Exploring the Role of Uncertainty for Corporate Investment Decisions in Germany

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Abstract:

This paper studies the impact of uncertainty on firm's investment outlays using the database of the Deutsche Bundesbank's corporate balance sheet statistics. The sample used for estimation contains 6,745 firms with almost 50,000 observations, covering the years 1987-1997. We estimate the effect of *sales uncertainty* and *cost uncertainty* on investment demand. Two key results emerge: First, there is a moderately strong and consistently *negative* effect of uncertainty on investment. If both uncertainty indicators are increased by one standard deviation, the estimated investment demand will fall by 6½% of its mean. Second, sales uncertainty and cost uncertainty are of roughly equal importance for investment.

Key Words:
Investment, Uncertainty, Panel Estimation

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1. The Problem

There are several channels through which uncertainty may affect firms' investment outlays. The oldest and most intuitive account focuses on firms' attitude towards risk, see, e.g., Hartman (1976) or the textbook exposition by Nickell (1978). Risk averse owners and their managers will systematically trade expected returns for certainty. The standard capital asset pricing model shows how this aversion is translated into the equilibrium framework. Risk – or better: undiversified risk – commands a premium that results in higher costs of capital.

Another potential avenue comes from financial constraints due to asymmetric information. Providers of outside finance demand higher returns (or limit their exposure) if they are not able to evaluate the investment opportunity with the same precision as the investor himself. The asymmetry might be graver – and the resulting constraints severer – if the prospects of the firm look more uncertain *from the outside*. This view is advocated and empirically tested by Minton and Schrand (1999). Ghosal and Loungani (2000) argue that the impact of uncertainty on investment might differ across firms, depending on their access to the capital markets.

But even financially unconstrained investors who maximise the expected value of their companies given an exogenous discount rate will not be indifferent towards risk. In recent years, the burgeoning literature on irreversibility and investment initiated by McDonald and Siegel (1986) and first summarised by Dixit and Pindyck (1994) emphasises the fact that the sunk costs of an investment project create an option value if the investment decision can be delayed. Generally, the right to perform a given investment project at a later date, when more information is available, bears a positive value for the firm, at least under imperfect competition. This value can be calculated just like the price of a call option on an interest bearing asset. Immediate investment will destroy this "option value", such that it has to be taken into account as an additional opportunity cost of capital. Abel and Eberly (1996) emphasise that the option value effect is mitigated under competitive conditions: if the

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marginal value of additional capital in the future does not depend on the investment decision taken in the present, the option value disappears.

Formally, the irreversibility literature describes investment behaviour as the solution to stochastic control problems. In order to trigger immediate commitment, the expected returns of an irreversible investment project must surpass a threshold value that is not only higher than the standard costs of capital but also – as any option value – an increasing function of risk. The irreversible investment theory has various implications which are highly relevant for policymakers. The model explains why the user costs of capital do not appear to have much influence on investment demand in many empirical investigations; neither in the aggregate nor on the firm level.[1] Changes in the user costs are relevant only for those firms which happen to be near their individual investment threshold, but not for the mass of firms operating below that threshold. Furthermore, the model predicts an attitude of "wait and see" even in the face of high expected returns when the economic environment is ambivalent and uncertain.

A different conclusion is reached by the literature stressing the convexity of the marginal product of capital, as in Abel (1983) and Hartman (1972, 1976). If variable factors, such as labour, energy or raw materials can be optimally adjusted *after* demand uncertainty is resolved, marginal returns of capital are not linear in product prices any more – the functional relationship will be convex, and Jensen's inequality makes *expected* profits an increasing function of risk, given optimal adjustment.

The deeper truth behind this result is that risk also contains an element of opportunity. By suitably adapting to the various possible situations *after* a commitment has taken place and uncertainty is resolved, the investor can systematically put a higher weight on favourable outcomes. In a way, this proposition is the mirror image of the irreversible investment argument. Whereas the latter stresses the importance of irreversibility for the *opportunity cost* of capital goods, the former conversely insists on the beneficial effect that free and unconstrained use of the complementary factors have on the expected *returns* in the face of uncertainty. This again indicates a lesson for economic policy: on the importance of individual flexibility for investment, be it with regard to the allocation of capital goods or the use of complementary factors.

Still, the Hartman-Abel argument renders the sign of the relationship between uncertainty and investment indeterminate. Depending on the type of project, the technology of the firm, its market power, and the stochastic nature of the relevant shock variable, different effects of

[1] See, for example, Chirinko, Fazzari and Meyer (1999). Harhoff and Ramb (2001) find a somewhat higher price elasticity of capital demand for the Bundesbank data set.

increased uncertainty are conceivable. In general, uncertainty can act as a deterrent from investment, be neutral or even create new incentives, see Dixit and Pindyck (1994, Chs. 6 and 11), Darby, Hughes Hallet, Ireland and Piscitelli (1999), or Böhm, Funke and Siegfried (2001).

