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ABSTRACT

This paper shows that, with (partial) irreversibility, higher uncertainty reduces the impact effect of demand shocks on investment. Uncertainty increases real option values making firms more cautious when investing or disinvesting. This is confirmed both numerically for a model with a rich mix of adjustment costs, time-varying uncertainty, and aggregation over investment decisions and time, and also empirically for a panel of manufacturing firms. These cautionary effects of uncertainty are large – going from the lower quartile to the upper quartile of the uncertainty distribution typically halves the first year investment response to demand shocks. This implies the responsiveness of firms to any given policy stimulus may be much lower in periods of high uncertainty, such as after major shocks like OPEC I and 9/11.

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1. Introduction

Recent theoretical analyses of investment under uncertainty have highlighted the effects of irreversibility in generating 'real options' (e.g. Dixit and Pindyck (1994)). In these models uncertainty increases the separation between the marginal product of capital which justifies investment and the marginal product of capital which justifies disinvestment. This increases the range of inaction where investment is zero as the firm prefers to 'wait and see' rather than undertaking a costly action with uncertain consequences. In short, investment behaviour becomes more cautious.

Firm-level data is attractive for investigating this effect of uncertainty on the degree of caution since empirical measures of uncertainty can be constructed based on share price volatility (e.g. Leahy and Whited (1996)). One important difficulty for direct testing of real options models of investment under uncertainty using firm data, however, is the extreme rarity of observations with zero investment in annual consolidated accounts. If we believed that these firms make a single investment decision in each year this lack of zeros would reject the canonical real options model of a single investment decision with its region of inaction. However, given the extensive evidence of discrete and lumpy adjustments in more disaggregated plant-level data (e.g. Doms and Dunne (1998)), this lack of zeros at the firm level is suggestive of aggregation over types of capital, production units and time.

Previous research has shown that aggregation does not eliminate the impact of lumpy micro investment decisions for more aggregated investment dynamics.[1] This raises the question of whether the effects of uncertainty and irreversibility on short run investment dynamics can be detected in an econometric study of firm-level investment spending. To investigate this issue we develop a model of the firm's investment decisions that allows for two types of capital, a rich specification of adjustment costs, time-varying uncertainty, alternative functional forms for the

[1] See, for example, Bertola and Caballero (1994), Caballero and Engel (1999), Abel and Eberly (2001), and Doyle and Whited (2001). Thomas (2002) and Veracierto (2002) find that in general equilibrium models the impact of non-convex investment costs on the business cycle may be small. These papers are necessarily based on relatively simple models of firm investment - including a constant level of uncertainty - to enable complex general equilibrium modelling. Our focus here is on much richer (partial equilibrium) micro models that include fluctuations in the level of uncertainty. These are appropriate for estimation on firm-level data.

revenue function and extensive aggregation over time and over production units. We solve this theoretical model numerically and simulate firm-level panel data. We use this simulated data in two ways. First we analyse it directly to confirm two properties of firm-level investment dynamics in this framework. One property is the effect of higher uncertainty on the degree of caution in investment decisions as noted above. We show that, with (partial) irreversibility, the impact effect on investment of a given firm-level demand shock tends to be weaker for firms that are subject to a higher level of uncertainty. We also show that the response of investment to demand shocks tends to be convex, as larger shocks induce firms to invest in more types of capital and at more production units (the extensive margin). This in turn induces more adjustment at the intensive margin, with these aggregation effects being reinforced by supermodularity in the production technology.

We also use our simulated data to show that both of these effects can be detected using a relatively simple dynamic econometric specification to approximate the complex firm-level investment dynamics implied by this framework. Our starting point is an error correction model (ECM) of investment that has been widely used in firm-level studies. We add two types of terms. First, an interaction between real sales growth and measured uncertainty tests for the more cautious response of investment to demand shocks at higher levels of uncertainty. Second, a non-linear sales growth term to test for convexity in the response of investment to demand shocks. Generalised Method of Moments (GMM) estimation on the simulated panel data indicates that we can reject the null hypothesis of a common, linear response of investment to demand shocks, provided the dynamic specification used is sufficiently rich for standard tests of overidentifying restrictions not to indicate severe misspecification of the econometric model.

We then apply the same econometric approach to study the investment behaviour of a sample of 672 publicly traded UK manufacturing companies over the period 1972 to 1991. We find evidence both of more cautious investment behaviour for firms subject to greater uncertainty, and of a convex response of investment to real sales growth. While there may be other explanations for these patterns in company investment dynamics, we conclude that the investment behaviour of large firms is consistent with a partial irreversibility model in which uncertainty dampens the short run adjustment of investment to demand shocks.

Finally, simple simulations using our estimated econometric model suggest that observed fluctuations in uncertainty can play an economically important role in shaping firm-level investment decisions. For example, we find that a one standard deviation increase in our measure of uncertainty, as occurred after 9/11 and the first OPEC oil crisis, can halve the impact effect of demand shocks on company investment. While we do not model the behaviour of labour demand, the existence of similar labour hiring and firing costs would imply that higher uncertainty would also make employment responses to demand shocks more cautious. This suggests that firms will generally be less responsive to monetary and fiscal stimulus in periods of high uncertainty, which is important for policy-makers trying to respond to major shocks during periods of high uncertainty.[2] Several papers have also reported evidence of an increase in firm-specific uncertainty in the US and other OECD countries in recent years,[3] which our analysis indicates could have significant effects on investment dynamics.

The plan of the paper is as follows. Section 2 considers two implications of uncertainty and irreversibility for investment behaviour, and confirms these numerically using simulated data. Section 3 develops our econometric investment equation and shows, using the simulated data, that tests based on this model can detect these effects on investment dynamics. Section 4 takes this econometric model to real company investment data to test for the presence of these effects, while section 5 examines their magnitude. Section 6 offers some concluding remarks.

2. Simulating investment dynamics under uncertainty

The typical model in the literature considers investment in a single partially irreversible capital good, with a Cobb-Douglas revenue function and demand conditions which follow a Brownian motion process with constant variance. Investment only

[2] See Bloom (2006) on the evidence for steep rises in uncertainty after major macro shocks.

[3] Campbell et al. (2001) study US firms in the period 1962-1997 and find an increase in the firm-level (but not market-level) volatility of annualised daily stock returns in the 1980s and 1990s compared to the 1960s and 1970s. See also Philippon (2003) for evidence of increased sales growth volatility for US firms, and Thesmar and Thoenig (2003) for similar evidence on French firms.

occurs when the firm's marginal revenue product of capital hits an upper threshold, given by the traditional user cost of capital plus an option value for investment. Similarly disinvestment only occurs when the marginal revenue product hits a lower threshold, given by the user cost for selling capital less an option value for disinvestment. The firm chooses to wait and do nothing if its marginal revenue product of capital lies between these two thresholds.

As the marginal revenue product of capital evolves stochastically over time this approach predicts that the firm will undertake sporadic bursts of investment or disinvestment, consistent with the typical evidence from plant-level data (see, for example, Doms and Dunne (1998) or Nilson and Schiantarelli (2003)). Abel and Eberly (1996) show by comparative statics that the option values are increasing in the (time invariant) level of uncertainty. This suggests that firms which face a higher level of uncertainty are less likely to respond to a given demand shock.

2.1. Aggregation and firm-level investment

Annual investment data for publicly traded UK and US firms, however, do not display the discrete switches from zero to non-zero investment regimes indicated by this basic model. In particular observations with zero investment spending are almost completely absent from their company accounts. Table 1 reports evidence from our sample of 672 UK manufacturing companies, and from a sample of UK manufacturing establishments that contain one or more plants at the same location. There are two distinct patterns of aggregation that can be observed: first aggregation across types of capital (structures, equipment and vehicles); and second aggregation across plants within the establishment or the firm. In both cases we observe a higher proportion of observations with zero investment when we consider more disaggregated data. There is also likely to be a third type of aggregation - temporal aggregation - as the frequency of shocks and investment decisions is likely to be much higher than that of the (annual) data.

[Table 1 about here]

In view of this we explicitly consider a framework in which firms invest in multiple types of capital goods, across multiple production units, and there is aggregation over time. These production units experience idiosyncratic unit-level productivity shocks as well as a common firm-level demand shock. In this more general framework, but in a model with a constant level of uncertainty and partial irreversibilities only, Eberly and Van Mieghem (1997) have shown that the optimal investment decisions for each unit will follow a multi-dimensional threshold policy. Extending this to allow for time-varying uncertainty and temporal aggregation provides two implications which are the focus of our simulation and empirical investigation.

The first implication is that the response of company investment to demand shocks should be lower at higher levels of uncertainty due to the "cautionary" effect of uncertainty. For each production unit or type of capital the option to wait and do nothing is more valuable for firms that face a higher level of demand uncertainty. Following a given positive demand shock investment by such firms is expected to be lower, as both less units (or types of capital) will invest (the extensive margin) and each unit (type) that does invest will invest less (the intensive margin), with any supermodularity in the production technology reinforcing these effects.[4] Similarly the impact of a given negative demand shock on firm-level disinvestment is also expected to be smaller for firms that face a higher level of uncertainty.

Second, the investment response will be convex in response to positive demand shocks and concave in response to negative demand shocks. When the firm experiences a positive demand shock it may invest in a greater number of production units or types of capital (the extensive margin) and it may invest more in each unit or type of capital (the intensive margin). Larger demand shocks will affect both margins, and any supermodularity in the production technology would make these two effects reinforcing. Thus, the more types of capital the firm is induced to invest in, the more it wants to invest in those types of capital which are already adjusting, generating a convex response. The same reasoning also suggests that the response of firm-level disinvestment to negative demand shocks will be concave.

[4] Supermodularity is a general concept for complementarity. A function $f{:}\mathbf{R}^n \to \mathbf{R}$ is defined as supermodular if $\forall\ x, x' \in \mathbf{R}^n,\ f(x) + f(x') \leq f(\min(x, x')) + f(\max(x, x'))$. If f is twice differentiable this implies $\frac{\partial^2 f(x_1, x_2, ..x_n)}{\partial x_i \partial x_j} \geq 0\ \forall\ i \neq j$. The Cobb-Douglas and CES production functions are both supermodular.

As these investment models do not have closed form solutions we cannot prove these properties analytically. In the next section we confirm them using numerical simulations.

