns to scale. We pursue this modification below.

9

Generalizing the model Before estimating the model we generalize this basic specification to make it more compatible with the data along four dimensions. First, we allow for "flexible capital" which can be installed within the period without adjustment costs. Second, we introduce the possibility of decreasing returns to scale (DRS) in production. Third, we incorporate exogenous technical progress, so that in the absence of shocks capital, investment and cash flow grow at a constant trend. Fourth, we introduce a fixed cost in production.

All four features are useful in improving compatibility between model and data. Flexible capital allows the model to better fit the persistence properties of investment. As discussed above, DRS allows the model to generate both a Q and a cash-flow effect, in addition to the lagged-investment effect. Technical progress introduces a time trend similar to the one present in the data. Finally, the fixed cost scales profitability and allows the model to match the average level of Q in the data.

The firm's problem in this generalized model is given by:

$$V(K, H, I_{-1}, X, z) = \max_{I, I^h, K'} zK^\alpha (H')^\omega X^{1-\alpha-\omega} - \theta X - I +$$
$$\beta \int V(K', H', I, z') F(dz', z),$$

subject to:

$$K' = I - I\phi(I/I_{-1}) + (1-\delta)K,$$
$$H' = I^h + (1-\delta)H.$$

The variable X denotes the level of exogenous technological progress. This variable grows at a constant rate $\gamma > 1$, $X' = \gamma X$. The parameter θ controls the fixed operating cost paid in every period. This cost, θX, is fixed with respect to the investment decision, but grows at rate X, so that it does not become irrelevant as the firm gains in size.

10

The variables H and I^h denote the stock of flexible capital and the investment in flexible capital, respectively. The production function depends on H' so the stock of flexible capital that is relevant for production is chosen after the shock is realized. Both stocks of capital depreciate at rate δ.

We assume that $\alpha + \omega < 1$. We can interpret this property as reflecting the presence of decreasing returns to scale (DRS) in production. Alternatively, we can think of $\alpha + \omega < 1$ as resulting from a setting in which the production function exhibits constant-returns to scale but the firm has monopoly power and faces a constant-elasticity demand function.

We assume that the adjustment cost function, ϕ, takes a quadratic form:

$$\phi(I/I_{-1}) = 1 - \xi(I/I_{-1} - \gamma)^2.$$

This formulation has the property that adjustment costs are zero when the firm grows at its steady state growth rate, γ. The parameter ξ controls the size of the adjustment cost.

We define cash-flow (CF_t) as:

$$CF_t = zK^\alpha(H')^\omega X^{1-\alpha-\omega} - \theta X,$$

which is revenue net of fixed operating costs.

Shock process We consider two versions of the shock process. First, we consider a version with a single regime. In this specification all shocks are idiosyncratic to the firm, there are no aggregate shocks. The shock follows a first-order Markov chain with support $z \in \{\mu - \sigma, \mu, \mu + \sigma\}$. We assume that the Markov chain for the single-regime model takes the form:

$$\pi = \begin{bmatrix} p^2 & 2p(1-p) & (1-p)^2 \\ p(1-p) & p^2 + (1-p)^2 & p(1-p) \\ (1-p)^2 & 2p(1-p) & p^2 \end{bmatrix}.$$

The first-order serial correlation of the shock implied by this matrix is: $\rho = 2p - 1$ (see Rouwenhorst (1995)).

Second, we consider a 'regime-switching' specification with two aggregate regimes, high and low. The aggregate stochastic process is governed by a two point Markov chain with a transition matrix given by:

$$A = \begin{bmatrix} a & 1-a \\ 1-a & a \end{bmatrix}.$$

The idiosyncratic shock has three states and is governed by the following Markov chain:

$$B = \begin{bmatrix} b_1 & b_2 & 1-b_1-b_2 \\ (1-b_1)/2 & b_1 & (1-b_1)/2 \\ 1-b_1-b_2 & b_2 & b_1 \end{bmatrix}$$

The support of the idiosyncratic shock z in a given aggregate regime $R \in \{L, H\}$ is given by:

$$z \in \left\{ \mu^R - \sigma^R, \mu^R, \mu^R + \sigma^R \right\}.$$

This formulation allows the idiosyncratic shock to have different means and different variances in the two aggregate regimes. To see how this formulation works, suppose we are in the high aggregate regime and consider a firm that is in the lowest of the three possible values. The productivity of this firm is $\mu^H - \sigma^H$. Suppose that, in the following period, the aggregate regime switches from high to low and the idiosyncratic productivity of the firm goes from the lowest to the highest of the three possible values. The new productivity of the firm is: $\mu^L + \sigma^L$.

A single regime process is a particular case of this specification, so the estimation algorithm can choose a single regime if it provides a better fit to the data. We find that the "regime-switching" specification allows the model to be consistent with three important features of the data. First, data moments are different in our two subsamples (1981-1992 and 1993-2003). Second, all variables exhibit skewness which arises naturally with regime switching. Third, regime-switching

can generate the imperfect correlation between cash flow and Q that we observe in the data.[7]

4. Estimating the model

We solve the model numerically using the procedure described in Appendix 6.3. Our solution method does not yield an analytical representation for the population moments implied by the model. For this reason, we estimate the model using the simulated method of moments proposed by Lee and Ingram (1991). We first use our data to estimate the vector of moments Ψ_D. Then, we find the parameter vector $\hat{\Phi}$ that minimizes the distance between the empirical and simulated moments, $\Psi(\hat{\Phi})$,

$$L(\hat{\Phi}) = \min \left[\Psi(\Phi) - \Psi_D\right]' W \left[\Psi(\Phi) - \Psi_D\right]. \tag{4.1}$$

