Uncertainty and Company Investment Dynamics: empirical evidence for UK firms

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October 2002

Abstract

This paper investigates the empirical relationship between investment and uncertainty, using data for a large panel of quoted UK companies. We highlight the effects of uncertainty on short run investment dynamics, and particularly on the response of company investment to demand shocks. This focus is motivated by the recent literature on partial irreversibility and real options, which suggests a weaker response of investment to demand shocks at higher levels of uncertainty, as firms place a higher value on the option to wait and pursue a more cautious investment strategy. We use simulated data from a model of this type to demonstrate that this effect can be detected as a weaker impact effect of real sales growth on investment for firms facing a higher level of uncertainty. Using a measure of uncertainty based on the volatility of the firm's daily stock returns, as in Leahy and Whited (1996), we find a similar interaction term between real sales growth and measured uncertainty in our econometric analysis of investment behaviour by a panel of 672 UK manufacturing firms between 1972 and 1991. We demonstrate that the estimated effects of uncertainty on short run investment dynamics are quantitatively significant and, as in Caballero, Engel and Haltiwanger (1995) and Cooper, Haltiwanger and Power (1999), we find that these effects are most important around turning points of the business cycle.

Keywords: Investment, uncertainty, real options, panel data

JEL Classification: D92, E22, D8, C23.

Acknowledgments: The authors would like to thank Jerome Adda, Manuel Arellano, Orazio Attanasio, Richard Blundell, Jason Cummins, Janice Eberly,

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Domenico Lombardi, Costas Meghir, Steve Nickell, Ian Preston, Isabel Reduto dos Reis, Helen Weeds and Frank Windmeijer. This research is part of the program of research at the ESRC Centre for the Micro-Economic Analysis of Public Policy at the IFS. Financial support of the ESRC is gratefully acknowledged.

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1. Introduction

Recent theoretical analyses of investment under uncertainty have highlighted the effects of (partial) irreversibility or other forms of non-convex adjustment costs in generating 'real options' on the investment decision. In these models uncertainty increases the separation between the marginal product of capital that justifies a positive investment action and that which justifies a disinvestment action. 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 consequences that are too uncertain. In short, investment behaviour becomes more cautious. The option to delay is more valuable at higher levels of uncertainty, suggesting that the firm is less likely to undertake an investment action in response to a given positive demand shock. This effect is symmetric - for example, under partial irreversibility, the firm is also less likely to undertake a disinvestment action in response to a given negative demand shock. Consequently, as emphasised by Abel and Eberly (1999) and Caballero (1999), the relationship between the level of uncertainty and the average *level of capital* accumulated by firms in the long run is theoretically ambiguous in this class of models. This suggests focusing empirical investigation on the effects of uncertainty on short run *investment dynamics*, and in particular on the impact effect of demand shocks on current investment spending.

Firm-level data is attractive for exploring this empirical relationship, since measures of uncertainty can be constructed at the firm level based on share price volatility (cf. Leahy and Whited, 1996), and controls for other influences on investment behaviour such as the availability of internal finance can be measured in company accounts. However, firm-level data presents one difficulty for direct testing of real options models of investment under uncertainty, which is the extreme rarity of observations with zero investment in the annual consolidated accounts of publicly traded firms. 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 which studies a single investment decision and predicts a region of inaction in which the firm chooses neither to invest nor to disinvest. It is plausible, however, that this prevalence of non-zero observations in firm-level data is due to aggregation, both over time and over multiple investment decisions in different types of capital, different plants, and different subsidiaries.

Previous research has shown that such aggregation would not eliminate the implications of the lumpy nature of individual investment decisions for aggregate investment dynamics; see, for example, Bertola and Caballero (1994), Caballero, Engel and Haltiwanger (1995), Caballero and Engel (1999) and Cooper, Haltiwanger and Power (1999). This raises the question of whether the effects of uncertainty on short run investment dynamics predicted by the real options approach can be detected in an econometric study of firm-level investment spending. To investigate this, we develop a simulation model in which firm-level investment is obtained by explicitly aggregating over multiple investment decisions, each subject to partial irreversibility. We show that estimating a dynamic error correction model of investment spending on the simulated data does allow us to detect a significant effect of uncertainty on company investment dynamics. More specifically, for firms that are subject to a higher level of uncertainty, we find a weaker impact effect of demand shocks, measured by real sales growth, on current investment in the simulated data. This approach also predicts a convex response of current investment to larger demand shocks, as investment induced in one type of capital tends to increase the marginal productivity of other types of capital, making further adjustments more likely. This non-linear response of investment to demand shocks is also detected when we use the simulated data to estimate our error correction specification.

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 1972-91. Following Leahy and Whited (1996), we use a measure of volatility in these firms' daily stock returns as an indicator of the level of uncertainty relevant for each firm's investment decisions in each year. As in the simulated data, we find significant evidence of a non-linear and heterogeneous effect of real sales growth on current investment, with a weaker impact effect of real sales growth on investment for firms facing a higher level of uncertainty. Whilst there may be other explanations for this effect of uncertainty on company investment dynamics, we conclude that the investment behaviour of large UK firms is consistent with a model in which uncertainty slows down the process of capital stock adjustment for the reasons highlighted in recent theretical models where the option to wait is valuable. We find no significant effect of higher uncertainty on capital accumulation in the long run, which is also consistent with the real options literature as noted above. Nevertheless our empirical estimates suggest that fluctuations in the level of uncertainty can have quantitatively significant effects on the behaviour of company investment, particularly around turning points in the business cycle.

The remainder of the paper is organised as follows. Section 2 discusses a basic model of investment under uncertainty with a single capital good, and presents some evidence which suggests that aggregation over multiple investment decisions is likely to be important in confronting the predictions of this kind of model with firm-level data. Section 3 describes an approach with rationalises the smoother series we see in firm-level investment data by explicitly considering aggregation over investment decisions in multiple capital goods. Section 4 presents an econometric specification which can be used to test for the non-linear and heterogeneous impact effect of demand shocks on current investment that we expect to find in this class of models. Section 5 reports estimates of this econometric specification using simulated data generated by a model of this type, which confirm that this approach would allow us to detect these effects in a sample of the size for which we have real investment data for publicly traded UK companies. Section 6 describes this data in more detail, and discusses our empirical measures of uncertainty. Section 7 reports the results of applying the same econometric approach to this company investment data, and evaluates the quantitative effect of uncertainty on company investment dynamics suggested by our preferred empirical specification. Section 8 concludes.

2. A model of investment under uncertainty

The recent theoretical literature on investment under uncertainty predicts threshold investment behaviour, and emphasises that the separation between the thresholds for investment and disinvestment depends on the level of uncertainty.[1] A basic model considers investment in a single capital good K, with a Cobb-Douglas

[1]See, for example, Pindyck (1988) for the case of a fully irreversible continuous investment decision; Dixit (1989) for a partially irreversible discrete investment decision; Bertola (1994) for a model where both demand and capital prices are stochastic; and Dixit and Pindyck (1994) for a general survey of this literature.

revenue function PK^α, where $0 < \alpha < 1$ and P is a stochastic demand term that follows a Brownian motion, and partial irreversibility in the sense that the price at which the firm may sell units of the capital good is below the price at which it can buy capital.[2] [NICK - PLEASE CHECK DETAILS HERE] In this case investment will only take place when the firm's marginal revenue product of capital $\alpha PK^{\alpha-1}$ hits an upper threshold, given by the traditional user cost of capital relevant for buying capital (b) multiplied by the option value relevant for investment ($\phi_I > 1$). Similarly disinvestment will only occur when the marginal revenue product hits a lower threshold, given by the user cost relevant for selling capital ($s < b$) divided by the option value relevant for disinvestment ($\phi_D > 1$).[3] The firm chooses to wait and do nothing if its marginal revenue product of capital lies between these two thresholds. This investment policy is summarised in Table 2.1.