2.2. The simulation model

We start by parameterising one model from the general class of supermodular homogeneous models that we are considering. Firms are assumed to operate a large collection of individual production units, with the number chosen to ensure that full aggregation has occurred. In the simulation this is set at 250 units per firm, chosen by increasing the number of units until the results were no longer sensitive to this number.[5]

Each unit faces an iso-elastic demand curve for its output, which is produced using labour and two types of capital. Demand conditions evolve as a geometric random walk with time-varying uncertainty, and have a unit-specific idiosyncratic component and a common firm-level component. Demand shocks, uncertainty shocks and optimisation occur in monthly discrete time. Labour is costless to adjust while both types of capital are costly to adjust.

2.2.1. The production unit model

In the basic model each production unit has a reduced form supermodular revenue function $R(X, K_1, K_2)$

$$R(X, K_1, K_2) = X^{\gamma} K_1^{\alpha} K_2^{\beta} \tag{2.1}$$

based on an underlying Cobb-Douglas production function after labour, a flexible factor of production, has been optimised out. Demand and productivity conditions have been combined into one index, X, henceforth called demand conditions. For computational tractability we normalize this demand conditions parameter through the substitution, $P^{\frac{1-\alpha-\beta}{\gamma}} = X$, so that the revenue function is homogeneous of degree

[5] In the UK Census of Production microdata the average size of a manufacturing production unit is about 20 employees. The mean size of firms in our sample is 4,440 employees, suggesting a mean of around 220 units per firm. Tests on specifications with different degrees of cross-sectional aggregation (5, 10 and 50 units per firm) and temporal aggregation (2, 4 and 6 periods per year) confirm the robustness of our results to these assumptions.

one in (P, K_1, K_2), where

$$R(X, K_1, K_2) = \widetilde{R}(P, K_1, K_2) \tag{2.2}$$
$$= P^{1-\alpha-\beta} K_1^{\alpha} K_2^{\beta}. \tag{2.3}$$

In the simulation we set $\alpha = 0.4$ and $\beta = 0.4$, corresponding to a 25% mark-up and constant returns to scale in the physical production function, with equal coefficients on each type of capital.

Demand conditions are a composite of a unit-level (P^U) and a firm-level (P^F) component, $P = P^U \times P^F$. The unit-level demand (or productivity) conditions evolve over time as an augmented geometric random walk with stochastic volatility:

$$P_t^U = P_{t-1}^U (1 + \mu(\sigma_t) + \sigma_t V_t^U) \qquad V_t^U \sim N(0,1) \tag{2.4}$$
$$\sigma_t = \sigma_{t-1} + \rho_\sigma(\sigma^* - \sigma_{t-1}) + \sigma_\sigma W_t \qquad W_t \sim N(0,1). \tag{2.5}$$

Here $\mu(\sigma_t)$ is the mean drift in unit-level demand conditions, σ_t^2 is the variance of unit-level demand conditions, σ^* is the long run mean of σ_t, ρ_σ is the rate of convergence to this mean, and σ_σ^2 is the variance of the shocks to this variance process. The terms V_t^U and W_t are the i.i.d. shocks to unit-level demand and variance conditions respectively.

The firm-level demand process is also an augmented geometric random walk with stochastic volatility, which for tractability we assume has the same mean and variance:

$$P_t^F = P_{t-1}^F (1 + \mu(\sigma_t) + \sigma_t V_t^F) \qquad V_t^F \sim N(0,1). \tag{2.6}$$

Hence, the overall demand process $\log P$ has drift $2\mu(\sigma_t)$ and variance $2\sigma_t^2$. While this demand structure may seem complex, it is formulated to ensure that units within the same firm have linked investment behaviour due to the common firm-level demand shocks and level of uncertainty, but also display some independent behaviour due to idiosyncratic shocks. The baseline value of $2\mu(\sigma_t)$ is set to 4% (average real sales growth), invariant to the level of uncertainty, although we also report below some experiments that allow for more general drifts.

The two types of capital are costly to adjust. We start by modelling only partial irreversibility adjustment costs whereby the resale price of a unit of capital is less than the purchase price. Capital type 1 is assumed more costly to adjust (for example, specialised equipment), while capital type 2 is less costly to adjust (for example, vehicles). For the simulation we set the resale loss for capital of type 1 to 50% and the resale loss for capital of type 2 to 20%.[6]

These adjustment costs are defined by the firm's adjustment cost function, $C(P, K_1, K_2, I_1, I_2)$. We assume, for numerical tractability, that newly invested capital enters production immediately, that both types of capital depreciate at an annualized rate of 10%, and that the firm has an annualized discount rate of 10%.

2.2.2. Solving the production unit model

The complexity of the model necessitates numerical simulation, but analytical results can be used to show that the problem has a unique-valued continuous solution,[7] and an (almost everywhere) unique policy function. This means our numerical results will be convergent with the unique analytical solution.

In principle we have a model with too many state variables to be solved using numerical methods given current computing power. The unit's optimization problem, however, can be simplified by noting that the revenue function, adjustment cost function, depreciation schedules and expectations operators are all jointly homogeneous of degree one in (P, K_1, K_2). This allows us to normalize by one state variable - capital type 1 - simplifying the model and dramatically increasing the speed of the numerical solution routine. This effectively gives us one state "for free", in that we estimate on two major state spaces ($\frac{P}{K_1}$ and $\frac{K_2}{K_1}$) but for three underlying state variables.

[6] Our choice of adjustment cost parameters is based on the literature where available, in particular Cooper and Haltiwanger (2006). The qualitative results from our analysis of the simulated data are not sensitive to moderate changes to the adjustment cost parameter values, although as discussed in section 3.2, they are sensitive to the type of adjustment costs considered.

[7] An application of Stokey and Lucas (1989) for the continuous, concave and almost surely bounded normalized returns and cost function for models with partial irreversibilities (this section) and quadratic adjustment costs; and Caballero and Leahy (1996) for the extension to models with fixed costs in section (3.2.2).

The optimization problem (before normalization) can be stated as:

$$\begin{aligned} V(P_t, K_{1t}, K_{2t}, \sigma_t) &= \max_{I_{1t}, I_{2t}} \widetilde{R}(P_t, K_{1t,} + I_{1t}, K_{2t} + I_{2t}) - C(P_t, K_{1t}, K_{2t}, I_{1t}, I_{2t}) \\ &\quad + \frac{1}{1+r} E[V(P_{t+1}, (K_{1t} + I_{it})(1-\delta), (K_{1t} + I_{it})(1-\delta), \sigma_{t+1})] \end{aligned}$$

where r is the discount rate, δ is the depreciation rate, $E[.]$ is the expectations operator, I_{jt} is investment in type j $(j = 1, 2)$ capital at time t and K_{jt} is the stock of type j capital. Using the homogeneity in (P, K_1, K_2) this can be re-written as:

$$\begin{aligned} K_{1t} V(P_t^*, 1, K_{2t}^*, \sigma_t) &= \max_{I_{1t}^*, I_{2t}^*} K_{1t} \widetilde{R}(P_t^*, 1 + I_{1t}^*, K_{2t}^*(1 + I_{2t}^*)) - K_{1t} C(P_t^*, 1, K_{2t}^*, I_{1t}^*, I_{2t}^*) \\ &\quad + \frac{1}{1+r} K_{1t+1} E[V(P_{t+1}^*, 1, K_{2t+1}^*, \sigma_{t+1})] \end{aligned}$$

where starred variables are $K_2^* = \frac{K_2}{K_1}$, $P^* = \frac{P}{K_1}$, $I_1^* = \frac{I_1}{K_1}$ and $I_2^* = \frac{I_2}{K_2}$. Upon normalization by K_{1t} this simplifies to:

$$\begin{aligned} V(P_t^*, 1, K_{2t}^*, \sigma_t) &= \max_{I_{1t}^*, I_{2t}^*} \widetilde{R}(P_t^*, 1 + I_{1t}^*, K_{2t}^*(1 + I_{2t}^*)) - C(P_t^*, 1, K_{2t}^*, I_{1t}^*, I_{2t}^*) \\ &\quad + \frac{(1 + I_{1t}^*)(1-\delta)}{1+r} E[V(P_{t+1}^*, 1, K_{2t+1}^*, \sigma_{t+1})] \end{aligned}$$

which is a function of only the state variables $(\frac{P}{K_1}, \frac{K_2}{K_1}, \sigma)$. We let uncertainty, σ_t, take five equally-spaced values from 0.05 to 0.5, with a symmetric monthly transition matrix that is approximately calibrated against (the variance and autocorrelation of) our stock-returns measure of uncertainty for UK listed firms, described in section 4.1 below. The simulation is run on a state space of $(\frac{P}{K_1}, \frac{K_2}{K_1}, \sigma)$ of (100,100,5).[8]

2.2.3. Aggregation to firm-level data

Simulated data is generated by taking the numerical solutions for the optimal investment functions and feeding in demand and uncertainty shocks at a monthly frequency. The simulation is run for 60 months to generate an initial ergodic distribution. Annual firm-level investment data is then generated by aggregating across the two types of capital, across the 250 units and across 12 months within each year. Capital stocks and the level of the demand conditions are summed across all units at the end of each year, while uncertainty is measured as the average yearly value.

[8] We also need the optimal control space of (I_1^*, I_2^*) of dimension (100,100), so that the full returns function in the Bellman equation has dimensionality (100,100,100,100,5). The program and a manual explaining the underlying techniques are available at http://cep.lse.ac.uk/matlabcode or from nbloom@stanford.edu.

2.3. Investigating the theoretical implications

Using the model and solution method outlined above we generate simulated investment and demand data for a panel of 50,000 firms and 25 years. We confirm the two implications for short run investment dynamics highlighted in section 2 by considering the relationship between firm-level annual investment rates and demand growth in this simulated data. As the drift in the demand process is common to all firms, and the idiosyncratic shocks are averaged across 250 production units, there is a simple correspondence between demand growth and the firm-level demand shock in this simulation.