Empirically, it is not easy to test an isolated hypothesis on the effect of uncertainty on investment expenditure. In general, for a given firm or sector, several mechanisms will be at work simultaneously. Even in the conceptually clean world of economic models, abstracting from risk aversion and endogenous costs of capital, it is hard to disentangle the separate aspects of the problem. The situation is much worse empirically, when many of the underlying determinants cannot be observed. A more modest strategy therefore consists in trying to pin down the net effects of uncertainty on investment behaviour, and at the same time gathering information on what kind of uncertainty is most important for investment decisions.

2. Related Empirical Literature and the Bundesbank Data Set

Attempts to investigate the effects of uncertainty on investment empirically are relatively recent. There are some disadvantages in using the more easily accessible aggregate data. First, most shocks relevant for investment decisions are firm specific, and are smoothed out in the aggregate. Macroeconomic or sectoral data thus might mismeasure uncertainty. Second, aggregation also conceals the *reaction* of firms to uncertainty. Caballero and Engel (1994) and Bertola and Caballero (1994) discuss the dynamics of aggregate investment if individual behaviour is guided by threshold behaviour, as is described by the more recent literature on investment and uncertainty. Even if firms undertake sporadic bursts of investments in order to keep their capital stock between an upper and a lower threshold, aggregate investment behaviour will be smooth and autocorrelated with low adjustment rates.[2]

The author is aware of only five publications that investigate the significance of uncertainty using firm level data: Leahy and Whited (1996), Minton and Schrand (1999), and Driver, Yip and Dakhil (1996) using data on US firms, Guiso and Parigi (1999) working on a panel of Italian companies, and Patillo (1998) utilising a panel of Ghanaian firms. In addition, however, there is a growing number of unpublished research papers. Among these are Bloom,

[2] The intuitive reason for this has already been mentioned above. It has to be conceded that there is a similar problem in using firm level investment data, since these are aggregates of plant level investments themselves. Bloom, Bond and van Reenen (2000) work out this problem theoretically and empirically: threshold behaviour will not be observed on the firm level, but it still plays a crucial part in determining the investment dynamics. Nevertheless, aggregation will be much less of a problem using firm level data, and our data set contains many very small firms.

Bond and van Reenen (2000) using data on companies quoted on the UK stock market; Peeters (1999) investigating a panel of Belgian and Spanish firms; Bo (1999) investigating Dutch firms; and Lensink and Sterken (1998) working on Czech firms. The forthcoming publication of Böhm, Funke and Siegfried (2001) identifies a *positive* uncertainty-investment link in a sample of 70 large listed German corporations, which turns negative for firms in very concentrated industries. Some of the other papers also produce ambiguous results. See Carruth, Dickerson and Henley (2000) for a recent survey of the empirical literature.

The Bundesbank's corporate balance sheet database constitutes the largest collection of accounting data for non financial firms in Germany. A detailed description is contained in Deutsche Bundesbank (1998), see also Friderichs and Sauvé (1999), and Stöss (2001). The collection of financial statements originates from the Bundesbank's function of performing credit assessments within the scope of its rediscount operations. Every year more than 70,000 annual accounts are collected, on a strictly confidential basis, by the Bundesbank's branch offices. Following checks and corrections for errors, they constitute the corporate balance sheet database. According to the turnover tax statistics, it represents roughly 75% of the total turnover of the West German manufacturing sector, albeit only 8% of the total number of firms.

Unfortunately, not all of these data can be employed in estimation. In order to maintain comparability, we limit ourselves to incorporated private firms. We exclude sole proprietorships and unincorporated partnerships because of differences in accounting rules, as well as all publicly owned enterprises, as the latter might not be profit oriented. Again for reasons of comparability, we only consider West German manufacturing firms, and we confine ourselves to the years 1987 - 1997. Earlier years are affected by the radical regulatory changes in accounting introduced in 1985, triggered by an EU directive on the harmonisation of financial statements. Furthermore, only part of our firm data permit the calculation of a real capital stock using the perpetual inventory method, principally because of missing investment data. In order to generate our uncertainty indicator as described in the next paragraph, we lose four consecutive observations, and still more are needed for Within estimates. After eliminating outliers, our sample still contains 6,745 firms with almost 50,000 observations. This sample is clearly not representative in a strict statistical sense, but it mirrors the west German industrial structure relatively well. Very often, balance sheet data only contain large and listed firms, whereas in our sample the median number of employees is 118, with a large portion of small and medium sized enterprises that make up the core of West German industry. The Appendix gives an overview containing the sectoral composition, descriptive statistics, and details on the variables used.