Table 2.1: The Threshold Behaviour of Investment.

Invest if:	$\alpha PK^{\alpha-1} \geq b \times \phi_I$
Do nothing if:	$s/\phi_D < \alpha PK^{\alpha-1} < b \times \phi_I$
Disinvest if:	$\alpha PK^{\alpha-1} \leq s/\phi_D$

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 to ensure that its capital stock remains within corresponding

[2]See Abel and Eberly (1996) for a rigorous analysis of the kind of model we describe in this section, with a continuous investment decision in a single capital good subject to partial irreversibility.

[3]Notice that with partial irreversibility, even under certainty, the user costs relevant for buying and selling capital will not be equal, due to the difference in the purchase price and the sale price of capital goods.

investment and disinvestment thresholds. These capital stock thresholds depend on various parameters of the model, such as the level of uncertainty about demand, the degree of irreversibility and the current state of demand.

As we discuss further below, general results about the effects of different levels of uncertainty on current investment behaviour cannot be obtained in this class of models. What can be shown is that the option values ϕ_I and ϕ_D that influence this investment decision are increasing in the level of uncertainty, so that the range of values for the marginal revenue product over which the firm prefers to do nothing is wider at higher levels of uncertainty.[4] [OTHER REFS ??] This suggests that firms facing a higher level of uncertainty will be less likely to invest (or disinvest) in response to a demand shock of a given size, or that their investment behaviour becomes more 'cautious'.

More precise statements about the expected impact of a demand shock on current investment at different levels of uncertainty cannot be obtained analytically, even in the single capital good case. One difficulty is that the effect of demand shocks is history-dependent in this framework, depending on how close the firm is initially to one of the thresholds. The ergodic distribution for the expected position of the capital stock in relation to these thresholds cannot always be obtained analytically. More fundamentally, however, although Abel and Eberly (1996) sign the effect of different levels of uncertainty on the investment and disinvestment thresholds, there is no closed-form solution that describes these thresholds. Hence we use numerical simulations in section 5 below to illustrate this effect of uncertainty on investment dynamics in a more general framework.[NICK: IS THIS OK?]

[4] Abel and Eberly (1996) derive these comparative static results for their model.

2.1. Aggregation within firms

Annual investment data for publicly traded UK firms do not display the discrete switches from zero to non-zero investment regimes indicated by this basic model of investment in a single type of capital. In particular, observations with zero investment spending are almost completely absent from their company accounts, and this is also apparent in plant-level data on manufacturing production establishments. There are, however, patterns in these micro data sets which provide more evidence of discrete threshold behaviour when we disaggregate the investment series, either by the unit of observation or by the types of investment considered.

Table 2.2 reports data from our sample of 672 UK manufacturing companies over the period 1972-91, separately for investment in land and buildings and in plant and machinery, as well as similar annual data for samples of UK manufacturing establishments, single plant establishments and small single plant establishments. There is a clear pattern of more frequent observations with zero investment when we consider less aggregated production units and more narrowly defined categories of capital goods. Similarly Table 2.3 shows that observations with both positive investment and disinvestment recorded in the same year are extremely common in the company data, but become less common for the less aggregated units of observation. Both patterns suggest that aggregation across different types of capital goods and production locations is likely to be important in the firm-level investment data, and obscures the importance of the zero investment regime in these figures. The issue of aggregation also appears to be relevant for the establishment-level data.

Notes: Firm-level data (11,098 obs.) from Extel UK and Datastream data on company accounts (see section 6 below). Establishment-level data (46,089 obs.) from UK

Table 2.2: Zero Investment Episodes: Frequency (%).

	Buildings & Land	Plant & Machinery	Vehicles	Total
Firms	5.9	0.1	n.a.	0.1
Establishments (all plants)	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

Table 2.3: Simultaneous Investment and Disinvestment: Frequency (%).

Firms	Establishments (all plants)	Single Plants	Small Single Plants
99.0	48.0	28.2	23.3

Census of Production Annual Respondents' Database (ARD; see Reduto dos Reis, 1999). Single plants (20,907 obs.) are the sub-sample of single plant establishments. Small single plants (15,277 obs.) are the sub-sample of single plant establishments with less than 250 employees.

[WHY DO WE HAVE 11,098 OBSERVATIONS HERE AND ONLY 6019, AT MOST, IN LATER TABLES??]

3. A model of firm-level investment under aggregation

To characterise the behaviour of firm-level investment in the presence of partial irreversibility, we explicitly consider a framework in which firms invest in multiple types of capital goods, and therefore must take many different investment decisions at any point in time. The basic insight from this type of analysis is that in almost all circumstances we may expect to see non-zero investment in some types of capital, for which the degree of partial irreversibility is low or zero (i.e. the difference between purchase price and sale price is small or zero), whilst the inaction regime remains relevant for other types of capital for which the degree of partial irreversibility is higher. In firm-level investment data which aggregates over multiple decisions subject to different degrees of irreversibility, we will rarely see total investment equal to zero, as firms frequently adjust those types of capital which are most flexible. Nevertheless the presence of threshold investment behaviour for other types of capital will continue to influence the firm's aggregate investment spending, and we should still expect the level of uncertainty to affect the short run dynamics of company-level investment.

Following Bloom (2000), we assume that each firm operates a number of production plants which experience idiosyncratic plant-level productivity shocks as well as a common firm-level demand shock. For convenience in calibrating the model to generate the simulated data used in section 5 below, we explicitly consider plant-level employment as well as investment decisions. Plants are assumed to have a Cobb-Douglas revenue function, $PK^{\alpha}L^{\beta}$, where P is a demand term, K is capital, L is labour and $0 < \alpha + \beta < 1$. Both factors are assumed to be partially irreversible, which in the case of employment can be thought of as reflecting sunk costs associated with hiring and firing, that are proportional to the numbers of workers hired or fired. The demand term is again treated as stochastic and evolves as a Brownian motion. This process is broken down into two Brownian sub-components. The first is a firm-level shock, common to all plants within the firm. The second is an idiosyncratic plant-level shock, which is independent across plants and normalised to have zero mean.[5] [NICK - IS THERE A SUPERMODULARITY ASSUMPTION MADE THAT SHOULD BE DISCUSSED HERE? THIS GIVES THE SIMPLEST INTUITION FOR THE CONVEX RESPONSE OF INVESTMENT TO DEMAND SHOCKS...]

[5]The assumption of independence across plants can be weakened to imperfect correlation, and is made here only to simplify the simulation model used in section 5.

For this framework, Eberly and Van Mieghem (1997) have shown that the optimal investment and employment decisions for each plant follow a threshold policy summarised in Table 3.1. Investment only occurs when the marginal revenue product of capital at that plant, $\alpha PK^{\alpha-1}L^{\beta}$, reaches a threshold given by the user cost of capital relevant for investment at that plant (b) multiplied by the option value relevant for investment at that plant ($\phi_I > 1$). And disinvestment only occurs when the marginal revenue product of capital reaches the user cost of capital relevant for disinvestment ($s < b$) divided by the option value relevant for disinvestment ($\phi_D > 1$). In between these thresholds the plant undertakes neither investment nor disinvestment. Heterogeneity across plants in the degree of irreversibility relevant for the type of capital used at that plant will be reflected in this region of inaction being more important for investment at some plants than others.[6] Even without such heterogeneity, the presence of idiosyncratic plant-level shocks will make the probability of some plants adjusting their capital stock in response to a given firm-level demand shock higher for those plants that are currently closer to one of the thresholds.[7] [NICK - IS THIS RIGHT? IS THIS THE ONLY MECHANISM THAT OPERATES IN THE SIMULATION MODEL?] Thus this approach can rationalise why at any time we may see non-zero investment at some plants (or for some types of capital) co-existing with zero investment at other plants (or for other types of capital) within the same firm. Aggregate firm-level investment would of course be non-zero in such cases, even

[6]Alternatively, if each plant uses several different types of capital goods, there may be heterogeneity in the ratio of sale price to purchase price for each of these different types of capital. Formally this case is similar to the presence of multiple inputs, capital and labour, each subject to partial irreversibility, at each plant, and so is not considered explicity here.