Figure 1 presents Lowess smoothed non-parametric plots[9] of investment against demand growth for observations around the 10^{th}, 25^{th}, 50^{th}, 75^{th} and 90^{th} percentiles of the distribution of uncertainty (σ_t).[10] Investment rates are measured as annual investment divided by the capital stock at the beginning of the year, and annual demand growth is measured as the percentage change comparing the beginning and the end of the year. The first implication - that the short run response of investment to demand shocks will be lower at higher uncertainty - indicates that the slope of these response functions is lower at higher levels of uncertainty. It is evident that these non-parametric regression estimates do indeed become flatter as the level of uncertainty rises, consistent with the first implication. In quantitative terms, comparing investment responses to -10% and +25% demand growth, the gradient of the investment response to demand growth approximately doubles when moving from the third quartile to the first quartile of the distribution of uncertainty, and approximately triples when moving from the 90th percentile to the 10^{th} percentile. Hence, differences in the level of uncertainty generate substantial variation in the short run response of investment to demand shocks, and this is clearly seen in our

[9]Lowess smoothing estimates a linear regression at each data point, using Cleveland's (1979) tricube weighting over a moving window of 5% of the data, to generate a non-parametrically smoothed data series. Lowess is similar to Kernel smoothing but uses information on both the mean and the slope of the data, and so is more efficient in estimating functions with continuous first derivatives, which our aggregated data has asymptotically (in the number of production units).

[10]As this variance parameter has a five point process in the underlying monthly model, we obtain considerable clustering of observations around these values, even in the average annual firm data. Although we use 1.25 million generated observations, there are no observations in the sample at the 10th and 25th percentiles of uncertainty with annual demand growth above 27% and 64% respectively, so the lines are not estimated beyond these points.

simulated firm-level data despite extensive aggregation across two types of capital, 250 production units and 12 monthly decision periods.

The second implication - that the short run response of investment to demand shocks is non-linear - indicates that these response functions are convex for positive investment and concave for negative investment. Focusing first on positive investment, it is evident that all five curves are indeed convex, with a proportionally larger response to larger positive shocks. Looking at negative investment the picture is unclear because, even for large negative demand growth of -25%, most firms are still undertaking positive gross investment. This reflects the combination of longer run dynamics with pent-up investment demand, 4% demand drift and 10% depreciation, which even in the presence of relatively low degrees of irreversibility generates very few firm-level disinvestment observations (2% in our simulated data sample and 3% in the real UK data). Thus, we cannot identify the concavity in the disinvestment responses in either the simulation or in actual UK data, and therefore we concentrate on the convex response for positive investment in the remainder of the paper.

3. Evaluating our empirical specification

The next step is to investigate the empirical importance of these properties of short run investment dynamics in actual firm-level data, which requires an appropriate econometric specification. If we observed the true underlying demand shocks and demand variance this would be relatively straightforward as we could, for example, use the same the non-parametric approach used in the previous section to analyse short run investment responses to exogenous demand shocks. However, in real firm-level datasets we only observe proxies for demand growth such as sales growth and proxies for uncertainty such as share price volatility. Among other issues, this requires us to deal with the problem that outcomes like sales and share prices are jointly determined with the firm's investment decisions. To do this we consider GMM estimates of dynamic econometric investment equations.

Our starting point is a reduced form error correction model that provides a flexible distinction between short run influences on investment rates and longer term influences on capital stocks. This has been widely used in recent empirical studies of company investment behaviour.[11] Bloom (2000) shows that the actual capital stock series chosen by a firm under partial irreversibility has a long run growth rate equal to that of the hypothetical capital stock series that the same firm would choose under costless reversibility, essentially because the gap between these two series is bounded. This implies that the logarithms of the two series should be cointegrated, and thus provides one motivation for considering an error correction model of capital stock adjustment.[12]

This cointegration result indicates that

$$\log K_{it} = \log K_{it}^* + e_{it} \tag{3.1}$$

where K_{it} is the actual capital stock for firm i in period t, K_{it}^* is the capital stock this firm would have chosen in the absence of adjustment costs, and e_{it} is a stationary error term. We specify this hypothetical frictionless level of the capital stock as

$$\log K_{it}^* = \log Y_{it} + A_i^* + B_t^* \tag{3.2}$$

where Y_{it} is the (real) sales of firm i in period t, and A_i^* and B_t^* are unobserved firm-specific and time-specific effects reflecting possible variation across firms in the components of and response to the user cost of capital (Chetty, 2006). This formulation is consistent, for example, with the frictionless demand for capital for a firm with a constant returns to scale CES production function and iso-elastic demand, and implies that the logs of the actual capital stock and real sales are cointegrated, provided the user cost of capital is stationary.[13] Note that this does not impose that the actual capital stock and its hypothetical frictionless level are equal on average, since the error term e_{it} need not be mean zero. However, the partial irreversibility framework indicates that e_{it} will be serially correlated in a

[11] See, for example, Hall, Mairesse and Mulkay (1999) and Bond, Harhoff and Van Reenen (2003).

[12] The representation theorem of Engle and Granger (1987) shows that the dynamic relationship between two I(1) series that are cointegrated can be formulated as an error correction relationship.

[13] Both this specification and the results in Bloom (2000) are based on a single production unit with one type of capital. To check that this provides an accurate approximation for our aggregated firm-level data, we confirmed that log capital was cointegrated with log sales in our simulated data, with a coefficient of 1.008 on log sales. In sections 3.2 and 4.4 we also consider relaxing the restriction in (3.2) that this coefficient is unity.

highly complex way. Any parsimonious specification of these dynamics should be viewed as an approximation, the quality of which we will investigate using simulated investment data in the next section.

A basic error correction representation of the dynamic relationship between $\log K_{it}$ and $\log K_{it}^*$, using equation (3.2), would have the form

$$\Delta \log K_{it} = \beta \Delta \log Y_{it} + \theta(\log Y_{i,t-s} - \log K_{i,t-s}) + A_i + B_t + v_{it} \qquad (3.3)$$

where A_i and B_t are again unobserved firm-specific and time-specific effects and v_{it} is, at least approximately, a serially uncorrelated error term. A key property is that the coefficient θ on the error correction term should be positive, so that firms with a capital stock level below their target will eventually adjust upwards, and vice versa.

We use the approximation $\Delta \log K_{it} \approx (I_{it}/K_{i,t-1}) - \delta_i$, where I_{it} is gross investment and δ_i is the (possibly firm-specific) depreciation rate. To test for the effect of uncertainty on the impact effect of demand shocks (the first implication), we add an interaction term between a measure of uncertainty (SD_{it}) and current sales growth ($\Delta \log Y_{it}$). A negative coefficient on this interaction term would indicate that the short run response of investment to demand shocks is indeed lower at higher levels of uncertainty. To allow for other possible effects of uncertainty on the level of the capital stock in either the short run or the long run, we also consider further terms in both the change (ΔSD_{it}) and the level (SD_{it}) of our measure of uncertainty. To test for non-linearity in the short run response of investment to demand shocks (the second implication), we add a higher order term in current sales growth $(\Delta \log Y_{it})^2$. A positive coefficient on this squared term would be consistent with this implication, indicating a convex relationship between investment and demand shocks, recalling that our samples are dominated by observations on firms with positive gross investment.

These additional terms then give us an empirical specification of the form

$$\begin{aligned} \frac{I_{it}}{K_{i,t-1}} &= \beta_1 \Delta \log Y_{it} + \beta_2 (\Delta \log Y_{it})^2 + \beta_3 (SD_{it} * \Delta \log Y_{it}) \qquad (3.4) \\ &\quad + \theta(\log Y_{i,t-1} - \log K_{i,t-1}) + \gamma_1 SD_{it} + \gamma_2 \Delta SD_{it} + A_i + \delta_i + B_t + v_{it}. \end{aligned}$$

3.1. Testing our empirical specification on simulated data

To investigate whether this econometric approach can detect the properties of short run investment dynamics highlighted in section 2, we use our simulation model to generate data for a panel of 1,000 firms and 15 years. This allows us to consider whether this relatively simple dynamic econometric specification provides an adequate approximation to the complex investment dynamics suggested by models with partial irreversibility, and to compare specifications that use sales and a stock-returns measure of uncertainty with specifications that use the true underlying demand and uncertainty variables. Sales (Y_{it}) are generated from the revenue function and aggregated across production units and months. Monthly stock returns are generated by aggregating the value function across units and adding in monthly net cash flows (revenue less investment costs). The within-year standard deviation of these monthly returns (SD_{it}) provides our firm-level measure of uncertainty, which mimics the kind of measure used in our empirical analysis in section 4. Table 2 reports the sample correlation matrix for key variables in our simulated dataset. This demonstrates that the standard deviation of monthly stock returns is positively correlated with the underlying standard deviation of demand shocks (σ_{it}), supporting the use of this as an empirical measure of uncertainty. In what follows we use lower cases to denote natural logarithms, so for example, $y_{it} = \log Y_{it}$.

[Tables 2 and 3 about here]

In Table 3 we present the results of estimating the augmented error correction model of investment using this simulated firm-level panel. In column (1) we first report OLS estimates using as explanatory variables the annual measures of the 'true' demand (P) and uncertainty (σ) variables that were used to generate this simulated investment data. Our tests detect significant heterogeneity in the impact effect of demand shocks on firm-level investment, depending on the level of uncertainty, and significant convexity in the response of investment to demand shocks. We also find evidence of 'error correcting' behaviour, with the actual capital stock adjusting in the long run towards a target that is cointegrated with its frictionless level. We find no evidence here that a permanent increase in the level of uncertainty would affect the level of the capital stock in the long run, but there is an indication that increases in uncertainty reduce investment in the short run in ways that are not fully captured by our multiplicative interaction term.

Column (2) of Table 3 uses instead the empirical counterparts to the demand and uncertainty variables, based on annual levels of simulated sales (Y_{it}) and the within-year standard deviation of simulated monthly stock returns (SD_{it}). As these variables are jointly determined with investment decisions we treat them as endogenous and report GMM estimates. To mimic our empirical analysis of real company data more closely, we also allow for the possibility of unobserved firm-specific effects here, and estimate this specification in first-differences. The instruments used are the second and third lags of our simulated investment, capital, sales and uncertainty measures, following Arellano and Bond (1991). A Sargan-Hansen test of overidentifying restrictions does not reject this specification, and there is no significant evidence of second-order serial correlation in the first-differenced residuals. While the parameter estimates are less precise in this case, we again detect significant evidence that uncertainty influences the short run response of investment to demand shocks, and that this response is convex. It should be noted, however, that this was not always the case if we imposed simpler dynamic specifications that were rejected by the test of overidentifying restrictions (for example, if we omit the error correction term). This illustrates the potential importance of controlling for longer run investment dynamics when testing the properties of the short run responses to demand shocks. For other calibrations of the simulation model we found that alternative dynamic specifications or instrument sets may be required. The negative coefficient on the interaction term and the positive coefficient on the squared term, however, were found consistently across specifications that were not rejected by the test of overidentifying restrictions.