The weighting matrix W is computed using a block-bootstrap method on our panel dataset (see Appendix 6.4 for a description). This estimation method gives a larger weight to moments that are more precisely estimated in the data

We solve the minimization problem (4.1) using an annealing algorithm to reduce the risk of convergence to a local minimum.[8] Finally, the standard errors of the estimated parameters are computed as

$$\hat{\Omega} = \frac{(\Gamma' W \Gamma)^{-1}}{n},$$

where Γ is the matrix of derivatives,

$$\Gamma = \frac{\partial \Psi(\hat{\Phi})}{\partial \hat{\Phi}},$$

which we compute numerically. The estimation method is discussed in more details in Appendix 6.4.

---

[7]The median, across firms, of the correlation between Q and CF/K is 0.58.
[8]We also tested the robustness of our results by experimenting with various starting values of the model parameters.

4.1. Parameter and moment estimates: single regime

We choose the exogenous rate of technical progress to be $\gamma = 1.03$. This growth rate is equal to the real annual growth rate of corporate net cash flows from January 1981 to January 2004. We fix the sum $\alpha + \omega$ because we cannot separately identify $\alpha + \omega$ and ξ using the moments of the data that we consider. Both parameters control curvature, so when $\alpha + \omega$ changes, the value of ξ can be adjusted to restore the fit of the model. Hence, we set $\alpha + \omega = 0.8$, consistent with the estimate of the average degree of returns to scale across industries by Burnside (1996).

To estimate the models we include 12 moments in the Ψ_D vector: the mean, standard deviation, skewness, and first-order serial correlation of I/K, CF/K, and Q. Table 1 reports these moments in bold. The moments of CF/K help us identify the shock process. The standard deviation of I/K helps us identify ξ, while the mean of Q helps us identify the fixed cost, θ.

We report our parameter estimates and standard errors in Table 3. Our estimate of the adjustment cost parameter, ξ, is 0.297 (with a standard error of 0.0534). Our estimate of the fixed operating cost parameter, θ, is 99.94 (with a standard error of 0.4987) which corresponds to 22.7 percent of average cash flow. The weight on flexible capital, ω, is very small (0.025 with a standard error of 0.0036). With the average shock z normalized to one, we estimate the spread between shocks to be 0.588. Finally, the estimated Markov chain exhibits strong persistence with the parameter ρ equal to 0.6840 (recall that our data has annual frequency).

Table 1 shows that the single-regime model does a reasonable job at matching the average values of Q, I/K and cash-flow/K. In terms of volatility, I/K and cash-flow/K are somewhat more volatile in the model than in the data, while the volatility of Q is only about 40 percent of the volatility we observe in the

data. These results are related. To make Q more volatile, the algorithm increases the volatility of z. This increase results in volatilities for I/K and cash-flow$/K$ that are too high relative to the data. Also, the model does not generate enough persistence in Q and generates too much persistence in I/K and cash-flow$/K$. Finally, the skewness properties of the single regime model are very different from those in the data. The model produces basically no skewness, while Q, I/K and cash-flow$/K$ all show strong skewness in the data.

To evaluate the performance of our model from a different angle we estimate investment regressions on a panel of firms constructed by simulating our model. We report the results in Table 4. The model generates the same patterns we observe in the data. Lagged investment in isolation has more explanatory power than Q and cash flow. When we use lagged I/K, the log of Q, and the log of cash-flow$/K$ as explanatory variables we obtain a strong coefficient on lagged investment, as well as Q and cash flow effects. The lagged investment effect is however somewhat stronger than the one observed in the data (coefficient value of 0.5970 in the model vs 0.4187 in the data).

4.2. Parameter and moment estimates: two regimes

We choose the same values of γ and $\alpha + \omega$ used in the single regime model. To estimate the regime–switching model we add to the moments used in estimating the single-regime model some moments computed in the two subsamples: the mean of Q and CF/K and the standard deviation of CF/K. These additional moments help us identify the support and transition matrix of the shocks. Table 1 reports in bold all the moments targeted by the estimation algorithm.

We report the point estimates and standard errors of the estimated parameters in Table 3. Our estimate of the adjustment cost parameter, ξ, is 0.9447 (with a standard error of 0.0384). This value is close to that obtained by CEE using

15

macro data.[9] The estimated value of the fixed operating cost parameter, θ, is 85.5 (with a standard error of 1.2380) which corresponds to 19.8 percent of average cash flow. The weight on flexible capital, ω, is relatively small (0.0693 with a standard error of 0.0005). It implies that flexible capital represents on average 8.5 percent of total capital, and that investment in flexible capital is on average 5.1 percent of total investment. To put this value in context, software investment, which is arguably a flexible form of investment, accounted for 7 percent of total investment expenditure in the National Income and Product Accounts in 1993, the middle point of our sample.