[7]Idiosyncratic shocks at the plant level can also explain the simultaneous presence of investment and disinvestment at different plants within the same firm.

though the interaction of uncertainty and irreversibility still plays an important role in determining this aggregate level of investment spending.

Table 3.1: The Simulation Thresholds for Investment and Hiring.

Invest if	$\alpha PK^{\alpha-1}L^{\beta} \geq b \times \phi_I$	Hire if	$\beta PK^{\alpha}L^{\beta-1} \geq h \times \phi_H$
Do Nothing	$s/\phi_D < \alpha PK^{\alpha-1}L^{\beta} < b \times \phi_I$	Do Nothing	$f/\phi_F < \beta PK^{\alpha}L^{\beta-1} < h \times \phi_H$
Disinvest if	$\alpha PK^{\alpha-1}L^{\beta} \leq s/\phi_D$	Fire if	$\beta PK^{\alpha}L^{\beta-1} \leq f/\phi_F$

The behaviour of plant-level employment has a similar characterisation, with a separation between the marginal revenue products of labour that justify hiring and firing reflecting sunk costs associated with these actions, generating a region of inaction where the plant neither hires nor fires. In terms of Table 3.1 we have $h > f$ and $\phi_H, \phi_F > 1$. Again this framework can rationalise why the firm may be hiring at some plants (or for some types of workers) but not at others.

This approach has two interesting implications for the short run dynamics of firm-level investment series which are the focus of our empirical investigation. First it suggests that the response of company investment to demand shocks of differing sizes is likely to be non-linear. When the firm experiences a positive demand shock, there are both extensive and intensive margins at which investment may respond. The first margin is the decision to invest or not at each plant, or more generally in each type of capital. Larger demand shocks will lead more types of capital to reach their investment threshold, inducing more plants within the firm to invest. The second margin is the decision about how much to invest in those plants or types of capital that do adjust. Supermodularity in the production technology - the marginal product of one type of capital (or labour) depends non-negatively on the levels of the remaining capital and labour inputs - suggests that these two effects are likely to be 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 where adjustment is more flexible or that are initially closer to their investment threshold. This indicates that the response of investment to positive demand shocks is likely to be convex in the size of the shock, with a larger shock inducing more plants or types of capital to adjust and therefore increasing the levels of investment chosen at those plants that would still have adjusted in response to a smaller shock.

Whilst this suggests a convex relationship between demand shocks and investment for firms that experience positive shocks and undertake positive investment, the same reasoning suggests that the relationship between demand shocks and investment is likely to be concave for firms that experience negative demand shocks and undertake disinvestment. Here a larger negative demand shock induces more plants or types of capital to adjust downwards, which tends to reduce the marginal products of other inputs and produces more disinvestment at those margins that would still have adjusted in response to a smaller shock. Overall, since firms may experience both positive and negative shocks, it is unclear which of these effects would dominate in general. Nevertheless, in data like that for our sample of UK firms in the period 1972-91, where positive investment spending dominates disinvestment and both real sales and real capital stocks are growing substantially on average, we would expect the convex response of firm-level investment to positive demand shocks to dominate the overall short run dynamic behaviour of observed company investment. In section 5 we generate simulated investment data for these firms by treating their actual data on real sales growth as realisations of the firm-level demand shocks and using a calibrated version of this modelling framework. This convex relationship between company investment and real sales growth is indeed what we find when estimating a simple econometric investment equation on this simulated data.

As well as indicating this non-linear response of investment to demand shocks at a given level of uncertainty, the second implication of this framework is that the response of company investment to demand shocks is likely to be heterogeneous across firms facing different levels of uncertainty. This is a generalisation of the more 'cautious' investment behaviour suggested by the basic investment model with a single capital good discussed in section 2 above. For each plant or type of capital, the option to wait and do nothing is more valuable for firms that face a higher level of demand uncertainty. This is reflected in a higher threshold level of the marginal revenue product being required to induce positive investment, and a lower threshold level being required to induce disinvestment. Following a given positive demand shock, investment is expected to occur at fewer plants for a firm that faces a higher level of uncertainty, and lower investment levels are expected to be chosen at those plants that do adjust. For both reasons the impact of the demand shock on firm-level investment is expected to be smaller. 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, as fewer plants are induced to disinvest and less disinvestment occurs at those that do. In general, the impact effect of demand shocks on company investment is expected to be weaker for firms that are subject to greater uncertainty, regardless of whether positive shocks or negative shocks dominate in the sample of firms we consider.

Again we confirm in section 5 that this weaker impact effect of demand shocks on company investment is found when estimating a simple econometric investment equation on simulated data generated by a model of the type described in this section.

4. An empirical specification

To investigate the empirical importance of the non-linear and heterogeneous dynamics suggested by these models of investment under uncertainty, we require an econometric specification that can be used to test for a convex relationship between company investment and demand shocks, and for a weaker impact effect of demand shocks on company investment at higher levels of uncertainty. So far as we are aware, no-one has derived a structural investment equation that can be estimated directly and that captures these 'real options' effects of uncertainty on investment in the partial irreversibility framework.[8] [TOO STRONG? LIKELIHOOD APPROACH THAT ORAZIO WAS WORKING ON...] We consider instead a reduced form error correction specification that provides a flexible distinction between short run influences on investment levels and longer term influences on capital stocks, and that has been widely used in previous empirical studies of company investment behaviour.

Bloom (2000a) shows that the actual capital stock series chosen by a firm under

[8] Abel and Eberly (1994, 1996) derive a structural relationship between investment rates and average q that allows for both partial irreversibility and fixed adjustment costs. However they assume both perfect competition and constant returns to scale, which implies that the options to invest or disinvest at a later time are not valuable in their model.

Several authors have calibrated structural models to investigate quantitatively the impact of fixed adjustment costs on investment dynamics, or used indirect inference to estimate key parameters of such models. See, for example, Caballero and Engel (1999) and Cooper, Haltiwanger and Power (1999). [OTHER REFS ??]

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 logs of the two series should be cointegrated, and thus provides one motivation for considering an error correction model of capital stock adjustment.[9] The extensive literature on the firm's optimal capital stock in a static factor demand context with costless reversibility then provides a basis for formulating the long run or target capital stock level in our empirical error correction model.

Consistent with the functional form assumptions used in our simulation model, our specification for firm i's target capital stock (K_{it}^*) in period t has the log-linear form

$$\log K_{it}^* = \log Y_{it} + A_i^* + B_t^* \tag{4.1}$$

where Y_{it} is real sales of firm i in period t, A_i^* is an unobserved firm-specific effect and B_t^* is a time-specific effect, common to all firms. If the log of the user cost of capital can be decomposed additively into firm-specific and time-specific components, this specification is consistent with the optimal capital stock under costless reversibility for a firm with a Cobb-Douglas production function and an isoelastic product demand curve.