Considering the magnitude of this effect of uncertainty, we find that the predicted impact effect of sales growth on investment rates increases by 79% when moving from the third quartile to the first quartile in the distribution of measured uncertainty, and by 168% when moving from the 90th percentile to the 10th percentile. These differences are quantitatively similar to those that we estimated directly for the underlying model in section 2.3.

This suggests that our econometric tests have power to detect these properties of short run investment dynamics, at least using this simulated dataset. Interestingly we also find that the longer run capital stock adjustment process is approximated quite well by our error correction specification, and that our GMM estimates using measured sales and uncertainty variables even provide quantitative estimates of the effect of uncertainty on short run responses to demand shocks that are in the right ballpark.

In columns (3) and (4) of Table 3 we confirm that these properties of short run investment dynamics are also found using two alternative specifications of our simulation model, which approximate Hartman (1972) and Abel (1983) type effects of uncertainty on the expected marginal revenue product of capital (MRPC).[14] In column (3) we set the drift in the demand process $2\mu(\sigma_t) = 0.04 + \frac{\sigma_t^2}{2}$, so that the expected MRPC is increasing in uncertainty. As expected, this generates a positive long run effect of the level of uncertainty on the level of the capital stock. Nevertheless we can still detect the negative effect of uncertainty on the short run response of investment to demand shocks, and the convex shape of these short run responses. In column (4) we set the drift $2\mu(\sigma_t) = 0.04 - \frac{\sigma_t^2}{2}$, so that the expected MRPC is decreasing in uncertainty. This generates a negative long run effect of uncertainty on the level of the capital stock, but has little impact on either the interaction term between demand growth and uncertainty or on our higher order demand growth term. This suggests, first, that our econometric tests of the properties of short run

[14] In a competitive model with shocks to output prices and a flexible factor (such as labour) the marginal revenue product of capital (MRPC) is convex in demand conditions, so uncertainty has a positive impact on the expected MRPC. For example, with a revenue function $R = ZK^aL^b$ (where Z is a demand process, K is capital and L is labour), after optimizing out labour net revenue equals $CZ^{\frac{1}{1-b}}K^{\frac{a}{1-b}}$ (where C is a constant) and the MRPC equals $\frac{aC}{1-b}Z^{\frac{1}{1-b}}K^{\frac{a+b-1}{1-b}}$. If Z is a geometric Brownian process with drift μ and variance σ then $E[dZ^{\frac{1}{1-b}}/Z^{\frac{1}{1-b}}] = (\mu + \frac{b}{1-b}\frac{\sigma^2}{2})\frac{dt}{1-b}$, so the expected growth of MRPC equals $(\mu + \frac{b}{1-b}\frac{\sigma^2}{2})\frac{1}{1-b}$, which is increasing in uncertainty. However, as Caballero (1991) notes, the sign of this effect is sensitive to assumptions such as the degree of imperfect competition, and whether the underlying shocks are to prices or quantities. Under alternative assumptions the marginal revenue product of capital can become concave in demand conditions, with a negative impact of uncertainty. To *qualitatively* simulate these positive and negative Hartman-Abel effects in our linear homogeneous specification, we adjust our demand drift term by $\pm\frac{\sigma^2}{2}$, noting that the *quantitative* effects would also depend on the exact convexity/concavity of the underlying MRPC in demand conditions.

investment dynamics appear to be robust (at least to these modifications), and secondly, that the longer run effects of uncertainty are theoretically ambiguous and need to be determined empirically. This echoes the discussions both in Leahy and Whited (1996), who outline a range of potentially positive and negative effects of uncertainty, and in Abel and Eberly (1999), who note the ambiguous long run effects of uncertainty on capital stock levels in a partial irreversibility framework.

3.2. Simulation robustness tests

To assess the generality of our predictions on the uncertainty-demand growth interaction term and on the demand growth squared term, we now investigate whether these effects are found for an alternative revenue function, and for alternative types of adjustment costs.

[Table 4 about here]

3.2.1. A CES specification

The simulation model and assumptions require only a supermodular homogeneous unit revenue function, so we can replace the Cobb-Douglas revenue function (2.1) with a function of a CES aggregator over the two types of capital

$$R(X, K_1, K_2) = X^{\alpha}(K_1^{\beta} + K_2^{\beta})^{\frac{\gamma}{\beta}} \tag{3.5}$$

The associated linear homogeneous revenue function is then defined by $\widetilde{R}(P, K_1, K_2) = P^{1-\gamma}(K_1^{\beta} + K_2^{\beta})^{\frac{\gamma}{\beta}}$, where $P = X^{\frac{\alpha}{1-\gamma}}$. We set $\beta = 0.5$ and $\gamma = 0.8$.

Column (1) of Table 4 presents OLS results for simulated firm-level data with this alternative CES specification, using the true demand and uncertainty variables. We again find that the short run response of investment to demand shocks is convex, and that higher uncertainty reduces this impact effect of demand shocks on investment. First-differenced GMM estimates, using sales as a measure of demand and stock-return volatility as a measure of uncertainty, also yielded a significant positive coefficient on the sales growth squared term and a significant negative coefficient on the uncertainty interaction term.[15] This suggests that our empirical tests can detect

[15] Coefficients (standard deviations) of 0.627 (0.132) on the sales growth term and -1.452 (0.467) on the uncertainty interaction term.

these effects on short run investment dynamics with this alternative specification of the revenue function.

3.2.2. General adjustment costs

A number of previous papers, including Abel and Eberly (1994), Cooper and Haltiwanger (2006) and Bloom (2006) have noted that different forms of adjustment costs can have significantly different implications for investment behaviour. Our core predictions are based on a model with partial irreversibilities, but in this section we investigate whether they are also found using two additional types of adjustment costs: fixed disruption costs and quadratic adjustment costs.

Fixed disruption costs

When new capital is added into the production process some downtime may result in a fixed loss of output however large the investment. For example, the factory may need to close for a fixed period while a refit is occurring. For the simulation we assume the fixed cost of adjustment for either type of capital is 5% of annual sales, which is approximately calibrated on a monthly basis from the annual estimates in Cooper and Haltiwanger (2006).

Quadratic adjustment costs

The costs of investment may also be related to the rate of adjustment with higher costs for more rapid changes, which we specify as $C_{quad,j} = \lambda_m K_m (\frac{I_m}{K_m})^2$ for $j = 1, 2$. For the simulation we assume that $\lambda_j = 0.3$ for both types of capital, again calibrated roughly on a monthly basis from Cooper and Haltiwanger's (2006) annual estimates.[16]

Since both of these adjustment costs are jointly homogeneous of degree one in (P, K_1, K_2) the cost function $C(P, K_1, K_2, I_1, I_2)$ is also homogeneous, permitting the same normalization by capital type 1 and the resulting accelerated numerical solution as outlined in section 2.2.

Column (2) of Table 4 presents OLS results for simulated firm-level data with

[16] For simplicity we have assumed that both the fixed and the quadratic adjustment costs are identical for the two types of capital, with no cross effects. In experiments allowing for different levels of these adjustment costs for the two types of capital, we found qualitatively similar results. Our approach could allow for more general specifications of these adjustment costs, with cross effects, but we leave this for future research.

fixed adjustment costs only, again using the true demand and uncertainty variables. Interestingly, in this case we find that higher uncertainty has the opposite effect on the impact effect of demand shocks on investment. This suggests that the 'cautionary effect' of uncertainty on short run investment dynamics is sensitive to the form of adjustment costs, even within the class of non-convex adjustment costs. The reason for this positive effect is that, under fixed costs, investment is undertaken as a jump process with the level of investment determined so as to return $\frac{P}{K_1}$ and $\frac{P}{K_2}$ to target levels between their thresholds, rather than to hold them continuously at their investment thresholds as under partial irreversibility. When uncertainty rises and the thresholds move further apart, this target level moves by less, so that the gap between the target and the investment threshold grows and the amount of investment required to reach the target also grows. This positive impact of uncertainty on the level of investment undertaken at each investing unit offsets the negative effect of uncertainty on the number of investing units, leading to a positive effect of uncertainty on the response of investment to demand shocks in our simulation with fixed costs only. Since the magnitude of these opposing effects is likely to be sensitive to the exact parameterization of the model, the sign of this short run effect is probably ambiguous under (pure) fixed costs. We also find no significant non-linearity in the response of investment to demand shocks in this experiment.

Column (3) of Table 4 reports the OLS results for a simulation with quadratic adjustment costs only. In this case we find a smaller response of investment to demand shocks at higher levels of uncertainty, but again no significant indication of non-linearity in the short run responses. Again these results suggest that these properties of short run investment dynamics are sensitive to the type of adjustment costs. In this experiment we also find a strong long run effect of uncertainty in reducing the level of the capital stock,[17] although we note that this effect could be offset by a positive Hartman-Abel type effect of the kind considered in Table 3.

Finally in columns (4) and (5) we report the results for a simulation that combines all three types of adjustment costs, with the same parameter values used

[17] With fixed costs or partial irreversibilities, the value function is linear outside the central region of inaction, with slope equal to the purchase/resale price of capital, so that the value function is concave only in the region of inaction. With quadratic adjustment costs, the value function is globally curved, thereby generating greater global concavity.

previously. For both the OLS results using the 'true' explanatory variables in column (4), and for the first-differenced GMM results using the observable proxies in column (5), we find evidence that higher uncertainty makes the response of investment to demand shocks more cautious, and that this response is convex, with a proportionately larger response to larger shocks. At least for this combination of adjustment cost parameters, based on the evidence presented in Cooper and Haltiwanger (2006), we find that the properties of the short run investment dynamics seem to be dominated by the effects of partial irreversibility that we highlighted in section 2.

In other robustness tests we also experimented with, first, changing the discount rate from 10% to 5%, and second, relaxing the restriction in our econometric specification that the long run coefficient on log sales is unity, as in equation (3.2). The signs and statistical significance of the coefficients on the additional uncertainty interaction and squared demand growth terms in our augmented error correction models were robust in both cases, both in the OLS and first-differenced GMM results.[18]

4. Empirical results for company data

We use firm-level data for an unbalanced panel of 672 publicly traded UK manufacturing firms between 1972 and 1991. We use pre-1991 UK data because the accounting regulations required firms to report investment expenditure consistently throughout this period, together with the net book value of capital from acquisition of subsidiaries, and revenue from sales of fixed assets. We use data on publicly traded companies because this allows us to construct measures of uncertainty from high frequency stock market returns data.