The parameters that characterize the support and transition matrix for the shocks are presented in Table 3. In addition to a higher average productivity, the high aggregate regime also features a higher standard deviation. It is particularly interesting to note that the supports of the two aggregate regimes overlap. In fact, the low shock in the high aggregate regime ($\mu^H - \sigma^H$) is lower than the low shock in the low aggregate regime ($\mu^L - \sigma^L$). This configuration of shocks makes the model consistent with the imperfect correlation between investment, Q and cash-flow in addition to providing a better fit to subsample moments. For example, when the shock is in the low regime, cash-flow is low and investment opportunities are poor, leading to a low value of Q. In contrast, when the shock is in the high regime, cash flow is low but investment opportunities are good as the firm faces a relatively high probability of moving to high-cash-flow states in the future. Consequently, Q is high. These estimates emphasize the importance of a structure in which Q and cash-flow are not informationaly redundant. Finally, notice that the estimated Markov chain exhibits strong persistence: the probability of remaining in the same aggregate state is 0.98, while the probability of remaining in the same idiosyncratic

---

[9]CEE estimate $\phi''(1) = 2.48$, where $\phi''(1)$ is the second derivative of the adjustment cost function evaluated at the steady state. In our case the adjustment cost function is quadratic, so $\xi = \phi''(1)/2$ which yields $\phi''(1) = 1.86$.

state is 0.70.[10]

Table 1 reports summary statistics for variables simulated from the model. The algorithm matches all of the targeted moments much more closely than the single-regime version of the model. Not only does the introduction of aggregate regimes allow the procedure to match the serial correlations of Q and I/K, it also generates skewness in Q, I/K, and CF/K. There are, however, still some differences between the skewness patterns generated by the model and the data within subsamples. We conjecture that these differences are, at least in part, due to our choice of a relatively simple 2-state aggregate stochastic process.

The volatility in Q is greatly improved relative to the single regime version of the model. The standard deviation of Q is 70 percent higher in the regime-switching version of the model when compared to the single regime version. Still, the volatility of Q in the regime-switching model (0.45) is lower than that in the data (0.625). Erikson and Whited (2000) make a compelling case for the hypothesis that there is substantial measurement error in Q. Their estimates imply that we should increase the standard deviation of Q generated by the model by 47 percent to incorporate the effect of measurement error that is present in the data. Using this adjustment, we obtain a standard deviation of Q equal to: $0.45 \times 1.47 = 0.66$. This value is very close to our estimate of the volatility of Q (0.625).

Finally, in order to evaluate the role played by flexible capital we re-estimate the model setting ω to zero. We obtain very similar parameter estimates. The adjustment cost parameter is 0.98 instead of 0.9447 in the model with flexible capital. The fit to the data of the two versions of the model is similar with one exception: the serial correlation of investment is too high in the model without

---

[10]The high persistence of the aggregate regime helps the algorithm generate more volatility and skewness in Q. Reducing the persistence of the aggregate regime has little effect on other moments or on the results for simulated investment regressions.

flexible capital (0.93). Flexible capital, while a small share of investment in the model, is important to match the persistence of total investment even if it plays little role for other moments.

4.3. Simulated regression results

We now regress investment on its determinants using simulated data from the model with regime switching. We report our results in Table 4. Regressing I/K on $\ln(Q)$ yields an R^2 of only 0.26 and a coefficient of 0.0827 on $\ln(Q)$. Regressing I/K on $\ln(CF/K)$ yields an R^2 of 0.25 and a cash-flow coefficient of 0.0574. Including both $\ln(Q)$ and $\ln(CF/K)$ in the regression raises the R^2 to 0.32. Regressing I/K only on lagged I/K yields an R^2 of 0.36 and a lagged-investment coefficient of 0.5984. Finally, regressing I/K on lagged I/K, $\ln(Q)$ and $\ln(CF/K)$ we obtain a lagged investment effect of 0.45 and a R^2 of 0.49.

Comparing the model's result to the regression results from the second column of Panel C of Table 2 (in bold), the lagged-investment effect is very similar (around 0.4 in both cases). The Q effect is also similar in the model and in the data (0.03 versus 0.04). The cash-flow effect is negligible in the data, while it is weak but significant in the model (0.03).

5. Conclusions

We find that the investment adjustment cost specification proposed by Christiano, Eichenbaum and Evans (2005) provides a good fit to firm-level data. It can also explain the strong and robust lagged investment effect found empirically.

Since the CEE specification penalizes changes in the level of investment, the reader might find this result surprising. After all, aren't periods of zero investment followed by investment spikes and irreversibilities key features of micro data? It depends on the level of aggregation that we consider. Irreversibilities and jumps

18

are important in plant data. But they are not important for the large Compustat firms included in our sample. Doms and Dunne (1998) show that aggregating data for smaller firms or for individual plants tends to smooth out non-convexities in investment. An interesting question for future research is to investigate how the right model of investment varies with the level of aggregation and whether the CEE specification can emerge from aggregating adjustment cost models that are consistent with plant data.

The implication that lagged investment is an important driver of current investment is consistent with institutional information obtained from survey data collected by Bloom, Van Reenen, and Sadun (2009). These data cover roughly $4,000$ firms in the U.S., Europe and Asia. The authors find that, when senior managers decide on the investment budget of plant managers, the default is to set it equal to the previous year's budget. It is then up to the plant manager to argue for any changes. The bigger the difference between the plant manager's proposal and the budget of the previous year, the harder it is to get the revised budget approved.[11] An interesting issue for future research is to study of the incentive problems that might justify the investment budgeting process adopted by the firms in the Bloom et al. (2009) data.

---

[11]Nick Bloom described these results to us in private correspondence.

19

References

[1] Abel, Andrew, and Janice Eberly, "Investment and Q With Fixed Costs: An Empirical Analysis," working paper, 2002.

[2] Bloom, Nicholas, Raffaella Sadun and John Van Reenen "The organization of firms across countries," mimeo, Stanford University, 2009.

[3] Burnside, Craig "Production Function Regression, Returns to Scale and Externalities," *Journal of Monetary Economics*, 37: 177-201, 1996.