3. Towards a Measure of Uncertainty

3.1. What Possibilities Are There?

Uncertainty is a quality of investors' mental representation of the world, and it cannot be quantified with the same precision as prices or output. Basically, there are three different ways to construct uncertainty indicators on the firm level. The most direct method is to ask managers about the subjective certainty of their expectations. Primary data are expensive and difficult to obtain. As with all surveys, one has to make sure that the questionnaire is answered by the right person, that it is answered correctly and that it is answered at all. Guiso and Parigi (1999) exploit data on the subjective probability distribution of investors contained in a survey conducted by the Banca d'Italia, and Patillo (1999) uses a similar data set for 200 entrepreneurs in Ghana constructed with administrative help from the World Bank and the UK government. A cheaper alternative is to make use of regular industry survey data. In the course of their transnational study, Caselli, Pagano and Schivardi (2000) compute for each year the standard deviation of the balance of positive and negative answers to the survey questions conducted by the respective national research agency. The same method might be applied to generate sector specific data for the industries of a given country. For inferential purposes, however, we are more interested in firm specific data.

A second approach is to rely on high frequency financial market data and to use volatilities, either of commodity prices or exchange rates, or else of stock prices. The first line of research, exemplified in the paper of Darby, Hughes Hallet, Ireland and Piscitelli (1999), directly quantifies the degree of uncertainty with respect to some crucial economic variables; however, it cannot differentiate between firms. The use of stock market data, as in Bloom, Bond and van Reenen (2000), or Böhm, Funke and Siegfried (2001), assumes a strong form of market efficiency and implicitly equates firms' information on future profits to the information of market participants in general. The volatility of stock prices indicates the frequency with which market participants revise their expectations and therefore might allow inferences on their current degree of subjective certainty. Unfortunately, we do not know much about the relationship between the accuracy of managers' expectations with respect to unrealised investment opportunities, and the ups and downs of a firm's stock market valuation. One disadvantage of this approach is the *a priori* limitation to large and listed firms.

Finally, one can try to generate uncertainty indicators from annual or quarterly financial statements of individual firms, measuring the volatility of operating profits, cash flow and other variables. This is the route which will be taken here. Ghosal and Loungani (1996, 2000), Minton and Schrand (1999), Peeters (1999), and Bo (1999) proceed in the same fashion. Balance sheet or income statement data naturally yield firm specific indicators and thus can exploit the individual variability of a large panel data set, but one still has to find a convincing way to make them time specific as well.

3.2. Two Uncertainty Indicators From Accounting Data

Profit is the difference between sales and costs. For both of these we will construct uncertainty indicators. Let us consider first uncertainty with respect to real sales, S_t. We hypothesise that the logarithm of sales follows an autoregressive process of first order. Furthermore, it may be assumed that the firm is provided with more or less accurate information with regard to the state of the business cycle in the respective sector. This renders the following equation for investors' expectations:

$$\log S_{i,t} = a_i + b \log S_{i,t-1} + q_t^S + e_{i,t}^S \qquad (1)$$

The constant a_i is firm specific and depends on the size of the firm. The AR coefficient b quantifies the persistence of deviations from equilibrium, and its magnitude is thought of as being characteristic for an entire market or sector. The third term, q_t, is a cyclical component. It is time specific, but identical for all firms of a given sector and it will also account for the sectoral growth trend. The last term, $e_{i,t}^S$, is a time and firm specific real sales shock.

Graph 1 about here

This equation is estimated for 78 clusters of firms, constructed by first using two digit sectoral classifications and then the average number of employees as a grouping criterion. The number of firms per year in these unbalanced samples varies between 100 and 300, with a few outliers in both directions. A fixed effects estimator for equation (1) is used and the residuals – being estimates of $e_{i,t}^S$ – are stored. As an uncertainty indicator, finally, the root mean squared error from the residuals in $t-3$ to $t-1$ is calculated:

$$U_{i,t}^S = \sqrt{\sum_{h=t-3}^{t-1} \hat{e}_{i,h}^{S\;2}} \qquad (2)$$

This uncertainty indicator is generated for firms that are represented in our data set with at least 8 consecutive observations. This restriction is necessary because of the loss in degrees of freedom resulting from the inclusion of a firm specific constant in (1). Residuals for the current period are not used, for two reasons. One is structural. When making the investment decision in the course of the current period, the investor does not yet know the outcome at the end of the period. Second, using past shocks greatly alleviates the endogeneity problem.

Graph 2 about here

The indicator in (2) is firm specific, time-varying and forward looking in the following sense: it is assumed that the firm anticipates the dynamic development of its own sector or cluster perfectly. We filter out aggregate volatility, because it might partly reflect the economic downturns in Germany during the years 1992-1997. By doing so, we do not intend to downplay *aggregate uncertainty*, i.e. uncertainty with respect to monetary or fiscal policy or other macroeconomic variables. Quite the contrary: as aggregate uncertainty affects all firms in a given part of the economy simultaneously, multiplier effects are conceivable if firms interact closely. All the key results of the paper, with the exception of the instrumental variables estimations, can be reproduced using an uncertainty indicator generated by performing OLS regressions without time dummies for each firm separately.