[18] For the simulated data with a 5% discount rate, a consistent finding was that the effect of uncertainty on the short run response of investment to demand shocks was larger than we found with a 10% discount rate. This is consistent with the higher value of real options at a lower discount rate. These results are available on request from the authors.

4.1. Uncertainty measures

Although our formal model focuses on uncertainty about demand and productivity conditions, our measure of uncertainty is much broader in scope. In reality firms will be uncertain about a wide range of factors, including taxes, regulations, interest rates, wages, exchange rates and technological change. In an attempt to capture all relevant factors in one scalar measure, we follow the approach suggested by Leahy and Whited (1996) and use the standard deviation of daily stock returns for firm i in accounting year t, denoted SD_{it}. This provides a forward-looking indicator which is implicitly weighted in accordance with the impact of different sources of uncertainty on the firm's value.

A stock returns-based measure of uncertainty is also attractive because the data is reported at a sufficiently high frequency to use on an annual basis. For homoskedastic diffusion processes, the variance of the sample variance is inversely related to the sampling frequency (see Merton (1980)). Our sampling frequency of about 265 observations per year should yield low sample variance, so that movements in the measured variance should reflect changes in the underlying process rather than extreme draws.

One possible concern about this measure of uncertainty is that the variability in stock market returns may partly reflect noise unrelated to fundamentals (for example, share price bubbles). We address this by considering a second measure which normalizes the firm's daily share return by the return on the FTSE All-Share index, to eliminate the effect of any aggregate stock market bubbles. We also consider using the within-year standard deviation of the firm's monthly stock returns. Although estimates based on 12 monthly observations are subject to more sampling variation, this will reduce the impact of high frequency noise that may be present in daily observations.

A different concern is whether the volatility in stock returns would reflect the variance of demand or productivity shocks in our underlying theoretical framework. We have addressed this using our simulated data in the previous section where we find that econometric specifications using this observable proxy can detect the impact of underlying uncertainty on investment dynamics.

We have also compared our stock returns measure to other possible proxies for uncertainty. Using I/B/E/S data for UK firms, Bond et al. (2005) report that stock returns volatility is positively correlated with both the within-year variability of analysts' earnings forecasts, and with the cross-section dispersion across forecasts made by different analysts for the same firm.

Finally we note that our empirical finding on the relationship between uncertainty and the impact effect of demand growth is qualitatively similar to that obtained by Guiso and Parigi (1999), who used cross-sectional survey data on managers' subjective distributions of future demand growth to estimate the variance of firm-level demand shocks for a sample of Italian firms. This suggests that this property of short run investment dynamics can be detected using different empirical measures of uncertainty.

4.2. Investment and other accounting data

We obtained company accounts data, as well as data on stock returns, from Datastream. Investment in fixed capital assets is measured net of revenue from asset sales. Our capital stock measure is benchmarked using the book value of the firm's stock of net fixed assets, and subsequently updated using the investment data in a standard perpetual inventory formula. Real sales are obtained from data on nominal sales using the aggregate GDP deflator. Cash flow is measured as reported post-tax earnings plus depreciation deductions. Further details are provided in the Data Appendix.

4.3. Estimation results

Our main econometric results are estimated using the system GMM procedure developed by Arellano and Bover (1995) and Blundell and Bond (1998). This combines a system of equations in first-differences using suitably lagged levels of endogenous variables as instruments, as in the basic first-differenced GMM estimator (see Arellano and Bond (1991)), with equations in levels for which lagged differences of endogenous variables are used as instruments. Unobserved firm-specific effects are eliminated from the first-differenced equations by the transformation. The key requirement is that the additional instruments used in the levels equations should be uncorrelated with the unobserved firm-specific effects in the investment equation, which is tested using the Sargan-Hansen test of overidentifying restrictions. The advantage is that, if these additional instruments are valid, the system GMM estimator should have greater efficiency and smaller finite sample bias than the corresponding first-differenced GMM estimator. The reported results treat both sales and stock-returns volatility as endogenous variables, with the precise instruments used noted in the Tables. Similar results were found using a range of alternative instrument sets, and our main findings concerning the short run effects of sales growth and uncertainty on company investment were also found using the first-differenced GMM estimator.

Our main specification is based on equation (3.4), with current and lagged cash flow variables ($C_{it}/K_{i,t-1}$) as additional controls. Such terms are often found to be informative in microeconometric investment equations, and may reflect either financing constraints (see Fazzari, Hubbard and Petersen (1988)), expectations of future demand growth or profitability (see Bond et al. (2004)), or more generally measurement errors or mis-specifications (see, for example, Erickson and Whited (2000) and Cooper and Ejarque (2003)). In our case these cash flow terms are statistically significant, and are required to obtain empirical specifications that are not rejected by the test of overidentifying restrictions. However, as reported below, our main results on investment dynamics are robust to their exclusion.

[**Table 5 about here**]

Column (1) of Table 5 reports results for a basic linear error correction specification with these additional cash flow terms. We find that the key coefficient on the error correction term is correctly signed and statistically significant, suggesting that in the long run companies adjust their capital stocks towards a target that is proportional to real sales. We also find an impact effect of real sales growth that is positive and statistically significant, although considerably smaller than the long run elasticity of unity, and significant effects from the additional cash flow terms. There is marginally significant evidence of second-order serial correlation in the first-differenced residuals in this basic specification, although the Sargan-Hansen test does not reject the validity of the overidentifying restrictions. A simple goodness of fit statistic also suggests that this model has reasonable explanatory power for firm-level data of this kind.[19]

Column (2) of Table 5 adds a squared term in current real sales growth to this basic specification. In line with our results for the simulated data under partial irreversibility in section 3, we find significant positive coefficients on both the level and the square of real sales growth. Column (3) adds a range of uncertainty terms to this extended error correction specification. The main result of interest here is the significant negative coefficient on the interaction term. The linear uncertainty terms (the change in uncertainty and the lagged level of uncertainty), in contrast, are found to be only weakly significant, with a joint test of their exclusion from the specification in column (3) not rejected (p-value = 0.17). We include these terms here partly to ensure that the significant coefficient on the interaction term is not the result of omitting relevant linear uncertainty terms, and partly to investigate whether there is significant evidence of a long run effect of uncertainty on capital accumulation. The insignificance of the lagged level of uncertainty in column (3) formally rejects the presence of such a long run effect, although the imprecision with which we estimate this coefficient suggests that this test may not be very powerful.[20] Omitting this term in column (4) results in an insignificant coefficient on the short run change in uncertainty term, which we also omit from our preferred parsimonious specification in column (5). Thus the only effect of uncertainty on company investment behaviour that we can detect with a high degree of statistical confidence is the interaction with the impact effect of current real sales growth.

Table 6 investigates this interaction effect further. Here we decompose our stock returns measure of uncertainty (SD_{it}) into three components - a macroeconomic component, common to all firms in a particular year ($\overline{SD}_t$); a time-invariant firm-specific component ($\overline{SD}_i$); and an idiosyncratic time-varying component ($\widetilde{SD}_{it}$ =

[19] We report the squared correlation coefficient between actual and predicted levels of the investment rate. This squared correlation measure is equivalent to the standard R^2 in an OLS regression, and is recommended as a goodness of fit measure for instrumental variable regressions by, for example, Windmeijer (1995).

[20] That is, our results do not rule out the possibility of an economically significant negative long run effect of uncertainty on capital accumulation, although we cannot confirm the presence of such an effect with any confidence.

$SD_{it} - \overline{SD}_t - \overline{SD}_i$). Columns (1) to (3) include interactions between real sales growth and each of these uncertainty variables individually, while column (4) includes all three interaction terms jointly.

[Tables 6 and 7 about here]

The interaction between firm-level real sales growth and a purely macroeconomic measure of uncertainty, included in column (1) of Table 6, is the least informative of our three variables.[21] The interaction with a time invariant firm-specific measure of uncertainty, reported in column (2), is only weakly significant, while columns (3) and (4) show that it is the interaction between sales growth and the idiosyncratic time-varying component ($\widetilde{SD}_{it}$) of our uncertainty measure that is most informative. However, because the coefficients on the remaining interaction terms in column (4) are estimated imprecisely, we can easily accept the restriction of common coefficients on these three interactions, as imposed in our preferred empirical specification.

4.4. Robustness tests

We conducted a number of robustness tests, some of which are reported in Table 7. In column (1) we omit the cash flow variables, which causes the test of overidentifying restrictions to reject, but does not affect the sign or the significance of the coefficients on the interaction term between uncertainty and sales growth and on the squared sales growth term. In column (2) we add a further interaction with firm size, defining a 'big firm' dummy variable B_{it} which takes the value one for observations with real sales above the sample median, and zero otherwise. Our result indicates that the effect of uncertainty on the impact effect of sales growth on investment is not significantly different between the smaller and larger firms within our sample. The point estimate suggests that this effect may be smaller for the relatively large firms. One possible explanation is that our stock-returns measure may be a noisier proxy for the underlying uncertainty in the case of larger firms, due to the effect of conglomeration.

[21] The limited information that we find in macroeconomic as opposed to microeconomic variation in our uncertainty measure may help to explain why time-series studies of aggregate investment data have often not found significant effects of uncertainty variables.

In column (3) of Table 7 we use an alternative measure of uncertainty constructed after normalising each firm's stock returns by the return on the FTSE All-Share index for the same day. This measure gives a slightly larger and more precisely estimated coefficient on the interaction term than our basic results, possibly because some of the general stock market noise has been removed from this measure of uncertainty. In column (4) we use the within-year standard deviation of monthly stock returns (not normalised), rather than daily stock returns, to generate the uncertainty measure. Our results here are qualitatively similar, but in this case the coefficient on the interaction term is slightly smaller and less significant. This may be partly due to the greater sampling variance that results from the lower monthly sampling frequency,[22] suggesting that higher frequency stock returns data is valuable for obtaining a more powerful test.

In column (5) of Table 7 we implement an adjustment for financial leverage, following Leahy and Whited (1996), to eliminate the effect of gearing on the variability of stock returns.[23] Again we find that our key results on the properties of short run investment dynamics are robust. In this case we find that the coefficient on the interaction with sales growth is larger and more significant, possibly because controlling for leverage reduces some of the measurement error in our proxy for uncertainty.