[4] Christiano, Lawrence, Martin Eichenbaum, and Charles Evans "Nominal Rigidities and the Dynamic Effects of a Shock to Monetary Policy," *Journal of Political Economy*, 113: 1–45, 2005.

[5] Cummins, Jason G., Hassett, Kevin A. and Stephen D. Oliner "Investment Behavior, Observable Expectations, and Internal Funds," *American Economic Review*, 96: 796-810, 2006.

[6] Del Negro, Marco and Frank Schorfheide "Monetary Policy Analysis with Potentially Misspecified Models," *American Economic Review*, 99: 1415–50, 2009.

[7] Doms, Mark and Timothy Dunne, "Capital Adjustment Patterns in Manufacturing Plants," *Review of Economic Dynamics*, 1: 409-429, 1998.

[8] Erickson, T. and Toni Whited, "Measurement Error and the Relationship between Investment and 'q'," *The Journal of Political Economy*, 108: 1027-1057, 2000.

[9] Fernández-Villaverde, Jesús and Juan Francisco Rubio-Ramírez "Comparing Dynamic Equilibrium Models to Data: a Bayesian Approach," *Journal of Econometrics*, 123: 153-187, 2004.

[10] Gertler, Mark and Nobuhiro Kiyotaki "Financial Intermediation and Credit Policy in Business Cycle Analysis ," mimeo, New York University, 2010.

[11] Gilchrist, Simon and Charles Himmelberg, "Evidence on the Role of Cash Flow for Investment," *Journal of Monetary Economics* 36: 541-572, 1995.

[12] Hayashi, Fumio, "Tobin's Marginal Q and Average Q : A Neoclassical Interpretation," *Econometrica*, 50: 215-224, 1982.

[13] Hubbard, R. Glenn "Capital-Market Imperfections and Investment," *Journal of Economic Literature,* 36: 193-225, 1998.

[14] Jorgenson, Dale and Ralph Landau, *Tax Reform and the Cost of Capital: an International Comparison*, Washington, DC: Brookings Institution, 1993.

[15] Justiniano, Alejandro and Giorgio Primiceri "The Time Varying Volatility of Macroeconomic Fluctuations," *The American Economic Review*, 98: 604-641, 2008.

[16] King, Mervyn and Don Fullerton, *The Taxation of Income from Capital: a Comparative Study of the United States, the United Kingdom, Sweden, and West Germany*; University of Chicago Press, Chicago, 1984.

[17] Lkhagvasuren, Damba "Big Locational Differences in Unemployment Despite High Labor Mobility," mimeo, Northwestern University, 2006.

[18] Lee, B. and Ingram B. "Simulation estimation of time series models", *Journal of Econometrics*, 47: 197-205, 1991.

[19] Lucca, David. "Resuscitating Time-to-Build," mimeo, Federal Reserve Bank of New York, 2007.

[20] Matsuyama, Kiminori "A Learning Effect Model of Investment: An Alternative Interpretation of Tobin's q," mimeo, Northwestern University, 1984.

[21] Salinger, Michael A. and Lawrence Summers, "Tax Reform and Corporate Investment: A Microeconomic Simulation Study," in Martin S. Feldstein, editor, *Behavioral Simulation Methods in Tax Policy Analysis*, University of Chicago Press, 247-287, 1983.

[22] Smets, Frank and Rafael Wouters "Shocks and frictions in U.S. business cycles: A Bayesian DSGE approach," *American Economic Review*, 97:3, 586-606, 2007.

6. Appendix

6.1. Data Sources and Calculations

Annual data items from the dataset cstsann in the CRSP/Compustat Merged database, 1981-2003, are first listed, followed by the calculations underlying the constructed variables. Sources for non-Compustat items are given in parentheses.

- I : expenditures on property, plant, and equipment, data 30

- $CashFlow$: income before extraordinary items + depreciation and amortization + minor adjustments, calculated as follows (from the Compustat manual):

Income Before Extraordinary Items, 123

\+ Depreciation and Amortization, 125

\+ Extraordinary Items and Discontinued Operations, 124

\+ Deferred Taxes, 126

\+ Equity in Net Loss (Earnings), 106

\+ Sale of Property, Plant, and Equipment and Sale of Investments – Loss(Gain), 213

\+ Funds from Operations – Other, 217

\+ Accounts Receivable – Decrease (Increase), 302

\+ Inventory – Decrease (Increase), 303

\+ Accounts Payable and Accrued Liabilities – Increase (Decrease), 304

\+ Income Taxes – Accrued – Increase (Decrease), 305

\+ Assets and Liabilities – Other (Net Change), 307

= Operating Activities – Net Cash Flow, 308

- $inventories$: total inventories (end of period), data 3

- *debt*: long-term debt (end of period), data 9

- PPE, book value of capital: property, plant, and equipment,

    - data 182: PPE - Beginning Balance – check if it is still reported after 1997;

    - data 187: PPE - Ending Balance (Schedule V);

    - data 184: PPE - Retirements (Schedule V) - not reported after 1997;

    - data 185: PPE - Other Changes (Schedule V) - not reported after 1997.

- P_k, price of capital: implicit price deflator for nonresidential investment, Economic Report of the President, Table B-3, various years.