The cointegration result referred to above indicates that

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

where K_{it} is the actual capital stock for firm i in period t and e_{it} is a stationary error term. This does not impose that the actual capital stock and its hypotheti-

[9] 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.

cal reversible level are equal on average, since the error term e_{it} need not be mean zero. Nor does this impose any particular long run relationship between the level of uncertainty faced by a particular firm and the level of its capital stock - by allowing for a firm-specific effect as a component of e_{it}, we implicitly allow firms facing different levels of uncertainty to choose different levels of the capital stock on average. The partial irreversibility framework indicates that this deviation term is likely to be serially correlated - for example, firms that are close to their upper threshold for the capital stock in one period are likely to be in a similar position in the following period, unless they experience a large negative shock. This approach also suggests that this serial correlation is likely to have a highly complex form - the response of firm-level investment to a demand shock depends on the distribution of plants or types of capital between their investment and disinvestment thresholds, which in turn depends on the past history of shocks. 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 (4.1), would have the form

$$p(L)\Delta \log K_{it} = q(L)\Delta \log Y_{it} + \theta(\log Y_{i,t-s} - \log K_{i,t-s}) + A_i + B_t + v_{it}$$

where $p(L)$ and $q(L)$ are polynomials in the lag operator $L^r x_{it} = x_{i,t-r}$, A_i and B_t are again unobserved firm-specific and time-specific effects, related to similar components of the log of the user cost of capital or of e_{it}, and v_{it} is, at least approximately, a serially uncorrelated error term. The 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 a possibly firm-specific depreciation rate, to replace the capital stock growth rates by data on gross investment rates in our empirical specification. To test for the non-linearity and heterogeneity suggested by the partial irreversibility model, we consider two types of additional terms. The first are higher order terms in current real sales growth - for example, an additional $(\Delta \log Y_{it})^2$ term. Positive coefficients on both $\Delta \log Y_{it}$ and $(\Delta \log Y_{it})^2$ would be consistent with the convex relationship between investment and demand shocks suggested by our discussion in section 3. The second are interaction terms between measures of uncertainty and current real sales growth - for example, an additional $\sigma_i * \Delta \log Y_{it}$ term, where σ_i is a measure of the level of uncertainty faced by firm i. A negative coefficient on this interaction term would be consistent with the weaker impact effect of demand shocks on current investment, or more cautious investment behaviour, at higher levels of uncertainty suggested by the real options framework.

A simple example of the specification that we estimate using the simulated investment data in the next section is then given by

$$\frac{I_{it}}{K_{i,t-1}} = \beta_1 \Delta \log Y_{it} + \beta_2 (\Delta \log Y_{it})^2 + \beta_3 (\sigma_i * \Delta \log Y_{it}) + \theta(\log Y_{i,t-1} - \log K_{i,t-1}) + A_i + B_t + v_{it}. \tag{4.2}$$

Higher order dynamics or more general functional forms can easily be introduced if serious dynamic mis-specification is suggested by residual serial correlation, or by tests of the overidentifying restrictions exploited when we use Generalised Method of Moments procedures to estimate this model on our simulated panel data.

To apply this modelling approach to real data on company investment for our sample of UK firms, we generalise the specification to incorporate two further types of terms. The first are current and lagged values of a cash flow variable $C_{it}/K_{i,t-1}$, where C_{it} is cash flow for firm i in period t. The significance of such terms in reduced form empirical investment equations may be explained by a number of considerations that are omitted from standard theoretical models of investment under partial irreversibility: for example, the presence of financing constraints or capital market imperfections, stressed by Fazzari, Hubbard and Petersen (1988); the tendency of managers to overinvest free cash flow, suggested by Jensen (1986); or a component of the demand shock or other influences on future profitability that are predictable.[10] Our concern here is not to distinguish between these explanations but simply to ensure that any evidence of non-linear or heterogeneous impact effects of real sales growth on company investment that we find is not attributable to the exclusion of empirically relevant cash flow variables.[11]

The second type of terms that we add are current and lagged values of time-varying measures of uncertainty (σ_{it}). Variation over time in the level of uncertainty faced by an individual firm introduces an additional state variable into the investment problem, and the difficulty of solving this richer model has precluded almost all analysis of changing levels of uncertainty in the theoretical literature.[12] Nevertheless the impact on investment behaviour of changes in the level of uncertainty perceived by firms, for example following the terrorist attacks of September

[10]See Cummins, Hassett and Oliner (1999) and Bond, Klemm, Newton-Smith, Syed and Vlieghe (2002) for further discussion.

[11]Guiso and Parigi (1999) included cash flow terms in their econometric investment model for similar reasons.

[12]Hassler (1996) provides one exception in the context of a very simple (S,s) model.

11, 2001, is of first-order importance for macroeconomic policy. Hence it is interesting to investigate whether changes in levels of uncertainty over time have similar effects on investment dynamics to those suggested by a comparative static analysis of differences in levels of uncertainty across firms. Moreover there is considerable time series variation in the stock returns measure of uncertainty that we construct for our sample of UK firms (see section 6), that we do not want to exclude from our empirical investigation. In the empirical work this also allows us to investigate whether there is a significant long run effect of a higher level of uncertainty on the capital stock levels chosen by firms, which we could not separately identify from unobserved firm-specific effects if we were to rely exclusively on time-invariant measures of uncertainty.

Generalising our empirical specification to include short run and long run effects from these additional terms then gives a model of the form

$$
\begin{aligned}
\frac{I_{it}}{K_{i,t-1}} &= \beta_1 \Delta \log Y_{it} + \beta_2 (\Delta \log Y_{it})^2 + \beta_3 (\sigma_{it} * \Delta \log Y_{it}) + \theta (\log Y_{i,t-1} - \log K_{i,t-1}) \\
&\quad + \gamma_1 \Delta \sigma_{it} + \gamma_2 \sigma_{i,t-1} + \phi_1 \Delta \left(\frac{C_{it}}{K_{i,t-1}} \right) + \phi_2 \left(\frac{C_{i,t-1}}{K_{i,t-2}} \right) + A_i + B_t + v_{it}.
\end{aligned} \tag{4.3}
$$

We consider extended error correction models of this type in our analysis of UK company investment behaviour reported in section 7.

5. Results for simulated data

Before implementing this approach on investment data for UK companies, we first consider how it performs using simulated data generated by a multiple plant partial irreversibility model of the form described in section 3. This investigation serves three purposes. First it illustrates that the convex response of current investment to current demand shocks, and the weaker impact effect of demand shocks on investment spending at higher levels of uncertainty, are indeed found in simulated data from this kind of model. Second it confirms that we can detect these effects as significant positive coefficients (β_2) on a squared real sales growth term and significant negative coefficients (β_3) on an interaction term between uncertainty and real sales growth, in an extended error correction model of the kind discussed in the previous section. Third it suggests that a parsimonious error correction specification can provide a good approximation to the complex investment dynamics expected in the partial irreversibility framework.

Our simulation model is described in more detail in Bloom (2000). The parameters of the revenue function (see Table 3.1) are set at $\alpha = 0.25$ and $\beta = 0.5$, consistent with aggregate factor shares and production function evidence. The discount rate and depreciation rate which enter the user costs of capital are set at 10% and 8% respectively, and the quit rate for labour is assumed to be 10%. The ratio of the sale price to the purchase price of capital goods (s/b) is assumed to be 0.5, whilst the corresponding ratio of (f/h) for employment costs is set at 0.9, in line with the view that labour is a more flexible input than capital. Plant-level shocks are drawn from an i.i.d. normal distribution with mean zero and standard deviation ??. For each firm, the actual data on real sales growth are treated as realisations of the firm-level demand shocks, giving on average a drift of about 3% and a standard deviation of about 15%. This allows for heterogeneity across firms in the standard deviation of the firm-level demand shocks (σ_i) which is reflected in the calculation of the option values ($\phi_I, \phi_D, \phi_H, \phi_F$). [NICK: THIS IS

DELIBERATELY VAGUE. YOUR DESCRIPTION IN THE EARLIER DRAFT INDICATES THAT THE σ_i USED TO CALCULATE OPTION VALUES WERE SCALED STANDARD DEVIATIONS OF DAILY SHARE RETURNS. BUT THIS MIGHT SEEM INCONSISTENT WITH TREATING REAL SALES AS REALISATIONS OF THE STOCHASTIC DEMAND PROCESS???] These option values determine the thresholds which, together with the stochastic evolution of the marginal revenue products, generate the plant-level investment and employment series. The firm-level investment and employment data are obtained by adding up across all plants within the same firm, assuming that each firm operates 20 plants.[13] We initialise the simulation by assuming that each firm starts from its ergodic distribution of plants between their investment, disinvestment, hiring and firing thresholds. In turn this ergodic distribution is estimated numerically by starting from arbitrary levels and running a similar simulation over a 20 year period.[14]

This simulation procedure generates lumpy plant-level investment and employment data, but much smoother firm-level series. Bloom (2000) shows that simulated data from this kind of model can replicate key time series and cross section properties of actual data on investment and employment for publicly traded US manufacturing firms in the Compustat database.