We also considered specifications with the lagged level of log sales as an additional explanatory variable; together with the included error correction term, this relaxes the restriction that the long run elasticity of capital with respect to sales is unity. This additional term was insignificant in all cases, and our results on short run investment dynamics were completely robust to its inclusion. We also experimented with a range of additional non-linear and interaction terms, none of which were found to be statistically significant in our sample. For example, we included interactions

[22] Switching from daily to monthly returns data is expected to increase the sampling variance of SD_{it} five-fold. The monthly (weekly) measure of uncertainty has a correlation coefficient with the daily measure of 0.784 (0.900). Using the weekly uncertainty measure, the coefficient (standard error) on the uncertainty-sales growth interaction term was estimated to be -0.146 (0.082), about mid-way between the estimates using the daily and monthly measures.

[23] This is done by mutliplying SD_{it} by the ratio of equity to (equity+debt), with equity measured using the market value of shares (ordinary and preference) and debt measured using the book value of all long-term debt.

of our measure of uncertainty with squared sales growth, cash flow and the error correction term. The joint Wald test for the exclusion of these three terms gave a $\chi^2(3)$ statistic of 4.42, with a p-value of 0.219. Finally, we also investigated whether the coefficient on our interaction term was larger or more significant for firms in industries where market power is likely to be greater (as proxied by concentration ratios, trade barriers, etc.). An implication of real options theory is that this effect of uncertainty should be stronger for firms with more market power. We found no evidence that this was the case, although it could be that our industry-level proxies are inadequate measures of the firm's market power.

5. Quantifying the impact of uncertainty

The results presented in the preceding section detect a statistically significant effect of higher uncertainty in dampening the response of company investment to demand shocks. To evaluate the size of this effect we conducted a simple simulation using the model in column (5) of Table 5, in which we track the predicted response of investment and the capital stock to an unanticipated, permanent 2.5% increase in real sales.[24] Figure 2 plots the predicted response of investment rates for observations at different levels of uncertainty, highlighting the large 'cautionary' effect of higher uncertainty on the short-run investment response. Here we find that moving from the third quartile to the first quartile in the distribution of our measure of uncertainty doubles the impact, while moving from the 90th percentile to the 10th percentile increases it by four-fold. This substantial impact of uncertainty is similar to the findings from our calibrated simulation model reported in section 2.3, suggesting that an effect of this size is consistent with a real options explanation.

This indicates that increases in uncertainty around major shocks, like 9/11 and the OPEC oil shocks, could seriously reduce the responsiveness of investment to monetary or fiscal policy.[25] Over the longer term these short run effects are slowly cancelled out due to the cointegration between capital and sales, as illustrated in

[24] See Bloom, Bond and Van Reenen (2003) for more details of these and further simulations. The exact size of the sales shock makes relatively little difference to the results.

[25] For comparison, the increase in average uncertainty for our sample firms after the first OPEC oil crisis is similar in magnitude to the increase from the first quartile to the third quartile of our sample distribution.

Figure 3, but our estimates suggest that the 'short run' effects persist for a significant period. Even after ten years there is still a noticeable difference between the predicted increases in capital stocks, in response to the same demand shock, at different levels of uncertainty.

6. Conclusions

This paper develops two implications of partial irreversibility for the short run dynamics of investment. First, investment will respond more cautiously to a given demand shock at higher levels of uncertainty (due to wider thresholds for the zone of inaction), and second investment will have a convex response to positive demand shocks (due to aggregation and supermodularity). We confirm these implications using numerical methods to solve a model with two types of capital, a rich mix of adjustment costs (partial irreversibility, quadratic and fixed), time-varying uncertainty, alternative functional forms for the revenue function and aggregation over time and over production units. We propose and evaluate an econometric specification that is designed to test for these properties of short run investment dynamics using firm-level data. We report evidence that both effects are found using a measure of uncertainty based on stock-returns volatility for a large panel of manufacturing firms. Through both numerical and econometric simulations we show that these effects are economically important - the investment response to a demand shock is doubled by moving from the third quartile to the first quartile in the distribution of our measure of uncertainty, and quadrupled by moving from the 90th to the 10th percentile.

This indicates that the one standard deviation increase in measures of uncertainty observed around major shocks, like 9/11 and the OPEC oil shocks, could seriously reduce the responsiveness of investment to subsequent monetary or fiscal policy. While we do not model the behaviour of labour demand, the existence of similar labour hiring and firing costs would imply that higher uncertainty would also make firms more cautious in their employment responses. This is important as policy-makers typically want to respond to major shocks, but the behavioural responses to any given policy stimulus may be much lower than normal in these periods of high uncertainty.

The empirical results indicate that the short run investment dynamics for large manufacturing firms are consistent with the predictions of a partial irreversibility model in which higher uncertainty reduces the impact effect of demand shocks on investment. Of course, there may be other explanations that could account for the same patterns in company investment dynamics. One possibility is that firms subject to greater uncertainty may place less weight on recent information in updating their expectations of future growth prospects. Discriminating between these and other explanations for our empirical findings presents an interesting challenge for future research.

In future work we plan to build on this research in at least three further directions. First, by looking at the implications of uncertainty for adjusting other factors of production, such as labour, R&D and information communication technologies. Second, by moving beyond our calibration of the micro-model to undertake a full simulated method of moments estimation of the adjustment cost parameters under time-varying uncertainty, multiple factors of production and extensive aggregation. Finally, by using this approach to investigate the impacts of uncertainty on both the level and the distribution of micro and macro activity.

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Data Appendix

The company data is taken from the consolidated accounts of manufacturing firms listed on the UK stock market. We deleted firms with less than three consecutive observations, broke the series for firms where accounting periods fell outside the range 300 to 400 days (due to changes in year ends), and excluded observations for firms where there are jumps of greater than 150% in any of the basic variables. This data is obtained from the Datastream on-line service.

Investment (I). Total new fixed assets (DS435) less sales of fixed assets (DS423).

Capital Stock (K): Constructed by applying a perpetual inventory procedure with a depreciation rate of 8%. The starting value was based on the net book value of tangible fixed capital assets (DS339) in the first observation within our sample period, adjusted for previous inflation. Subsequent values were obtained using accounts data on investment and asset sales, and an aggregate series for investment goods prices.

Sales (Y): Total sales (DS104), deflated by the aggregate GDP deflator.

Cash Flow (C): Net profits (earned for ordinary, DS182) plus depreciation (DS136).

Uncertainty (σ). The computation of this variable is described in the text. For each company we take the daily stock market return (Datastream Returns Index, RI). This measure includes on a daily returns basis the capital gain on the stock, dividend payments, the value of rights issues, special dividends, and stock dilutions. We then compute the standard deviation of these daily returns on a year by year basis, matched precisely to the accounting period. We trim the variable so that values above five are set equal to five. The results are robust to dropping these ten observations.

TABLE 1: Episodes of Zero Investment in Different Types of Data

	% of observations with zero investment			
	Buildings	Equipment	Vehicles	Total
Firms	5.9	0.1	n.a.	0.1
Establishments	46.8	3.2	21.2	1.8
Single Plants	53.0	4.3	23.6	2.4
Small Single Plants	57.6	5.6	24.4	3.2

Note : Firm-level data (6,019 annual observations) from Extel and Datastream. Establishment-level data (46,089 annual observations) from UK Census of Production (see Reduto dos Reis, 1999).

TABLE 2: Sample Correlations in the Simulated Data

	$I_{it}/K_{i,t-1}$	Δy_{it}	Δp_{it}	SD_{it}	σ_{it}
investment rate $I_{it}/K_{i,t-1}$	1.000	0.823	0.618	0.081	-0.067
sales growth Δy_{it}		1.000	0.395	0.018	-0.224
demand growth Δp_{it}			1.000	-0.018	-0.006
standard deviation of returns SD_{it}				1.000	0.645
uncertainty σ_{it}					1.000

Note : These are Pearson correlation coefficients of the relevant variables (e.g. the correlation of Δy_{it} and Δp_{it} is 0.395) taken over the simulated data for 1,000 firms and 15 years

TABLE 3: Econometric Estimation on the Simulated Data

Dependent Variable: $I_{it}/K_{i,t-1}$	**(1)**	**(2)**	**(3)**	**(4)**
Estimation Method	OLS	GMM	OLS	OLS
Type of data for P and σ	True	Empirical	True	True
Hartman-Abel effects	No	No	Positive	Negative
Demand Growth, Δp_{it}	0.395	0.539	0.387	0.416
	(0.041)	(0.083)	(0.040)	(0.040)
Demand Growth Squared, Δp_{it}^2	0.028	0.864	0.028	0.028
	(0.005)	(0.212)	(0.004)	(0.005)
Change in Uncertainty, $\Delta\sigma_{it}$	-0.095	-0.042	-0.020	-0.755
	(0.046)	(0.019)	(0.160)	(0.161)
Uncertainty, σ_{it}	0.005	-0.080	0.373	-0.402
	(0.021)	(0.097)	(0.080)	(0.066)
Uncertainty $\times$ Demand Growth, $\sigma_{it} * \Delta p_{it}$	-0.441	-0.440	-1.500	-1.733
	(0.108)	(0.166)	(0.368)	(0.373)
Demand ECM, $(p-k)_{i,t-1}$	0.190	0.439	0.189	0.187
	(0.008)	(0.105)	(0.008)	(0.008)
2nd order serial correlation (p-value)		0.185		
Sargan-Hansen test (p-value)		0.856		

Note : Standard errors are robust to arbitrary autocorrelation and heteroskedasticity. GMM coefficients are one-step estimates. Columns (1), (3) and (4) estimate using the underlying 'true' demand and variance data, while column (2) estimates using the 'empirical' proxies: sales (instead of demand) and the standard deviation of stock returns (instead of demand variance). The instruments used in column (2) are lags 2 and 3 of the variables $\frac{I_{it}}{K_{i,t-1}}$, Δy_{it}, ΔSD_{it}, and $(y-k)_{it}$. Instrument validity is tested using a Sargan-Hansen test of the overidentifying restrictions. Serial correlation is tested using an LM test on the first-differenced residuals (Arellano and Bond, 1991). To maintain a constant sample across specifications we use years 4 to 15 in all columns, providing 12,000 observations on a balanced panel of 1,000 firms. Implementation of Hartman-Abel effects is described in the text.