Graphs 1 and 2 show the overall distributions of the idiosyncratic sales shock and the resulting uncertainty indicator. As the uncertainty indicator derives from the squares of symmetrically, almost normally distributed shocks, its distribution is skewed to the right, akin to a Chi^2-distribution. The inclusion of q_t in equation (1) has eliminated the business cycle dependence of the indicator, but there remains a broad variability – between firms as well as within firms. This can be seen from the summary statistics in the Data Appendix.

The counterpart of our indicator for sales uncertainty is *cost uncertainty*. We generate a cost variable as follows:

$$\textit{operating costs} = \textit{sales} - \textit{operating profits}, \tag{3}$$

and use output prices as deflators. Of course, operating costs are highly correlated with real sales. Therefore, we generate *orthogonal residuals* by regressing real operating costs on real sales. This is done by estimating the equation

$$\log C_{i,t} = c_i + d_i \log S_{i,t} + e_{i,t}^C \tag{4}$$

separately for each firm that provides at least 8 consecutive observations, using OLS. Here, $C_{i,t}$ denote real operating costs and $e_{i,t}^C$ is a firm and time specific cost shock. The objective, of course, is not to estimate firm specific cost functions, but simply to filter out all direct and indirect linear effects of $S_{i,t}$ on $C_{i,t}$ in order to obtain pure cost shocks. The cost residuals are aggregated in the same way as before, leading to an uncertainty indicator labelled $U_{i,t}^C$.

4. The Estimation Equation

In order to investigate the significance of uncertainty for West German industrial companies, we will not impose too many restrictions. As a benchmark, we derive an accelerator equation from the standard neoclassical model. Then we test whether the inclusion of an uncertainty term has additional explanatory power and try to quantify the net effect.

The model platform corresponds to that used recently by Chirinko, Fazzari and Meyer (1999), Mairesse, Hall and Mulkay (1999), and Harhoff and Ramb (2000). The investor is supposed to maximise the present value of the firm:

$$V = \sum_{t=0}^{\infty} \frac{1}{(1+r_t)^t} \left[p_t f(K_t, L_t) - w_t L_t - p_t^I I_t \right] \rightarrow \text{max!} \tag{5}$$

$$\text{s.t. } K_t = (1-\delta) K_{t-1} + I_t \ , \tag{6}$$

with r_t representing the discount rate, p_t the product price, p_t^I the price of capital goods, K_t the stock of real capital, L_t the labour input, w_t the wage rate, δ the rate of depreciation and I_t real investment. Abstracting from irreversibility, uncertainty, delivery lags, costs of adaptation and taxes, one can transform the maximisation problem as follows:

$$p_t f(K_t, L_t) - w_t L_t - p_t^I K_t + \frac{1-\delta}{1+r_t} p_{t+1}^I K_t \rightarrow \text{max!} \tag{7}$$

for each period. Following Eisner and Nadiri (1968), one can use the generalised CES-function:

$$f(K_t, L_t) = A_t \left[\beta L_t^{\frac{\sigma-1}{\sigma}} + \alpha K_t^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}\nu} , \tag{8}$$

where A_t is productivity and σ and ν are the elasticities of substitution and scale, respectively. For non increasing returns, the first order condition to this static optimisation problem is:

$$f_K(K_t, L_t) = \frac{p_t^I}{p_t}\left(\frac{r_t+\delta}{1+r_t} - \frac{\mathrm{D}p_{t+1}^I}{p_t^I}\frac{1-\delta}{1+r_t}\right), \tag{9}$$

together with a similar equation for $f_L(K_t, L_t)$. The right hand side of (9) defines the user cost of capital, Z_t. Substitution yields:

$$\log K_t = \theta \log S_t + \log h_t , \tag{10}$$

with $\theta = \left(\sigma + \frac{1-\sigma}{\nu}\right)$ and $h_t = A_t^{\frac{\sigma-1}{\nu}} \cdot \left(\frac{\nu\alpha}{Z_t}\right)^{\sigma}$. (11)

The variable h_t depends on the time varying terms A_t and Z_t. The elasticity of capital to sales is unity ($\theta = 1$), if the production function has constant returns to scale ($\nu = 1$), or if its elasticity of substitution is unity ($\sigma = 1$), that is, in the Cobb-Douglas case. A log linear demand equation can also be derived for the case of increasing returns to scale, $\nu > 1$. If the firm is rationed on the product market, it will have to solve a cost minimisation problem. Then we have $\theta = 1/\nu$ in (10) and h_t will be a term that depends on relative factor prices and the CES parameters. In terms of first differences we obtain from (10):

$$\Delta \log K_t = \theta \Delta \log S_t + \Delta \log h_t \ . \tag{12}$$

The first term, $\Delta \log K_t$ is approximately equal to $I_t / K_{t-1} - \delta$. The depreciation rate will be subsumed into the unobservable firm specific latent variable in the estimation procedures below. The change in $\log h_t$ can be represented by time dummies in our regression equation, at least as far as global productivity shocks and changes in the user costs are concerned, and by individual constants in order to catch trends in the course of the firm's technological progress. Individual productivity shocks are confined to the error term of the equation and might create an endogeneity problem.