The simulated capital stock (K^S) and investment (I^S) data used here is based on real sales (Y) data for the sample of 672 publicly traded UK manufacturing firms in the period 1972-91 that we use in section 7, and describe in more detail

[13]Perhaps surprisingly, the number of plants we assume for each firm has little effect on the estimates of our investment equations on the simulated panel data. Results similar to those in Table 5.1 were also obtained assuming each firm operates 2 or 200 plants.

[14]Again the estimation results were not found to be sensitive to this initialisation procedure. [OK?]

in the next section. In Table 5.1 we report the results of estimating some simple econometric investment equations on this simulated data. These equations are estimated using the first-differenced Generalised Method of Moments (GMM) procedure developed by Arellano and Bond (1991), to allow for the possibility of unobserved firm-specific effects. The instruments used are noted in the Table, and the estimation results were robust to a range of alternative instrument sets that we considered.

Table 5.1: GMM Estimates Using The Simulated Investment Data.

Dependent Variable ($I^S_{it}/K^S_{i,t-1}$)	**(1)**	**(2)**	**(3)**	**(4)**
Sales Growth (Δy_{it})	0.501	0.412	0.317	0.461
	(0.038)	(0.026)	(0.025)	(0.072)
Error Correction Term $(y - k^S)_{i,t-1}$		0.274	0.263	0.266
		(0.024)	(0.021)	(0.011)
Sales Growth Squared $(\Delta y_{it})^2$			0.453	0.446
			(0.062)	(0.060)
Uncert.×Sales Growth ($\sigma_i * \Delta y_{it}$)				-0.085
				(0.041)
2nd order serial correlation (p)	0.000	0.758	0.223	0.231
Sargan-Hansen (p)	0.000	0.252	0.127	0.214

NOTES:- The total number of observations in all columns is 5347, using an unbalanced panel of 672 firms and an estimation period of 1973 to 1991. A full set of year dummies is included in every specification. Estimation uses a first-differenced GMM estimator computed in DPD98 for Gauss (see Arellano and Bond, 1998). One step coefficients and heteroskedasticity-consistent standard errors are reported. The instruments used columns are lags of the variables: $\left(\frac{I^S_{i,t-2}}{K^S_{i,t-3}}\right)$ and $\left(\frac{I^S_{i,t-3}}{K^S_{i,t-4}}\right)$, $\Delta y_{i,t-2}$ and $\Delta y_{i,t-3}$, $(y - k^S)_{i,t-2}$ and $(y - k)_{i,t-3}$. Instrument validity is tested using a Sargan-Hansen test of the overidentifying restrictions for the corresponding two step GMM estimator. The Arellano-Bond test for no second-order serial correlation in the first-differenced residuals is also reported.

Column (1) reports a simple accelerator model in which the growth rate of the capital stock is related to the growth rate of real sales (Δy_{it}).[15] The estimated coefficient on current real sales growth is positive and highly significant, but much smaller than the value of unity that is the correct long run output elasticity of the capital stock in this simulated data. In line with our expectations, there is highly significant evidence of residual serial correlation, and consequently the validity of lagged endogenous variables as instruments here is soundly rejected by the test of overidentifying restrictions.

Column (2) adds a lagged error correction term ($y_{i,t-1} - k^s_{i,t-1}$), allowing a more flexible dynamic relationship between the actual capital stock and its hypothetical costlessly reversible counterpart, which is proportional to real sales in our simulation design, whilst imposing the long run unit elasticity. The estimated coefficient on this error correction term is highly significant and correctly signed, picking up the fact that firms whose capital stock becomes too low relative to their real sales tend to adjust upwards eventually, and vice versa. The inclusion of this term is sufficient to remove the indication of significant residual serial correlation, and the use of lagged endogenous variables as instruments is no longer rejected by the test of overidentifying restrictions. This suggests that this parsimonious first order error correction specification provides a reasonable approximation to the complex dynamics expected in the presence of partial irreversibilities. [HOW DOES THIS RELATE TO COOPER-WILLIS MIND-THE-GAP PAPER??]

Column (3) adds a squared term in current real sales growth to investigate the non-linear effect of demand shocks on current investment expected in this framework. The positive coefficients estimated on both the level and the square of

[15] Lower case roman letters are used here to denote natural logarithms of the corresponding upper case variables.

real sales growth are consistent with the convex relationship discussed in section 3 above. The statistical significance of these coefficients confirms that we can detect this convexity by introducing a quadratic term into a simple error correction model, using annual company data for a sample of this size.

Column (4) adds a further interaction term to investigate how the impact effect of demand shocks on current investment differs across firms that face different levels of uncertainty.[16] The negative coefficient on this interaction term is in line with our expectation that this impact effect will be weaker for firms subject to a higher level of uncertainty, as they react more cautiously to the realisation of a given demand shock. Again this coefficient is found to be statistically significant, which points to the usefulness of introducing an interaction term between a measure of uncertainty and current real sales growth into a basic error correction specification in order to test for this effect of uncertainty on short run investment dynamics.

We conclude from this section that if the company investment data were in fact generated by a partial irreversibility model, we should be able to represent the capital stock adjustment process quite well using an extended error correction model of the type discussed in section 4. Moreover we should be able to detect evidence of the implied non-linear and heterogeneous investment dynamics by including higher order terms in current real sales growth and an interaction between current real sales growth and a measure of uncertainty.

[16] This specification corresponds to that given in equation (4.2) above.

6. UK company data

Our main interest is to investigate whether the dynamics we observe in real data display similar patterns to those suggested by this partial irreversibility approach, and in particular whether the impact effect of demand shocks depends on the level of uncertainty in the way described above. Firm-level data is attractive relative to more disaggregated plant-level data because we can construct useful measures of uncertainty using high frequency data on stock returns. Firm-level data is attractive relative to more aggregated industry-level or macro data because we observe rich variation across firms in the level of measured uncertainty. Furthermore, company accounts provide detailed information on financial variables such as cash flow and gearing, which are not available in establishment-level or industry-level data. In principle, though, the empirical approach we adopt in this paper could be applied to more aggregated data at the industry or macro level.

The next section discusses our empirical measure of uncertainty and relates this to the concept of demand uncertainty used in our simulation model. The following section briefly describes the investment, sales and cash flow data that we obtain from UK company accounts. A Data Appendix provides more detail on the sample and the construction of these series.

6.1. The measurement of uncertainty

Although the model described above focuses on the effects of demand uncertainty on firm-level investment, the notion of uncertainty that we are interested in empirically is much broader in scope. In reality firms will be uncertain about future prices, interest rates, wages rates, exchange rates, technologies, consumer tastes, taxation and other government policies. In an attempt to capture all relevant factors in one scalar measure of firm-level uncertainty, we follow Leahy and Whited (1996) in using the standard deviation of daily stock returns, **adjusted for gearing [??]**, for firm i in period t, denoted σ_{it}. The measure of stock returns includes, on a daily return basis, the capital gain on the stock, dividend payments, rights issues, and stock dilutions. The volatility in these stock returns provides a forward looking indicator of the volatility of the firm's environment, which is implicitly weighted in accordance with the impact of different sources of uncertainty on the firm's value. To allow for possible effects of market-wide bubbles or fads we also calculated a second measure of uncertainty, using the standard deviation of the firm's daily stock returns normalized by the return on the FTSE All-Share index. Results using this normalized measure were very similar to those reported below, and are available on request from the authors. We also obtained qualitatively similar results whether we used the standard deviation or the variance as our measure of uncertainty, and whether or not we adjusted the volatility of daily stock returns for different levels of gearing.