TABLE 4: Robustness Tests on the Simulated Data

Dependent Variable: $(I_{it}/K_{i,t-1})$	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Estimation Method	OLS	OLS	OLS	OLS	GMM
Type of data for P and σ	True	True	True	True	Empirical
Adjustment Costs	Partial	Fixed	Quad	All	All
Revenue Function	CES	Cobb-Douglas	Cobb-Douglas	Cobb-Douglas	Cobb-Douglas
Demand Growth, Δp_{it}	0.400	0.586	0.486	0.378	0.630
	(0.041)	(0.093)	(0.051)	(0.039)	(0.065)
Demand Growth Squared, Δp_{it}^2	0.029	-0.012	-0.004	0.011	0.403
	(0.004)	(0.031)	(0.015)	(0.004)	(0.114)
Change in Uncertainty, $\Delta\sigma_{it}$	-0.389	-1.031	-0.048	-0.666	-0.064
	(0.158)	(0.283)	(0.220)	(0.141)	(0.042)
Uncertainty, σ_{it}	-0.006	-0.505	-1.216	0.033	0.101
	(0.071)	(0.131)	(0.090)	(0.066)	(0.294)
Uncertainty $\times$ Demand Growth,	-1.566	1.766	-0.844	-1.791	-0.701
$\sigma_{it} * \Delta p_{it}$	(0.373)	(0.854)	(0.427)	(0.346)	(0.294)
Demand ECM Term, $(p-k)_{i,t-1}$	0.186	0.205	0.323	0.180	0.204
	(0.008)	(0.024)	(0.020)	(0.006)	(0.098)
2nd order serial correlation (p-value)					0.267
Sargan-Hansen test (p-value)					0.875

Note Standard errors are robust to arbitrary autocorrelation and heteroskedasticity. GMM coefficients are one-step estimates. Columns (1) to (4) estimate using the underlying 'true' demand and variance data, while column (5) estimates using the 'empirical' proxies: sales (instead of demand) and the standard deviation of stock returns (instead of demand variance). The instruments used in column (5) are lags 2 and 3 of the variables $\frac{I_{it}}{K_{i,t-1}}$, Δy_{it}, ΔSD_{it}, and $(y-k)_{it}$. Instrument validity is tested using a Sargan-Hansen test of the overidentifying restrictions. Serial correlation is tested using an LM test on the first-differenced residuals (Arellano and Bond, 1991). To maintain a constant sample across specifications we use years 4 to 15 in all columns, providing 12,000 observations on a balanced panel of 1,000 firms.

TABLE 5: Econometric Estimates using UK Company Data

Dependent Variable: $(I_{it}/K_{i,t-1})$	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Sales Growth (Δy_{it})	0.259	0.151	0.382	0.400	0.413
	(0.072)	(0.059)	(0.136)	(0.139)	(0.139)
Change in Cash Flow $(\Delta(C_{it}/K_{i,t-1}))$	0.206	0.263	0.260	0.255	0.272
	(0.135)	(0.132)	(0.124)	(0.126)	(0.125)
Lagged Cash Flow $(C_{i,t-1}/K_{i,t-2})$	0.303	0.269	0.272	0.288	0.273
	(0.086)	(0.082)	(0.083)	(0.081)	(0.076)
Error Correction Term $(y-k)_{i,t-1}$	0.062	0.056	0.054	0.054	0.053
	(0.030)	(0.029)	(0.026)	(0.026)	(0.026)
Sales Growth Squared $(\Delta y_{it})^2$		0.481	0.512	0.494	0.500
		(0.175)	(0.152)	(0.150)	(0.151)
Change in Uncertainty (ΔSD_{it})			-0.023	-0.012	
			(0.012)	(0.008)	
Lagged Uncertainty $(SD_{i,t-1})$			-0.015		
			(0.011)		
Uncertainty $\times$ Sales Growth			-0.162	-0.165	-0.167
$(SD_{it} * \Delta y_{it})$			(0.067)	(0.068)	(0.068)
Goodness of Fit - Corr$(I/K, \widehat{I/K})^2$	0.259	0.287	0.285	0285	0.307
Serial correlation (p-value)	0.048	0.102	0.069	0.078	0.091
Sargan-Hansen (p-value)	0.510	0.709	0.699	0.629	0.560

Note One-step coefficients and standard errors robust to autocorrelation and heteroskedasticity are reported. The number of observations in all columns is 5,347, using an unbalanced panel of 672 firms over 1973 to 1991. A full set of year dummies is included in all specifications. Estimation uses a system GMM estimator (see Blundell and Bond, 1998) computed in DPD98 for Gauss. The instruments used in columns (3) to (5) are, in the first-differenced equations: $\left(\frac{I_{i,t-2}}{K_{i,t-3}}\right)$ and $\left(\frac{I_{i,t-3}}{K_{i,t-4}}\right)$, $\Delta y_{i,t-2}$ and $\Delta y_{i,t-3}$, $\left(\frac{C_{i,t-2}}{K_{i,t-3}}\right)$ and $\left(\frac{C_{i,t-3}}{K_{i,t-4}}\right)$, $(y-k)_{i,t-2}$ and $(y-k)_{i,t-3}$, and $SD_{i,t-2}$, $SD_{i,t-3}$ and $SD_{i,t-4}$; and in the levels equations: $\Delta\left(\frac{I_{i,t-1}}{K_{i,t-2}}\right)$, $\Delta\Delta y_{i,t-1}$, $\Delta\left(\frac{C_{i,t-1}}{K_{i,t-2}}\right)$, $\Delta\Delta(y-k)_{i,t-1}$ and $\Delta SD_{i,t-1}$. Columns (1) and (2) use this instrument set but with the uncertainty variables excluded. Instrument validity is tested using a Sargan-Hansen test of the overidentifying restrictions. Second-order serial correlation in the first-differenced residuals is tested using an LM test (Arellano and Bond, 1991). The goodness of fit measure is the squared correlation coefficient between actual and predicted levels of the dependent variable.

TABLE 6: Separating Time, Firm and Residual Variation in Uncertainty

Dependent Variable: $(I_{it}/K_{i,t-1})$	**(1)**	**(2)**	**(3)**	**(4)**
Sales Growth (Δy_{it})	0.127	0.141	0.474	0.499
	(0.052)	(0.053)	(0.182)	(0.184)
Change in Cash Flow $(\Delta C_{it}/K_{i,t-1})$	0.270	0.263	0.287	0.280
	(0.124)	(0.127)	(0.122)	(0.124)
Lagged Cash Flow $(C_{i,t-1}/K_{i,t-2})$	0.271	0.274	0.269	0.273
	(0.078)	(0.083)	(0.079)	(0.081)
Error Correction Term $(y-k)_{i,t-1}$	0.054	0.056	0.047	0.049
	(0.027)	(0.027)	(0.026)	(0.026)
Sales Growth Squared $(\Delta y_{it})^2$	0.497	0.507	0.534	0.537
	(0.170)	(0.157)	(0.148)	(0.162)
Time Uncertainty × Sales Growth	0.016			-0.051
$(\overline{SD}_t)*(\Delta y_{it})$	(0.150)			(0.135)
Firm Uncertainty × Sales Growth		-0.130		-0.136
$(\overline{SD}_i)*(\Delta y_{it})$		(0.105)		(0.107)
Residual Uncertainty × Sales Growth			-0.225	-0.230
$(\widetilde{SD}_{it})*(\Delta y_{it})$			(0.102)	(0.103)
Goodness of Fit - Corr$(I/K, \widehat{I/K})^2$	0.307	0.298	0.311	0.288
2nd order serial correlation (p-value)	0.096	0.094	0.132	0.106
Sargan-Hansen (p-value)	0.399	0.490	0.383	0.452

Note : One-step coefficients and standard errors robust to autocorrelation and heteroskedasticity are reported. The number of observations in all columns is 5,347, using an unbalanced panel of 672 firms over 1973 to 1991. A full set of year dummies is included in all specifications. Estimation uses a system GMM estimator (see Blundell and Bond, 1998) computed in DPD98 for Gauss. The instruments used in all columns are, in the first-differenced equations: $\left(\frac{I_{i,t-2}}{K_{i,t-3}}\right)$ and $\left(\frac{I_{i,t-3}}{K_{i,t-4}}\right)$, $\Delta y_{i,t-2}$ and $\Delta y_{i,t-3}$, $\left(\frac{C_{i,t-2}}{K_{i,t-3}}\right)$ and $\left(\frac{C_{i,t-3}}{K_{i,t-4}}\right)$, $(y-k)_{i,t-2}$ and $(y-k)_{i,t-3}$, and $SD_{i,t-2}$, $SD_{i,t-3}$ and $SD_{i,t-4}$; and in the levels equations: $\Delta\left(\frac{I_{i,t-1}}{K_{i,t-2}}\right)$, $\Delta\Delta y_{i,t-1}$, $\Delta\left(\frac{C_{i,t-1}}{K_{i,t-2}}\right)$, $\Delta\Delta(y-k)_{i,t-1}$ and $\Delta SD_{i,t-1}$. Instrument validity is tested using a Sargan-Hansen test of the overidentifying restrictions. Second-order serial correlation in the first-differenced residuals is tested using an LM test (Arellano and Bond, 1991). The goodness of fit measure is the squared correlation coefficient between actual and predicted levels of the dependent variable.