We assume that the production possibilities are given by the capital stock at the beginning of the current period. We specify a distributed lag in order to account for short term adaptation dynamics and add contemporaneous and lagged real cash flow per unit of capital growth rates of cash flow as further regressors to capture financial constraints and possible effects of expectation formation. Finally, we introduce uncertainty indicators, calculated as described in Sect. 3. In the simple world of the accelerator model, they should turn out insignificant. As a behavioural equation to be estimated, we obtain for company *i*:

$$\frac{I_{i,t}}{K_{i,t-1}} = \sum_{m=0}^{M} \beta_{t-m}^{S} \hat{S}_{i,t-m} + \sum_{n=0}^{N} \beta_{t-n}^{F} \frac{F_{i,t-n}}{K_{i,t-n-1}} + \beta^{U} U_{i,t} + u_{i,t}, \tag{13}$$

with $$u_{i,t} = \alpha_i + \lambda_t + \zeta_{i,t}, \tag{14}$$

where differences of logarithms are denoted by a hat. $U_{i,t}$ is one of the two uncertainty indicators described above, $F_{i,t}$ represents cash flow, $K_{i,t-1}$ is the real capital stock carried over from the end of last period and $u_{i,t}$ is a latent term. It is composed of a firm specific constant α_i, a time specific shock λ_t equal for all firms, and finally an idiosyncratic transitory shock $\zeta_{i,t}$. In this quite general specification, the data are allowed to determine the adaptation dynamics.

5. Sales Uncertainty and Investment Demand

Preliminary analysis recommends a lag length of no more than three years. All results in this paper, however, are robust against variation of the lag length. The Random Effects model is clearly rejected by the Hausman test. Therefore, we limit our inference procedure to the use of variation *within* firms. In Table 1 we present results which eliminate the distorting impact of the latent firm specific variable, but do not yet address the potential endogeneity problem. Columns (1) and (2) contain the Mean Difference (LSDV) and First Difference estimations of the accelerator model *without* uncertainty indicator. Robust standard errors are given in parentheses, allowing for autocorrelation within firms as well as heteroscedasticity in general. Both cash flow and real sales growth are highly relevant for the individual investment decision. The sum of the real sales coefficients may be interpreted as the elasticity of capital demand with respect to output. The value of about 25% is well below the constant returns benchmark of 100%. This result is quite common for within estimates on the firm level. It might reflect a downward bias as a result of measurement errors – because of, e.g., faulty deflators – or non-constant returns to scale.[3] The cash flow variable is also highly significant.

Inclusion of the uncertainty indicator yields a negative coefficient which is significant at the 1% level, for the LSDV estimation as well as for the First Difference estimation, for both lag lengths considered. For a given firm, an increase in uncertainty, as indicated by the root of a

[3] If returns to scale are increasing on an individual level, then either firms are demand constrained, or product markets are imperfect. Furthermore, endogenous growth theory has demonstrated that returns to scale may be constant for a given firm in a given year, but increasing for a group of firms if investment causes externalities. But these questions are outside the focus of this paper.

moving average of squared residuals from a simple panel regression, is associated with a lower level of investment demand. The results do not show us whether this reduction is temporary or permanent. First Difference estimators lead to slightly higher coefficients, which indicates that recent shocks might be more important for the firms than those further back.

The results in Table 1 might be affected by contemporaneous correlation between the residuals of the investment equation and the real sales and cash flow terms. Endogeneity of the uncertainty variable itself is improbable, as the indicator only uses observations up to the period preceding investment.

A common procedure in dealing with endogeneity in the context of panel data is to transform the regression equation by first differencing in order to get rid of the individual specific effect and then to use levels of past observations as instruments for the variables potentially affected by endogeneity. The basic approach was proposed by Anderson and Hsiao (1981). In their seminal article, Arellano and Bond (1991) developed a GMM estimator using a different number of orthogonality conditions according to the number of available lags.

In the estimation problem at hand, this approach has a serious drawback. The uncertainty indicator, $U_{i,t}$, is not contemporaneously correlated with $\zeta_{i,t}$, because it uses only observations up to $t-1$. Yet, after differencing, we have to find instruments for $\Delta U_{i,t} = U_{i,t} - U_{i,t-1}$, because of correlation with the transformed residual, $\zeta_{i,t} - \zeta_{i,t-1}$. The residuals from which the uncertainty indicator are constructed are supposed to form the *unforeseen* part of the movement in sales or costs. Therefore it is difficult to find valid predetermined instruments.