- u, investment tax credit: obtained by year for 51 asset classes from Dale Jorgenson. These data are aggregated to the two-digit industry level using the BEA historical cost capital flow matrix (asset by industry by year). Specifically, the weight of asset type n in industry j in year t is calculated as $w_{n,j,t} \equiv I_{n,j,t} / \sum_n I_{n,j,t}$. The investment tax credit applied to industry j in year t, $u_{j,t}$, is then constructed as the weighted sum $u_{j,t} = \sum_n w_{j,n,t} u_{j,n,t}$.

- z, value of depreciation allowances: obtained by year for 51 asset classes from Dale Jorgenson. These data are aggregated to the two-digit industry level using the BEA historical cost capital flow matrix (asset by industry by year). Specifically, the weight of asset type n in industry j in year t is calculated as $w_{n,j,t} \equiv I_{n,j,t} / \sum_n I_{n,j,t}$. The value of depreciation allowances in industry j in year t, $z_{j,t}$, is then constructed as the weighted sum $z_{j,t} = \sum_n w_{j,n,t} z_{j,n,t}$.

- τ, corporate tax rate: obtained from King and Fullerton (1984), table 6.4, and Fullerton and Karayannis (in Jorgenson and Landau (1993)), p. 343, updated to 2003 by Dale Jorgenson.

- *market value of equity*: closing stock price times number of common shares outstanding (end of period) plus redemption value of preferred stock (end of period) = prc * shrout/1000 + data56, where,

    - prc: closing stock price from msf file (monthly stock - securities);

    - shrout: Common shares outstanding from msf file (monthly stock - securities);

    - data 56: Preferred Stock - Redemption Value.

- L, useful life of capital goods: by two-digit industry, the useful life of capital goods is calculated as $L_j \equiv \frac{1}{N_j} \sum_{i \in j} \frac{PPE_{i,t-1} + DEPR_{i,t-1} + I_{i,t}}{DEPR_{i,t}}$, where N_j is the number of firms, i, in industry j. Using the double-declining balance method, the implied depreciation rate for industry j, δ_j, is $2/L_j$.

- K, replacement value of capital stock: Using the method of Salinger and Summers (1983) the replacement value of the capital stock is constructed by firm from its book value using the recursion: $K_{i,t} = \left(K_{i,t-1} \frac{P_{K,t}}{P_{K,t-1}} + I_{i,t} \right) (1 - \delta_j)$, where the recursion is initialized using the book value of capital.

- Tobin's Q: [(market value of equity)$_{t-1}$ + (debt)$_{t-1}$ - (inventories)$_{t-1}$]/K_t.

6.2. Sample Selection

Starting from the dataset cstsann in the CRSP/Compustat Merged database, the following filters were applied:

- If the firm was involved in a merger or acquisition, then delete (using aftnt35: ='01' as indication of a Merger & Acquisition)

- end-of-period capital (data 187) is not missing

- investment (data 30) is not missing

- operating profit (data 178) is not missing

- incorrect capital accumulation (only for data before 1994, due to data184 and data185 not being reported after 1997)

- if disinvestment > end-of-period capital then delete

- if operating loss is greater than end-of-period capital then delete

- if operating profit is greater than 2.5 times end-of-period capital then delete

- if q is missing or q<0 then delete

- if investment (data 30) < 0 then delete

- if dis-investment (data107) < 0 then delete

6.3. Solution Method

To solve the firm's problem we first write it in terms of detrended variables: $k = K/X$, $h = H/X$, $i = I/X$, and $i^h = I^h/X$. The value function is homogeneous of degree one in K, H, I_{-1}, and X. This property follows from the fact that we can write the value function as a sum of functions that are homogeneous of degree one in these four variables. The homogeneity property allows us to rewrite the problem of the firm as:

$$v^*(k, h, i_{-1}, z) = \max_{i,k',h'} \left[z k^\alpha h^\omega - \theta - i - i^h + \beta\gamma \int v^*(k', h', i, z') F(dz', z) \right],$$

subject to:

$$\gamma k' = i \left[1 - \xi(\gamma i/i_{-1} - \gamma)^2 \right] + (1 - \delta)k. \tag{6.1}$$

$$\gamma h' = i^h + (1 - \delta)h.$$

To reduce the dimension of the state space we optimize out h' and use the fact that h matters for the value of the firm but not for choosing the optimal level of h'. The resulting firm problem is:

$$v(k, i_{-1}, z) = \max_{i,k'} \left[A z^{1/(1-\alpha)} k^{\omega/(1-\alpha)} - \theta - i + \beta\gamma \int v(k', i, z') F(dz', z) \right],$$

subject to the constraint (6.1). The constant A is given by:

$$A = \left[\frac{\alpha}{1 - \beta(1 - \delta)} \right]^{\alpha/(1-\alpha)} \left[1 - \frac{\alpha}{1 - \beta(1 - \delta)} \right].$$

The original value function is given by:

$$v^*(k, h, i_{-1}, z) = v(k, i_{-1}, z) + (1 - \delta)h.$$

We obtain numerical solutions to the model with CEE adjustment costs using the following algorithm developed in Lkhagvasuren (2006):

1. Define a coarse grid for (k, i_{-1}, z);

2. Choose a guess for $v(k, i_{-1}, z)$ and evaluate it on the coarse grid;

3. Choose a fine grid for i_{-1};

4. Generate a fine grid for k compatible with fine grid for i_{-1} using the resource constraint, (6.1);

5. Use bilinear interpolation to evaluate $v(k, i_{-1}, z)$ for every value of z on the fine grid for i_{-1} and z;[12]

6. Find the optimal value of i for every (k, i_{-1}, z) combination;

7. Save the new value of $v(k, i_{-1}, z)$ evaluated on the coarse grid;

8. Save the policy function for i, $i(k, i_{-1}, z)$, evaluated on the fine grid;

9. Check whether the value function has converged;

10. If the value function has converged then stop; else go to step 5;

To simulate the model we can use a bilinear interpolation of $i(k, i_{-1}, z)$ evaluated for every z, for every pair (k, i_{-1}) evaluated on the fine grid. This interpolation procedure avoids k and i_{-1} having to take values on the real line.