A stock returns-based measure of uncertainty is attractive empirically because the data is reported accurately at a sufficiently high frequency to use an annual measure. When using homoskedastic diffusion processes the variance of the sample variance is inversely related to the sampling frequency (see, for example, Merton (1980)). Our sampling frequency of about 265 observations per year therefore suggests low sample variance, so that movements in the measured variance should reflect changes in the underlying process rather than individual extreme draws.[17]

[17] The work by Andersen and Bollerslev (1998) is informative on this point. They also use high frequency financial data (\$/¥ exchange rate) with 288 recordings per period and calculate that the implied measurement errors are less than 2.5% of the true volatility.

A further advantage of using repeated observations on a time-varying measure of uncertainty is that we can investigate whether the level of uncertainty has a significant effect on capital accumulation in the longer term, whilst controlling for the presence of unobserved firm-specific influences. A disadvantage of using this particular measure is that the variability in stock market returns may not only reflect the fundamentals of the firm's environment, for example, if share prices are also influenced by bubbles. Guiso and Parigi (1999) used survey data on managers' subjective distributions of future demand growth to estimate the variance of firm-level demand shocks more directly. The results which we report below are qualitatively similar to theirs, even though we use different measures of uncertainty and, unlike them, we have panel data rather than a single cross section.

The important assumption we make in using this measure of uncertainty to evaluate the partial irreversibility model described earlier is that stock returns volatility is monotonically related to underlying demand uncertainty. For a simple model with a Cobb-Douglas revenue function, a Brownian motion demand process and costlessly reversible capital, this assumption would be valid, at least in the absence of share price bubbles. In this case the firm's value is a linear function of demand, such as $V(K,P) = AK^{\alpha}P$, **where this functional relationship is independent of demand**. [I DON'T UNDERSTAND THIS STATEMENT. IS THE POINT THAT DEMAND IS THE ONLY SOURCE OF UNCERTAINTY AND K IS DETERMINISTIC GIVEN DEMAND IN THE FULLY FLEXIBLE MODEL??] In this case the variance of the firm's market value (σ_V^2) would be proportional to the underlying variance of demand shocks (σ_P^2), for example $\sigma_V^2 =$

$A^2 K^{2\alpha} \sigma_P^2$.

In the presence of partial irreversibilities, however, the firm's market value also includes option values which themselves are functions of uncertainty. As this precludes any general result, we focus here on the canonical model in the theoretical literature, with a single capital good subject to partial irreversibility, a Cobb-Douglas revenue function and a Brownian motion demand process.[18] Abel and Eberly (1996) demonstrate that the value function in this model has the general form $V(K, P) = A_1 K^{\alpha 1} P^{\beta 1} + A_2 K^{\alpha 2} P^{\beta 2} + B K^{\beta} P$, which can be solved numerically to derive the value function. **[NICK TO ADD ??]** We obtained this value function numerically for a range of values of demand uncertainty.[19] For all the values we considered we found that the variance of the firm's value was monotonically related to the underlying variance of the demand shocks. This comparative static result suggests that higher demand uncertainty is associated with higher stock returns volatility in this partial irreversibility model, consistent with our use of stock returns volatility as the measure of uncertainty in our empirical analysis.

Figure 1 reports the average value of this measure of uncertainty across the firms present in our sample for each calendar year. In the time series dimension there is a spike in uncertainty in 1975, around the time of the first OPEC oil shock. There is another peak in 1988, when the annual measures of stock returns volatility are affected by the October 1987 stock market crash. Consistent with Davis and Haltiwanger (1992), however, we also find that this macroeconomic variation

[18]This is a restricted version of the simulation model we used in section 4, in which each firm operates a single plant and labour adjustment is assumed to be costlessly reversible.

[19]This was done using Mathematica 3.0 following the suggested solution algorithm in the appendix of Abel and Eberly (1996). The program and results are available from the authors on request.

in our uncertainty measure is much less important that firm-level idiosyncratic shocks. Only 17% of the total variance in our uncertainty measure is accounted for by macro shocks, common to all firms in a particular year. Of the remaining variation, around half is due to permanent differences between firms in the level of measured uncertainty, and around half is due to transitory idiosyncratic fluctations.

6.2. Investment and other accounting data

The company accounts data is obtained from Datastream and consists of 672 manufacturing companies whose shares were quoted on the UK stock market for at least three consecutive years between 1972 and 1991.[20] Investment in fixed capital assets is measured net of revenue from asset sales, which may nevertheless underrecord the value of disinvestment. 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. The Data Appendix provides further details and Table 6.1 reports some summary statistics for the sample.

As a preliminary step, Table 6.2 presents some basic descriptive regressions. There is a significant negative correlation between investment rates and our measure of uncertainty, which is illustrated in column (1). Column (2) adds the growth rate of real sales and the interaction between this variable and our measure of un-

[20] The reporting of investment in UK company accounts changes in 1991, so that we cannot obtain completely consistent series for later years.

Table 6.1: Descriptive Statistics for 672 firms, 6019 observations.

	mean	*median*	*standard deviation*			*min.*	*max.*
			total	*within*	*between*		
$(I_{it}/K_{i,t-1})$ (investment rate)	0.128	0.093	0.13	0.11	0.10	-0.11	1.21
Δy_{it} (real sales growth)	0.031	0.026	0.16	0.14	0.09	-0.79	1.22
σ_{it} (s.d. of stock returns)	1.56	1.41	0.68	0.53	0.47	0.01	5.00
$(C_{it}/K_{i,t-1})$ (cash flow term)	0.18	0.140	0.16	0.09	0.17	-0.09	1.96
Employment	8,400	1,481	24,492	8,461	19,450	26	21,200
Observations per firm	11.3	11	4.7	0	4.7	3	20

certainty. It is the latter variable which is crucial for considering the effects of uncertainty on short run investment dynamics. There is a standard accelerator effect of sales growth but, more importantly, the coefficient on sales growth is significantly lower for firms with more volatile stock returns. Consistent with our analysis of the partial irreversibility model, the impact effect of sales growth on investment is found to be weaker for firms that face a higher level of uncertainty. In the final column we control for cash flow as an additional regressor. The cash flow term is highly significant and its inclusion results in the linear uncertainty term becoming insignificant. More importantly, though, the interaction between uncertainty and sales growth remains negative and significant. Although these simple regression results do not control for unobserved firm-specific effects or any sources of endogeneity, it is interesting to note that the main implication of the partial irreversibility approach for the effect of uncertainty on investment dynamics appears to be consistent with the raw data.

NOTES:- The total number of observations in all columns is 6019, using an unbalanced panel of 672 firms and an estimation period of 1972 to 1991. Estimation by OLS. Heteroskedasticity-consistent standard errors are reported.

Table 6.2: Descriptive Investment Regressions.