We therefore propose an IV estimator for (13) and (14) that circumvents the need to find predetermined instruments for $U_{i,t}$. An alternative way of purging the explanatory variables of their correlation with the latent individual specific error is to use their own first differences as instruments in the level equation. These do not contain an individual specific effect any more, since it is differenced out, yet they are highly correlated with the levels. The idea of "reversing" the Anderson-Hsiao technique by using differences as instruments for levels, was explored by Arellano and Bover (1995) and Blundell and Bond (1998) in developing the system GMM estimator. All the level variables in (13) can be instrumented this way, with the exception of contemporary real sales and contemporary cash flow, because of potential endogeneity. These two variables are instrumented simply by the average first differences of contemporaneous cash flow and contemporaneous real sales in the relevant cluster of firms.

Table 2 shows the results for IV estimation. The results for the neoclassical sales terms are similar to the estimates in Table 1, whereas the cash flow term turns insignificant. The coefficient of the uncertainty term remains significant with $P = 0.015$, calculated on the basis of robust standard errors, and it is numerically somewhat larger than the estimates in Table 1.

The results have been subject to a large number of robustness checks. Apart from experimenting with various lag lengths and different sample sizes according to the minimum number of observations required for the uncertainty indicator, we used several different ways to generate the uncertainty indicator. We used the Anderson-Hsiao approach to obtain consistent estimates of the AR coefficient. In many cases this leads to extremely high standard errors for the estimated coefficients. Therefore we also used an Anderson-Hsiao estimation for the whole sample, not differentiating between clusters. Furthermore, we estimated (1) imposing $b = 1$ for each cluster, although the unit roots hypothesis is rejected for most cases – see Breitung (1997) on the distribution of the Anderson-Hsiao estimator in the case of unit roots. Finally, we estimated a version of (1) without time dummies using OLS for each firm separately. All these estimates consistently yield negative coefficients for the uncertainty indicator, of quite similar magnitudes to the ones presented. Estimating differential effects for large and small firms using dummy variable techniques does not reveal sizeable differences in the attitude of firms towards risk.

6. Cost Uncertainty and Investment

In this section we test the relevance of cost uncertainty for investment. Again, we estimate a fixed effects model, using both the LSDV and the First Difference estimators. In order to save space, only the results for a lag length of three periods are presented, the estimates for a lag length of two are almost identical. Table 3 can be read as a continuation of Table 1. The first two columns report the results for an estimation using cost uncertainty only, and the two columns on the right hand side refer to an equation that contains both uncertainty indicators at the same time.

Table 3 about here

The first two columns show that cost uncertainty also has a significant negative impact on investment. Compared to the estimations in the preceding paragraph, the absolute value of the cost uncertainty coefficient is higher. However, we have to take into account that the cost uncertainty indicator is less dispersed than the indicator for sales uncertainty. The standard deviation of U_t^S is almost three times the standard deviation of the cost uncertainty indicator, see the Appendix. One standard deviation of the sales uncertainty indicator will lower the predicted ratio of investment to installed capital by about 3.0% of the latter variable's mean, and the respective ratio for cost uncertainty is 3.4%. The last two columns show that the estimations are almost unaltered if the two uncertainty indicators are combined in one equation. Again, we performed a series of robustness checks, which turned out satisfactory in most respects. However, the instrumental variable approach developed in the last section did not lead to consistent results.

7. Conclusion

From a theoretical point of view, the impact of uncertainty on investment is ambiguous. Our empirical investigation demonstrates that in Germany uncertainty in fact does have a systematic impact on investment, which is consistently *negative*. Quantitatively, the estimated effect is moderate, but by no means negligible. An increase by one standard deviation of our indictors for sales uncertainty and cost uncertainty together will lower predicted investment by approximately 6½% of the mean value. The weight of uncertainty with respect to sales and costs seems to be about equal.

The evidence presented in this paper emphasises the significance of irreversibility, financial constraints or outright risk aversion for the capital accumulation decision. It is the Hartman-Abel effect that renders the relationship between uncertainty and investment theoretically indeterminate. This effect needs a variable factor that can be costlessly adjusted *after* investment has taken place and uncertainty has been resolved. In Germany, given the high short term complementarity between labour and capital in the manufacturing sector and the substantial firing costs, any such factor will not be labour.

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Data Appendix

Table A1 shows the Industry Composition of our sample.

Table A1 about here

As the estimated equations contain lagged exogenous variable, the number of observations in regressions is reduced to 29,527 or less, depending on the actual specification. The sample covers the West German industrial structure relatively well, also with regard to the share of small and medium sized enterprises. This can be seen from Table A2:

Table A2 about here

Table A3 gives summary statistics for the variables used: the mean, the standard deviations of levels and mean deviations, and the first three quartiles. Table A4 is the correlogram for the variables used in regression.

Table A3 and Table A4 about here

Some definitions and details with respect to the variables follow:

Investment (I): The data on additions to plant, property and equipment come from the detailed schedule of fixed asset movements (*Anlagenspiegel*). The schedule also includes their value at historical costs. Not all firms show their investment data in the *Anlagenspiegel*, and, furthermore, missing investment data and zero investment are coded by the same symbol in the raw data. An extremely cautious procedure was chosen to impute a zero value only in cases where this is logically inevitable, in all other cases the variable is coded as missing.