---

[12]Bilinear interpolation is an extension of linear interpolation for bivariate functions. Suppose we know the values of the function $f(x, y)$ evaluated at four points: (x_1, y_1), (x_2, y_1), (x_1, y_2), and (x_2, y_2). Then $f(x, y) \simeq \frac{f(x_1, y_1)}{(x_2 - x_1)(y_2 - y_1)}(x_2 - x)(y_2 - y) + \frac{f(x_2, y_1)}{(x_2 - x_1)(y_2 - y_1)}(x - x_1)(y_2 - y) + \frac{f(x_1, y_2)}{(x_2 - x_1)(y_2 - y_1)}(x_2 - x)(y - y_1) + \frac{f(x_2, y_2)}{(x_2 - x_1)(y_2 - y_1)}(x - x_1)(y - y_1).$

6.4. Estimation Method

The objective of the simulated method of moments is to find the parameter vector $\hat{\Phi}$ that minimizes the distance between empirical (Ψ_D) and simulated moments $(\Psi(\Phi))$:

$$L(\hat{\Phi}) = \min \left[\Psi(\Phi) - \Psi_D\right]' W \left[\Psi(\Phi) - \Psi_D\right]. \tag{6.2}$$

The weighting matrix, W, is obtained using the variance-covariance matrix of the empirical moments, Ω_D:

$$W = \frac{1}{\Omega_D(1 + 1/k)}, \tag{6.3}$$

where $k = length\ of\ simulation/length\ of\ sample$. We estimate the matrix Ω_D using a block-bootstrap method as follows. We form m samples. Each sample consists of data for n firms drawn with replacement from our data set. For each of the m samples we compute the vector of empirical moments. We use the m observations on the vector of moments to estimate the variance-covariance matrix of the empirical moments, Ω_D.

We solve the minimization problem (6.2) using an annealing algorithm. The first step consists in choosing initial values for the parameter vector, Φ, admissible ranges for the parameters, as well as the "*temperature*" and the step size. As we discuss below, the temperature controls the probability that, given the best parameter vector so far, Φ^*, we accept a parameter vector Φ' that yields a worse fit $(L(\Phi') > L(\Phi^*))$. This procedure is used to avoid convergence to a local minimum. We start with a high temperature value, so that the algorithm explores different regions of the parameter space.
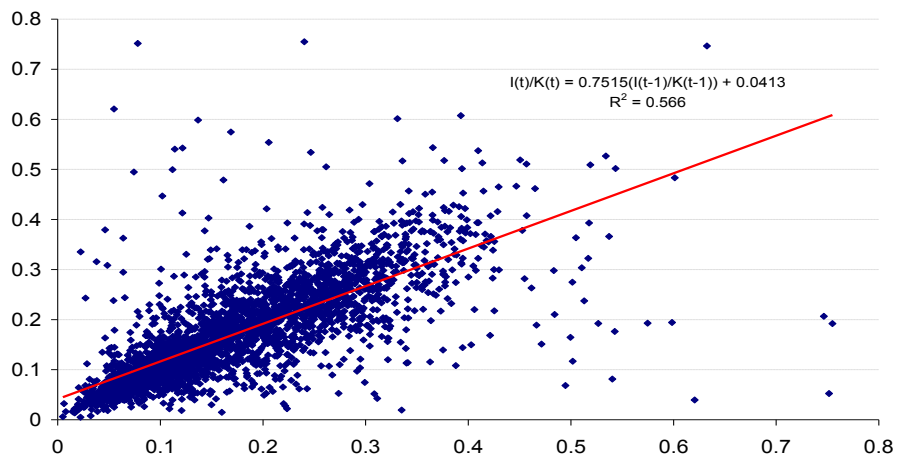
The second step is to generate a new parameter vector, Φ', by adding random shocks to the elements of Φ^* within their admissible range. Next we solve the model using value-function iteration for the parameter vector Φ' and simulate 1940 representative firms (each with 23 years of data). Since the number of firms

in our Compustat sample is equal to 194, this implies that k in (6.3) equals 10. The fourth step consists in computing the simulated moments and $L(\Phi')$. If $L(\Phi') < L(\Phi^*)$ we set $\Phi^* = \Phi'$. If $L(\Phi') > L(\Phi^*)$ we set $\Phi^* = \Phi'$ with probability $\exp\left[-\left(L(\Phi') - L(\Phi^*)\right)/temperature\right]$. Finally, we reduce the values of temperature and step size before going back to step two. The vector of parameter estimates is the one that generates the lowest value of L. We denote this vector by $\hat{\Phi}$.

To verify the convergence properties of our estimation procedure, we used a simple robustness check. Starting with a parameter vector $\tilde{\Phi}$, we simulate a panel of firms and compute the simulated moments, $\Psi(\tilde{\Phi})$. We then use the SMM procedure described above to fit these moments. Ideally, we would like the parameter estimates $\hat{\Phi}$ to be as close as possible to the true parameter values $\tilde{\Phi}$ (the ones that generated the data). Failure to do so may indicate that the estimation procedure is not adequate or that the model parameters are not identified. We find that our procedure can recover reasonably well the true parameter values. This result is also confirmed by the fact that we obtain similar parameter estimates across SMM runs with different starting values.