TABLE 7: Robustness Tests on UK Company Data

Dependent Variable: $(I_{it}/K_{i,t-1})$ Experiment	**(1)** No cash flow	**(2)** Size splits	**(3)** FTSE normed	**(4)** Monthly returns	**(5)** Leverage adjusted
Sales Growth (Δy_{it})	0.509	0.379	0.464	0.374	0.443
	(0.121)	(0.137)	(0.153)	(0.166)	(0.119)
Change in Cash Flow $(\Delta C_{it}/K_{i,t-1})$		0.283	0.282	0.279	0.306
		(0.123)	(0.124)	(0.126)	(0.119)
Lagged Cash Flow $(C_{i,t-1}/K_{i,t-2})$		0.272	0.272	0.268	0.257
		(0.076)	(0.075)	(0.077)	(0.073)
Error Correction Term $(y-k)_{i,t-1}$	0.163	0.052	0.052	0.050	0.060
	(0.025)	(0.026)	(0.026)	(0.026)	(0.028)
Sales Growth Squared $(\Delta y_{it})^2$	0.500	0.479	0.462	0.482	0.557
	(0.172)	(0.151)	(0.146)	(0.154)	(0.155)
Uncertainty × Sales Growth	-0.142	-0.185	-0.196	-0.122	-0.278
$(SD_{it} * \Delta y_{it})$	(0.065)	(0.069)	(0.075)	(0.069)	(0.087)
Big×Uncertainty×Sales Growth		0.082			
$(B_{it} * SD_{it} * \Delta y_{it})$		(0.060)			
Serial correlation (p-value)	0.049	0.056	0.080	0.083	0.064
Sargan-Hansen (p-value)	0.010	0.531	0.504	0.668	0.662

Notes: One-step coefficients and standard errors robust to autocorrelation and heteroskedasticity are reported. The number of observations in all columns is 5,347, using an unbalanced panel of 672 firms over 1973 to 1991. A full set of year dummies is included in all specifications. The dummy variable B_{it} indicates real sales above the sample median. The uncertainty measure in column (5) has been multiplied by the ratio equity/(equity+debt). Estimation uses a system GMM estimator (see Blundell and Bond, 1998) computed in DPD98 for Gauss. The instruments used in all columns are, in the first-differenced equations: $\left(\frac{I_{i,t-2}}{K_{i,t-3}}\right)$ and $\left(\frac{I_{i,t-3}}{K_{i,t-4}}\right)$, $\Delta y_{i,t-2}$ and $\Delta y_{i,t-3}$, $\left(\frac{C_{i,t-2}}{K_{i,t-3}}\right)$ and $\left(\frac{C_{i,t-3}}{K_{i,t-4}}\right)$, $(y-k)_{i,t-2}$ and $(y-k)_{i,t-3}$, and $SD_{i,t-2}$, $SD_{i,t-3}$ and $SD_{i,t-4}$; and in the levels equations: $\Delta\left(\frac{I_{i,t-1}}{K_{i,t-2}}\right)$, $\Delta\Delta y_{i,t-1}$, $\Delta\left(\frac{C_{i,t-1}}{K_{i,t-2}}\right)$, $\Delta\Delta(y-k)_{i,t-1}$ and $\Delta SD_{i,t-1}$. Instrument validity is tested using a Sargan-Hansen test of the overidentifying restrictions. Second-order serial correlation in the first-differenced residuals is tested using an LM test (Arellano and Bond, 1991). The goodness of fit measure is the squared correlation coefficient between actual and predicted levels of the dependent variable.

Figure 1: Average investment response to demand shocks at different levels of uncertainty, simulated data.

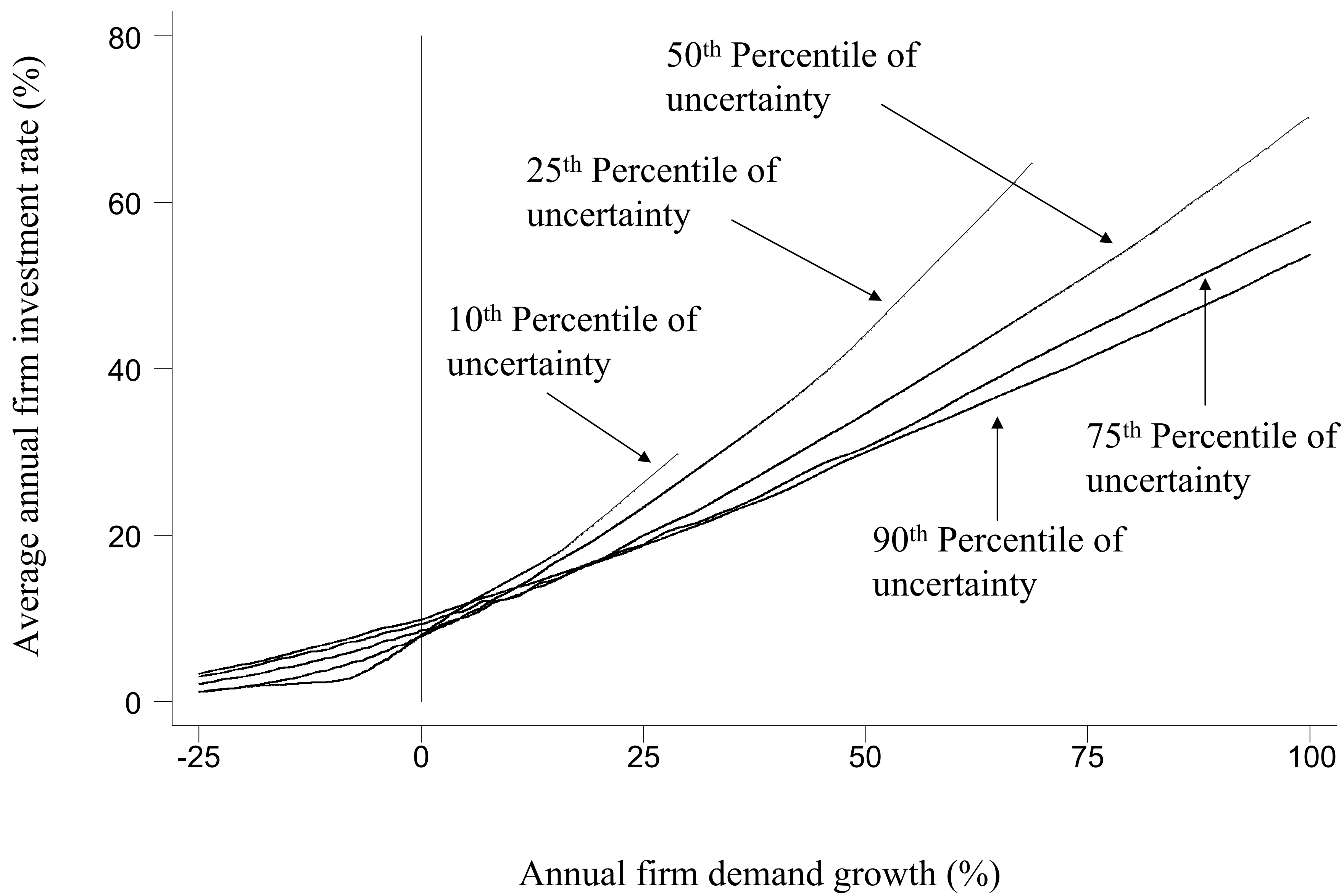

Figure 2: Investment response to a sales shock at different levels of uncertainty, UK firm-level data

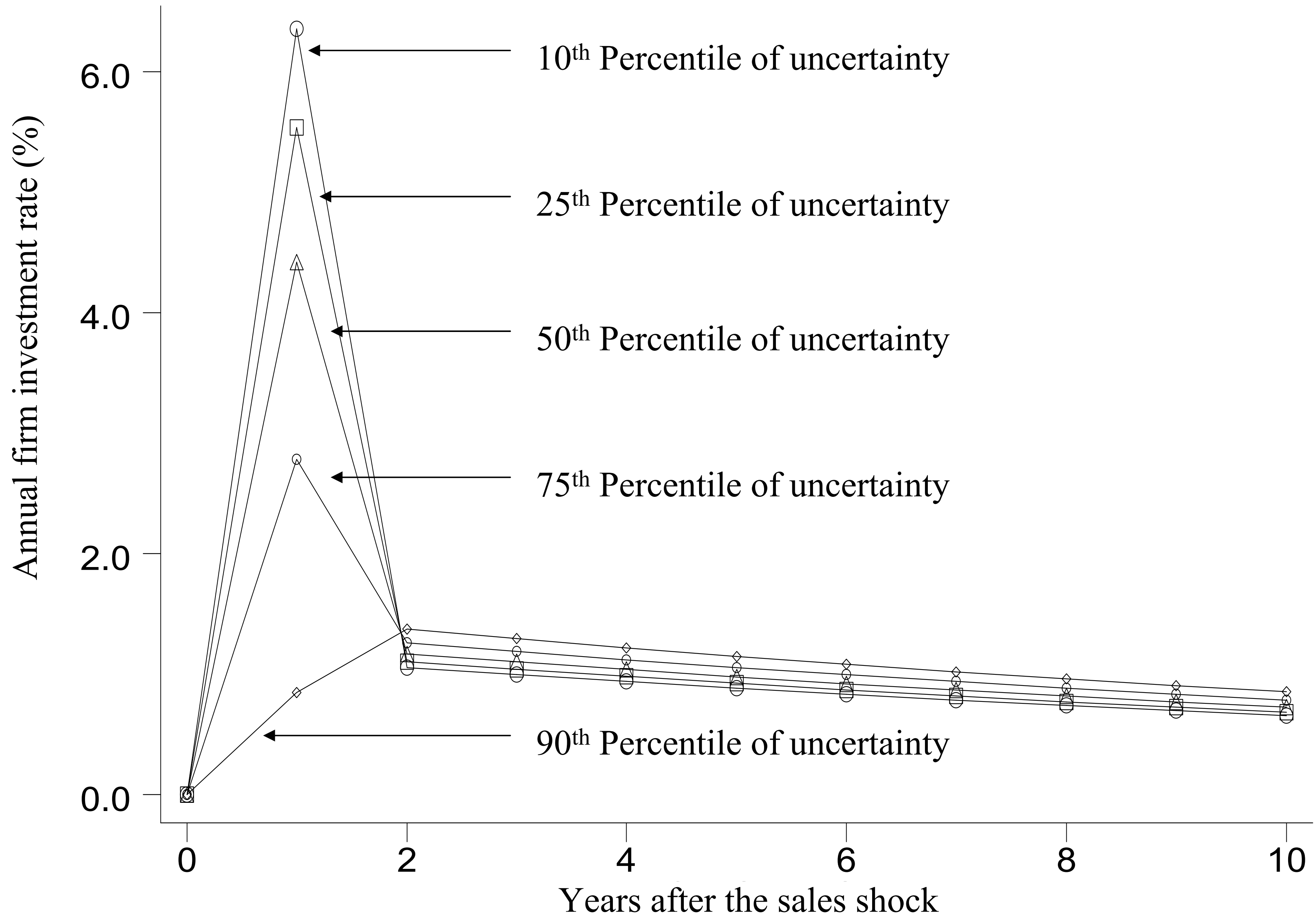

Figure 3: Capital stock response to a sales shock at different levels of uncertainty , UK firm-level data