Capital Stock (K) is computed by adjusting the historic cost values taken from the *Anlagenspiegel* for inflation, and by applying a perpetual inventory procedure with a sector specific depreciation rate for all years following the first year for which historic cost data and investment data are available:

$$P_{j,t}^{I} K_t = (1-\delta_j) P_{j,t-1}^{I} K_{t-1} \left(\frac{P_{j,t}^{I}}{P_{j,t-1}^{I}} \right) + P_{j,t}^{I} I_t \ , \qquad (15)$$

where $P_{j,t}^{I}$ is a sector specific price of investment goods, I_t is real investment and δ_j the sector specific depreciation rate. The starting value is based on the net book value of tangible fixed capital assets in the first observation within our sample period, adjusted for inflation in previous years. Subsequent values are obtained using accounts data on investment and national indices for investment goods prices.

Real Sales (S): This is sales deflated by a sector-specific index for output prices.

Cash Flow (C) is computed as net income plus depreciation, deflated by a sector-specific index for output prices.

Outlier Control: The data set is trimmed by excluding the upper and the lower 1% percentiles of $\Delta \log S$ and F_t / K_{t-1} and the two upper 1% percentiles of I_t / K_{t-1} .

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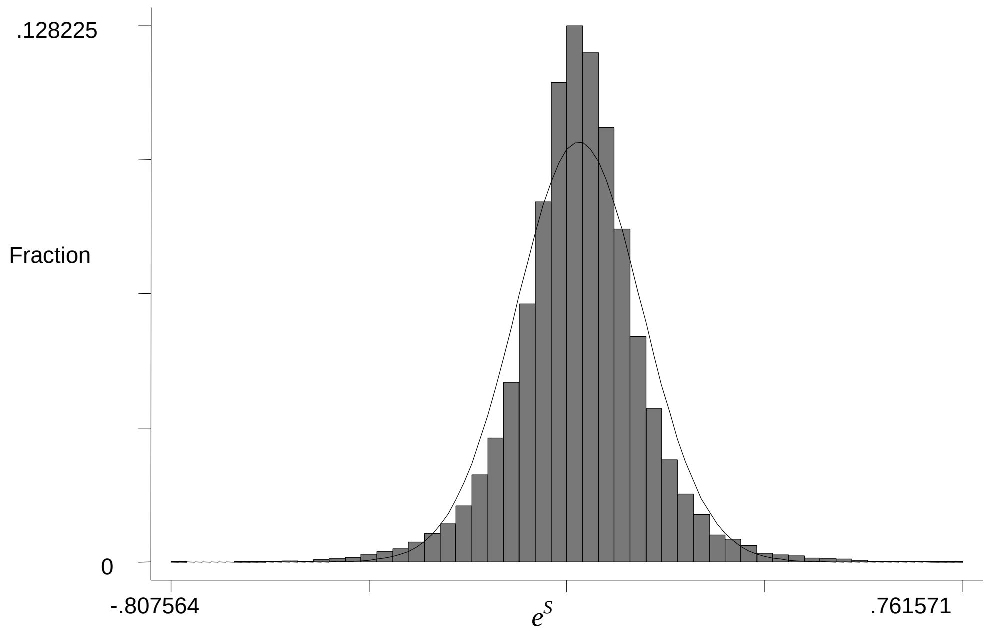
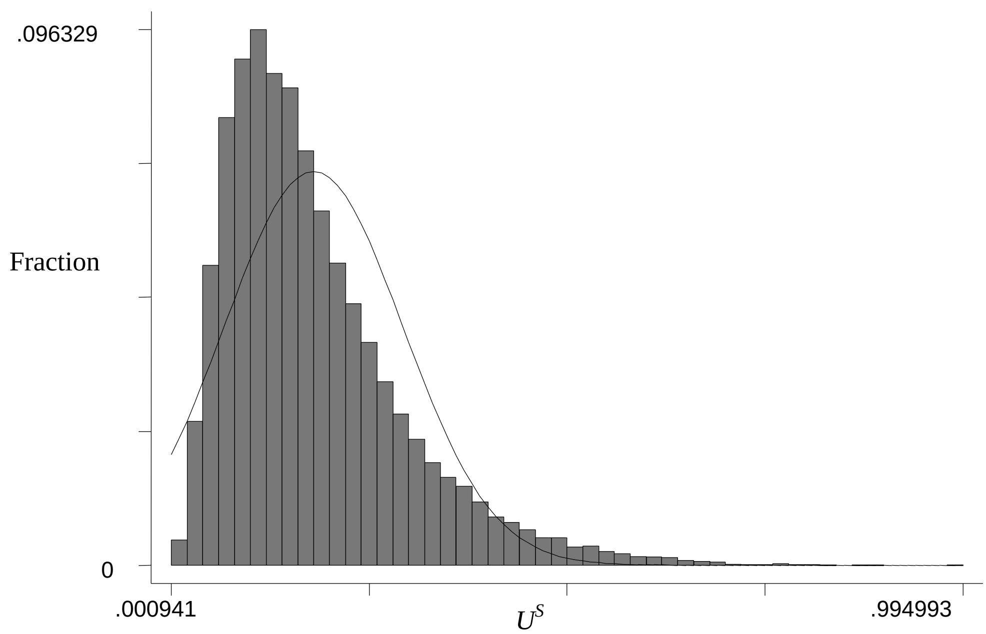