Figure 1 : Investment rate $(I/K)_t$ against $(I/K)_{t-1}$, Q_t and $(CF/K)_t$

I(t)/K(t) and I(t-1)/K(t-1)

$I(t)/K(t) = 0.7515(I(t-1)/K(t-1)) + 0.0413$
$R^2 = 0.566$

I/K and q

$I/K = 0.06\ln(q) + 0.1406$
$R^2 = 0.2881$

I/K and CF/K

$I/K = 0.0651Ln(CF/K) + 0.2796$
$R^2 = 0.2956$
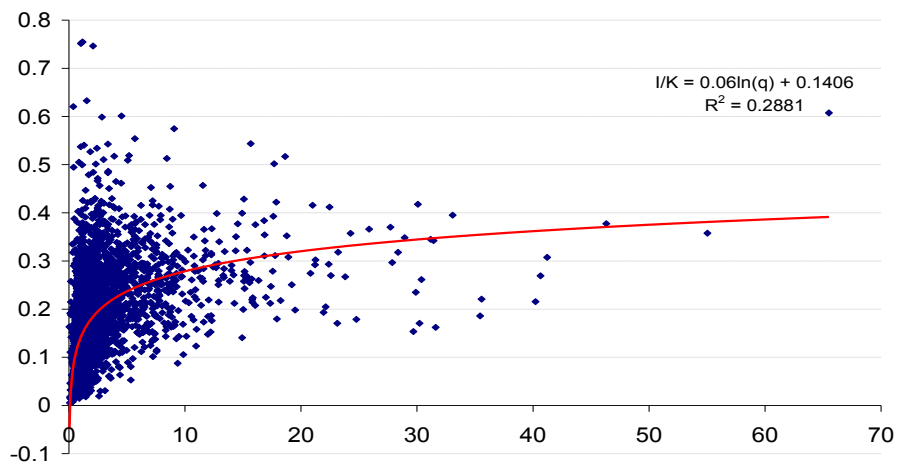
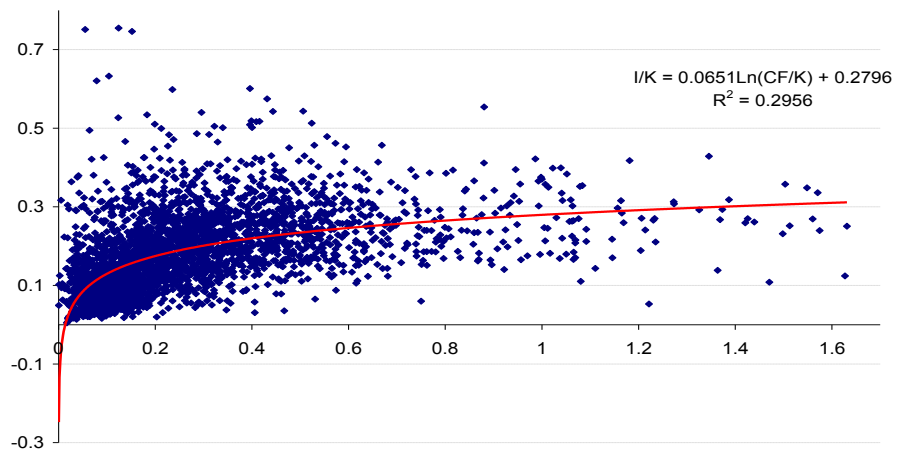# Table 1: Summary statistics, data and model implications

	Median across large firms (4th quartile of Compustat firms)*			Model	Model		
	Full sample	Subsamples		Single regime	Regime switching		
	1981-2003	**1981-1992**	**1993-2003**	**All**	**All**	**Low**	**High**
Time-series average							
Q	1.298	0.950	1.892	**0.972**	1.334	**0.941**	**1.710**
	(0.106)	(0.035)	(0.164)				
I/K	0.150	0.146	0.161	**0.154**	**0.152**	0.134	0.170
	(0.011)	(0.012)	(0.008)				
Cash Flow/K	0.169	0.155	0.199	**0.165**	0.170	**0.142**	**0.197**
	(0.014)	(0.014)	(0.017)				
Time-series standard deviations							
Q	0.625	0.256	0.589	**0.265**	**0.450**	0.125	0.302
	(0.083)	(0.023)	(0.081)				
I/K	0.055	0.050	0.046	**0.065**	**0.054**	0.044	0.057
	(0.003)	(0.003)	(0.003)				
Cash Flow/K	0.078	0.046	0.089	**0.093**	**0.077**	**0.049**	**0.089**
	(0.007)	(0.005)	(0.009)				
Skewness							
Q	0.577	0.160	0.350	**-0.091**	**0.698**	0.031	1.595
	(0.071)	(0.067)	(0.069)				
I/K	0.418	0.320	0.330	**-0.102**	**0.280**	-1.446	0.738
	(0.060)	(0.058)	(0.050)				
Cash Flow/K	0.245	-0.040	0.050	**-0.063**	**0.508**	0.028	0.015
	(0.054)	(0.062)	(0.066)				
Serial correlation							
Q	0.838	0.780	0.662	**0.636**	**0.860**	0.625	0.677
	(0.012)	(0.018)	(0.023)				
I/K	0.600	0.547	0.542	**0.768**	**0.596**	0.697	0.478
	(0.021)	(0.042)	(0.026)				
Cash Flow/K	0.540	0.498	0.370	**0.681**	**0.603**	0.563	0.538
	(0.034)	(0.045)	(0.056)				

Bootstrap standard errors are in parentheses.