Dependent Variable ($I_{it}/K_{i,t-1}$)	**(1)**	**(2)**	**(3)**
Uncertainty (σ_{it})	-0.015	-0.005	0.003
	(0.003)	(0.002)	(0.002)
Sales Growth (Δy_{it})		0.453	0.338
		(0.025)	(0.023)
Uncert.×Sales Growth ($\sigma_{it} * \Delta y_{it}$)		-0.033	-0.035
		(0.013)	(0.012)
Cash Flow ($C_{it}/K_{i,t-1}$)			0.381
			(0.011)

7. Results for UK company data

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 with suitably lagged levels of endogenous variables as instruments, as in the basic Arellano and Bond (1991) estimator, with equations in levels for which lagged first-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. Our preferred results in this study were obtained using the system GMM estimator with the instrument set reported in the notes to the Tables. Similar results were found using a wide 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 approach.[21]

Column (1) of Table 7.1 reports results for a basic linear error correction specification with additional cash flow terms. In line with previous research that has estimated similar models of company investment, we find that the key coefficient on the error correction term is correctly signed and statistically significant.[22] There is evidence that, in the long run, companies do 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.[23] A simple goodness of fit statistic also suggests that this model has reasonable explanatory power for firm-level data of this kind.[24]

[21] Bond, Elston, Mairesse and Mulkay (2002) and Bond, Harhoff and Van Reenen (1999) provide further discussion of GMM estimation in the context of error correction models of company investment.

We note that the additional instruments used for the levels equations in Tables 7.1 and 7.2 were not found to be valid, and hence were not used, in the results presented for the simulated data in Table 5.1. This is likely to be related to the initialisation required to generate the simulated data.

[22] See, for example, Bond, Elston, Mairesse and Mulkay (2002) and Bond, Harhoff and Van Reenen (1999).

[23] We note that we were unable to find valid instruments for specifications which did not include the cash flow variables, which is another reason why we include these terms in the reported models. Our main results on the properties of short run investment dynamics were robust to the exclusion of these cash flow terms, as discussed further below.

[24] 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).

Column (2) adds a squared term in current real sales growth to this basic specification. In line with our results for the simulated data in section 5, we find significant positive coefficients on both the level and the square of real sales growth. We thus find evidence of the convex relationship between current investment and current sales growth suggested by the partial irreversibility model with multiple capital goods, as discussed in section 3.

Column (3) adds our interaction term between measured uncertainty and real sales growth to this extended error correction specification. We also investigate whether there are short run or long run linear effects of uncertainty on capital accumulation. This specification corresponds to equation (4.3) in section 4. The main result of interest here is the significant negative coefficient on the interaction term, as we also found using the simulated data. Consistent with the implications of the partial irreversibility model, we find evidence of a weaker impact effect of real sales growth on current investment for firms that are subject to a higher level of uncertainty.

In contrast, the linear uncertainty terms are found to be only weakly significant.[25] We include these terms 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.[26] Omitting this term in column (4) re-

[25] A joint test of the exclusion of these two terms from the specification in column (3) does not reject this restriction (p-value = 0.17).

[26] That is, our results do not rule out the possibility of an economically significant negative

sults 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.

long run effect of uncertainty on capital accumulation, although we cannot confirm the presence of such an effect with any confidence.

Table 7.1: GMM 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 Sqrd. $(\Delta y_{it})^2$		0.481	0.512	0.494	0.500
		(0.175)	(0.152)	(0.150)	(0.151)
Change in Uncertainty ($\Delta\sigma_{it}$)			-0.023	-0.012	
			(0.012)	(0.008)	
Lagged Uncertainty ($\sigma_{i,t-1}$)			-0.015		
			(0.011)		
Uncert.×Sales Growth ($\sigma_{it} * \Delta y_{it}$)			-0.162	-0.165	-0.167
			(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
2nd order serial correlation (p)	0.048	0.102	0.069	0.078	0.091
Sargan-Hansen (p)	0.510	0.709	0.699	0.629	0.560

NOTES:- The total number of observations in all columns is 5347, using an unbalanced panel of 672 firms and an estimation period of 1973 to 1991. A full set of year dummies is included in every specification. Estimation uses a system GMM estimator (see Blundell and Bond, 1998) computed in DPD98 for Gauss (see Arellano and Bond, 1998). One step coefficients and heteroskedasticity-consistent standard errors are reported. The instruments used in columns (3) to (5) are: in the first-differenced equations, lags of the variables: $\left(\frac{I_{i,t-2}}{K_{i,t-3}}\right)$ 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 $\sigma_{i,t-2}$, $\sigma_{i,t-3}$ and $\sigma_{i,t-4}$; 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 $\Delta\sigma_{i,t-1}$. 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 for the corresponding two step GMM estimator. The Arellano-Bond test for no second-order serial correlation in the first-differenced residuals is also reported. The goodness of fit measure is the squared correlation coefficient between actual and predicted levels of the dependent variable.

Table 7.2 investigates this interaction effect further. Here we decompose our stock returns measure of uncertainty (σ_{it}) into three components - a macroeconomic component, common to all firms in a particular year ($\overline{\sigma}_t$); a time-invariant firm-specific component ($\overline{\sigma}_i$); and an idiosyncratic time-varying component ($\widetilde{\sigma}_{it} = \sigma_{it} - \overline{\sigma}_t - \overline{\sigma}_i$). Columns (1)-(3) include interactions between real sales growth and each of these uncertainty variables individually, whilst column (4) includes all three interaction terms jointly.

The interaction between the firm-specific measure of uncertainty and real sales growth included in column (2) is closest to the analysis of the effects of uncertainty on investment available in the theoretical literature on partial irreversibility, and corresponds to type of interaction term included using the simulated data in column (4) of Table 5.1. We find a negative coefficient on this interaction term which is similar in magnitude to that found for our preferred empirical specification in column (5) of Table 7.1. However this coefficient is estimated with much less precision than when we also exploit the time variation in our empirical measure of uncertainty. The interaction between firm-level real sales growth and a purely macroeconomic measure of uncertainty, included in column (1) of Table 7.2, is the least informative of our three variables.[27] Columns (3) and (4) show clearly that it is the information provided by the idiosyncratic time-varying component ($\widetilde{\sigma}_{it}$) of our stock returns uncertainty measure that is most useful in identifying the weaker impact effect of real sales growth on current investment for firms subject to higher uncertainty. However the coefficients on the remaining interaction terms in column (4) are estimated sufficiently imprecisely that we can easily accept the

[27]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 any significant effects of uncertainty variables.

restriction of common coefficients on these three interactions, as imposed in our preferred empirical specification.

We have conducted many robustness tests on these results, some of which we now report. First, cash flow has no strong theoretical justification for being included in these models. As noted earlier, omitting the cash flow variables resulted in significant evidence of mis-specification. For example, dropping both cash flow terms from the specification in column (5) of Table 7.1 caused the Sargan-Hansen test to reject the overidentifying restrictions (p-value = 0.010) and produced significant second-order serial correlation in the first-differenced residuals (p-value 0.049). Nevertheless, the interaction between uncertainty and sales growth was still found to be negative and significant in this specification, with a point estimate of -0.142 and a standard error of 0.065.

Secondly, we 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 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.

Thirdly, an implication of real options theory stressed by Guiso and Parigi (1999) is that the effect of uncertainty should be stronger for firms with more market power. We investigated whether the coefficient on our interaction term was largeer or more significant for firms in industries where market power is likely to be greater (as proxied by concentration, trade barriers, etc.). We found no evidence that this was the case, although it could be that our industry-level proxies are not good measures of the firm's market power.

Table 7.2: 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 Uncert.×Sales Growth $(\overline{\sigma}_t)*(\Delta y_{it})$	0.016			-0.051
	(0.150)			(0.135)
Firm Uncert. ×Sales Growth $(\overline{\sigma}_i)*(\Delta y_{it})$		-0.130		-0.136
		(0.105)		(0.107)
Resid. Uncert.×Sales Growth $(\widetilde{\sigma}_{it})*(\Delta y_{it})$			-0.225	-0.230
			(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)	0.096	0.094	0.132	0.106
Sargan-Hansen (p)	0.399	0.490	0.383	0.452

NOTES:- The total number of observations in all columns is 5347, using an unbalanced panel of 672 firms and an estimation period of 1973 to 1991. A full set of year dummies is included in every specification. Estimation uses a system GMM estimator (see Blundell and Bond, 1998) computed in DPD98 for Gauss (see Arellano and Bond, 1998). One step coefficients and heteroskedasticity-consistent standard errors are reported. The instruments used in all columns are: in the first-differenced equations, lags of the variables: $\left(\frac{I_{i,t-2}}{K_{i,t-3}}\right)$ 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 $\sigma_{i,t-2}$, $\sigma_{i,t-3}$ and $\sigma_{i,t-4}$; 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 $\Delta\sigma_{i,t-1}$. Instrument validity is tested using a Sargan-Hansen test of the overidentifying restrictions for the corresponding two step GMM estimator. The Arellano-Bond test for no second-order serial correlation in the first-differenced residuals is also reported. The goodness of fit measure is the squared correlation coefficient between actual and predicted levels of the dependent variable.

Finally, we constructed an alternative measure of uncertainty after normalising the firm's stock returns by the return on the FTSE All-Share index for the same day. This measure gave qualitatively similar but somewhat more precise coefficient estimates than our basic results, presumably because some of the general stock market noise has been removed from this measure of uncertainty. For example, in the specification corresponding to column (5) of Table 7.1, the coefficient on the uncertainty interaction term rises to -0.196 with a standard error of 0.074. All these additional results are available from the authors on request.

7.1. The quantitative impact of uncertainty on investment dynamics

The results presented in the preceding section suggest a statistically significant effect of higher uncertainty in retarding the responsiveness of company investment to demand shocks. To evaluate the size of this effect we conducted some simple simulations in which we increased real sales in the firm permanently by 2.5%, 5% and 10%. We then tracked the path of investment and the capital stock predicted by our preferred empirical specification as the firm responds to this shock. Our model suggests that firms with higher uncertainty will respond more slowly to this shock than firms with lower uncertainty. Consequently we examined the half life of the capital stock adjustment (how many years it takes the firm to get half-way towards its new long run capital stock level) at different percentiles of the empirical distribution of our measure of uncertainty (10th, 25th, 50th, 75th and 90th). Table 7.3 presents the results.

Table 7.3: Half Lives of Capital Stock Adjustment to Permanent Demand Shocks, by Uncertainty Percentiles.

	10^{th} (σ=0.84)	25^{th} (σ=1.08)	50^{th} (σ=1.41)	75^{th} (σ=1.89)	90^{th} (σ=2.46)
2.5%	8	9	10	11	13
5%	8	9	10	11	12
10%	7	8	9	11	12

The exact size of the demand shock makes relatively little difference to the results. For the smallest shock, moving from the 25th percentile to the 75th percentile of the uncertainty distribution increases the half life by two years. This is the order of magnitude by which our measure of aggregate uncertainty increased between 1973 and 1975, a very large change by historical standards.

These simulation results are illustrated in more detail in Figures 2 and 3, which track the predicted paths of investment and the capital stock over a ten year period following a permanent 2.5% demand shock, at different levels of uncertainty. As expected, the largest effects of uncertainty on investment are manifest in the first year. For example, moving from the 25th percentile to the 75th percentile of the uncertainty distribution halves the size of the first-year effect of this demand shock on investment spending. We thus find that uncertainty can be quantitatively important in reducing the impact effect of demand shocks on investment. The effects on investment are much smaller in subsequent years, but the effects on capital accumulation illustrated in Figure 3 remain quite significant over this ten year horizon.

A second gauge of the importance of the non-linear and heterogeneous investment dynamics that we find is provided by considering the improvement in the goodness of fit of our preferred investment model in column (5) of Table 7.1, which includes both the uncertainty interaction term and the squared sales growth term, relative to the more standard linear specification in column (1) of Table 7.1. To do this we calculate separately for each year the correlation between actual and predicted company investment rates, using both our preferred specification and the standard model. We plot the *difference* between these two goodness of fit series in Figure 4 (left axis), as a time-varying indicator of the improvement in fit that results from accounting for the non-linear and heterogeneous dynamics suggested by models of investment under uncertainty in the presence of partial irreversibilities. In Figure 4 (right axis) we also plot the yearly average rate of change of real sales growth as an indicator of the turning points in the business cycle. Turning points in the business cycle are characterised by rapid changes in the rate of real sales growth, as growth rates slow down going into recession or speed up heading into a boom.

It can be seen from Figure 4 that the improvement in fit tracks the positive turning points of the business cycles (correlation of 0.564), with large improvements evident in the late 1970s as the UK was recovering from the first oil shock, and again in the early 1980s when the UK was recovering from the second oil shock and an exceptionally tight monetary squeeze. Interestingly this finding parallels the results of Caballero, Engel and Haltiwanger (1995) and Cooper, Haltiwanger and Power (1999), who report that taking into account the non-linearities induced by fixed adjustment costs leads to an improvement in their ability to track aggregate investment most notably around turning points in the investment cycle.[28]

8. Conclusions

In this paper we have investigated the implications of a model of investment with partial irreversibility for firm-level investment dynamics. Patterns that we find in micro datasets for more disaggregated production units and more narrowly defined types of capital motivate an explicit treatment of firm-level investment spending

[28] The estimation approach of both papers differs from ours in that they estimate investment models at the plant level and track the cross-sectional distribution of plant-level investment to model aggregate investment.

as an aggregate over multiple investment decisions in different plants or different types of capital goods. This approach leads us to expect a convex relationship between current demand shocks and current investment spending, and a weaker impact effect of demand shocks on current investment for firms that are subject to a higher level of uncertainty. We propose a simple econometric approach to test for the presence of such non-linear and heterogeneous investent dynamics, by adding higher order and interaction terms to a standard error correction model of capital stock adjustment dynamics, in which the capital stock and real sales are cointegrated in the long run. By estimating this model using simulated data, we confirm that this approach can detect a convex relationship between investment and real sales growth, and a weaker impact effect at higher levels of uncertainty, when the investment data are generated by a multiple plant partial irreversibility model.

In our empirical analysis we estimate an extended error correction specification using data on investment and real sales for a panel of 672 publicly traded UK manufacturing companies between 1972 and 1991. As in the simulated data, we find evidence that higher levels of uncertainty reduce the impact effect of real sales growth on company investment, and that there is a convex relationship between current investment and real sales growth. These effects are shown to be quantitatively as well as statistically significant. Accounting for this non-linearity and heterogeneity in short run investment dynamics is shown to be particularly important around turning points in the business cycle.

There may of course be reasons other than the real options stressed in the partial irreversibility approach why company investment should respond more cautiously to demand shocks at higher levels of uncertainty. Firms subject to higher uncertainty may use higher discount rates, particularly if their owners or managers are only imperfectly diversified.[29] They may place less weight on the current state of demand in forming expectations of future levels of demand or profitability. Higher uncertainty may itself make firms more pessimistic about the likely rate of future demand growth. Nickell (1978a, 1978b) obtains a similar prediction from a different model that emphasises adjustment lags. The development of tests that can discriminate between some of these alternative explanations is an important area for future research. In this paper, we hope to have established that real sales growth does have a weaker impact effect on investment at higher levels of uncertainty, and that the behaviour of company investment dynamics is strikingly similar to that predicted by theoretical models that emphasise partial irreversibility and real options.

[29]See Himmelberg, Hubbard and Love (2002) for an interesting model in which incentive contracting considerations prevent the risk-spreading benefits of diversification from being fully exploited.

9. Data Appendix

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

Investment (I). Total new fixed assets less fixed asset sales: DS435-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 in the first observation within our sample period, adjusted for previous years 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 a 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 year, and adjust for the firm's debt-equity ratio as in Leahy and Whited (1998). We trim the variable so that values above five are set equal to five. The results are robust to dropping these ten observations.

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