*For each variable, we compute the time series average for each firm in the sample, and report the median across firm
 "Q" is Tobin's Q, I is investment in property, plant, and equipment, and K is the capital stock.
Construction of the variables is described in the text and in the data appendix.

Table 2: Data regressions

Dependent variable I/K, standard errors in parenthesis

Panel A : Pooled OLS

Regressors	1	2	3	4	5
Data					
Constant	0.1406 (0.0016)	0.2796 (0.0032)	0.0413 (0.0023)	0.2190 (0.0052)	0.0849 (0.005)
$(I/K)_{t-1}$			0.7515 (0.0116)		0.6253 (0.0132)
$\ln(Q_t)$	0.0600 (0.0016)			0.0331 (0.0023)	0.0126 (0.0019)
$\ln(\text{Cash Flow}/K)_t$		0.0651 (0.0020)		0.0387 (0.0024)	0.017 (0.0020)
R^2	0.29	0.30	0.57	0.34	0.61

Panel B : Panel regressions with firm fixed effects

Regressors	1	2	3	4	5
Data					
Constant	0.1532 (0.0019)	0.1990 (0.0064)	0.0875 (0.0060)	0.1589 0.0073	0.0931 (0.0071)
$(I/K)_{t-1}$			0.4820 (0.0352)		0.4462 (0.0355)
$\ln(Q_t)$	0.0336 (0.0040)			0.0316 (0.0041)	0.0208 (0.0034)
$\ln(\text{Cash Flow}/K)_t$		0.0173 (0.0038)		0.0026 (0.0038)	0.0061 (0.0029)
R^2	0.29	0.30	0.57	0.30	0.60

Panel C : Dynamic Arellano-Bond panel regressions with firm fixed effects and robustness checks

Regressors	1	2	3	4	5
Data					
Constant	0.0894 (0.0053)	**0.0749 (0.0080)**	0.0961 (0.0096)	0.0889 (0.0150)	0.0633 (0.0091)
$(I/K)_{t-1}$	0.4707 (0.0301)	**0.4187 (0.0311)**	0.3785 (0.0284)	0.3086 (0.0621)	0.4192 (0.0351)
$\ln(Q_t)$		**0.0405 (0.0049)**	0.0624 (0.0063)	0.0556 (0.0091)	0.0430 (0.0059)
$\ln(\text{Cash Flow}/K)_t$		**-0.0014 (0.0033)**	-0.0017 (0.0032)	-0.0093 (0.0063)	0.0011 (0.0035)
Year dummies	No	**No**	Yes	No	No
Sample	1981-2003	**1981-2003**	1981-2003	1981-1992	1993-2003

Table 3: Parameter estimates

	Single regime	Regime switching
Estimated parameters		
Adjustment cost : ξ	0.297	0.9447
	(0.0534)	(0.0384)
Fixed cost: θ	99.94	85.5
	(0.4987)	(1.2380)
Discount factor: β	0.948	0.9493
	(0.0001)	(0.0003)
Shock range: σ	0.588	
	(0.0014)	
Low regime center shock: μL		0.866
		(0.0011)
High regime center shock: μH		1.134
		(0.0011)
Low regime shock range: σL		0.2606
		(0.0019)
High regime shock range: σH		0.5749
		(0.0045)
Regime switching parameter: a		0.9841
		(0.0023)
Transition parameter 1: b1		0.704
		(0.0043)
Transition parameter 2: b2		0.1979
		(0.0083)
Shock persistence: ρ	0.6840	
	(0.0036)	
Weight on flexible capital: ω	0.0250	0.0693
	(0.0036)	(0.0005)
Calibrated parameters		
Mean shock: μ	1.00	1.00
Returns to scale: $\alpha + \omega$	0.80	0.80
Depreciation rate: δ	0.12	0.12
Growth: γ	1.03	1.03

Standard errors in parenthesis

Table 4: Model regressions

Dependent variable I/K, standard errors in parenthesis

Panel A: Single-regime model, panel regressions with firm fixed effects

Regressors	1	2	3	4	5
Constant	0.162	0.2622	0.0357	0.4185	**0.1096**
	(0.0003)	(0.0006)	(0.0005)	(0.0019)	**(0.0024)**
$(I/K)_{t-1}$			0.7677		**0.597**
			(0.0032)		**(0.0037)**
$\ln(Q_t)$	0.1266			-0.2446	**0.0253**
	(0.0009)			(0.0028)	**(0.0028)**
$\ln(\text{Cash Flow}/K)_t$		0.0528		0.137	**0.0223**
		(0.0003)		(0.0010)	**(0.0010)**
R^2	0.34	0.46	0.59	0.55	**0.72**

Panel B: Regime-switching model, panel regressions with firm fixed effects

Regressors	1	2	3	4	5
Constant	0.1328	0.2549	0.0612	0.2073	**0.1315**
	(0.0001)	(0.0009)	(0.0003)	(0.0005)	**(0.0012)**
$(I/K)_{t-1}$			0.5984		**0.4468**
			(0.0018)		**(0.0017)**
$\ln(Q_t)$	0.0827			0.0538	**0.0309**
	(0.0003)			(0.0004)	**(0.0003)**
$\ln(\text{Cash Flow}/K)_t$		0.0574		0.0361	**0.0296**
		(0.0002)		(0.0003)	**(0.0002)**
R^2	0.26	0.25	0.36	0.32	**0.49**