Graph 1: Distribution of Sales Shock from Panel Estimation in Clusters



Graph 2: Distribution of Sales Uncertainty Indicator

Table 1: LSDV and First Difference Estimation with Sales Uncertainty **Dependent variable:** I_t / K_{t-1}						
Variable	**(1)** **LSDV**	**(2)** **First Diff.**	**(3)** **LSDV**	**(4)** **First Diff.**	**(5)** **LSDV**	**(6)** **First Diff.**
$\hat{S}_{i,t}$	0.1122** (0.0095)	0.0615** (0.0109)	0.1127** (0.0095)	0.0617** (0.0109)	0.1101** (0.0092)	0.0569** (0.0103)
$\hat{S}_{i,t-1}$	0.0817** (0.0091)	0.0432** (0.0106)	0.0827** (0.0091)	0.0435** (0.0106)	0.0793** (0.0087)	0.0425** (0.0095)
$\hat{S}_{i,t-2}$	0.0403** (0.0086)	0.0167 (0.0099)	0.0411** (0.0086)	0.0166 (0.0099)	0.0370** (0.0081)	0.0152 (0.0087)
$\hat{S}_{i,t-3}$	0.0106 (0.0086)	0.0049 (0.0095)	0.0112 (0.0086)	0.0056 (0.0096)		
$\sum \hat{S}_{i,t-m}$	0.2448** (0.0249) P<0.0005	0.1262** (0.0302) P<0.0005	0.2478** (0.0249) P<0.0005	0.1274** (0.0304) P<0.0005	0.2265** (0.0189) P<0.0005	0.1146** (0.0218) P<0.0005
$F_{i,t} / K_{i,t-1}$	0.0739** (0.0084)	0.0974** (0.0096)	0.0736** (0.0084)	0.0986** (0.0096)	0.0739** (0.0084)	0.0970** (0.0097)
$F_{i,t-1} / K_{i,t-2}$	0.0417** (0.0072)	0.0418** (0.0074)	0.0417** (0.0071)	0.0426** (0.0074)	0.0422** (0.0071)	0.0350** (0.0066)
$F_{i,t-2} / K_{i,t-3}$	0.0162** (0.0057)	0.0139* (0.0059)	0.0163** (0.0057)	0.0151* (0.0060)	0.0177** (0.0056)	0.0082* (0.0051)
$F_{i,t-3} / K_{i,t-4}$	0.0034 (0.0044)	0.0049 (0.0046)	0.0034 (0.0044)	0.0057 (0.0046)		
$\sum F_{i,t-n} / K_{i,t-n-1}$	0.1353** (0.0130) P<0.0005	0.1580** (0.0149) P<0.0005	0.1350** (0.0130) P<0.0005	0.1620** (0.0151) P<0.0005	0.1338** (0.0122) P<0.0005	0.1401** (0.0137) P<0.0005
U_t^S			-0.0457** (0.0172) P=0.008	-0.0727** (0.0225) P=0.001	-0.0449** (0.0172) P=0.009	-0.0599** (0.0214) P=0.005
No. obs.	29724	23005	29724	22979	29724	26018
No. firms	6745	6053	6745	6053	6745	6604
R^2	0.0790	0.0321	0.0793	0.0327	0.0792	0.0323

Further regressors: year dummies, constant. In parentheses: robust standard errors allowing for autocorrelation within firms as well as heteroscedasticity in general. P-values use robust standard errors. R^2-values relate to variation within firms. ** significant at 1% level; * significant at 5% level.

Table 2: IV Estimation with Sales Uncertainty **Dependent variable:** I_t / K_{t-1}		
Variable	**(1)** **IV in Levels**	**(2)** **IV in Levels**
$\hat{S}_{i,t}$	0.0653 (0.0489)	0.0246 (0.0467)
$\hat{S}_{i,t-1}$	0.1021 (0.0224)**	0.0727 (0.0124)**
$\hat{S}_{i,t-2}$	0.0693 (0.0167)**	0.0455 (0.0112)**
$\hat{S}_{i,t-3}$	0.0382 (0.0147)**	
$\sum \hat{S}_{i,t-m}$	0.2749 (0.0811)** P=0.001	0.1428 (0.0580)* P=0.014
$F_{i,t} / K_{i,t-1}$	0.0181 (0.1062)	0.0909 (0.0652)
$F_{i,t-1} / K_{i,t-2}$	0.0105 (0.0230)	0.0075 (0.0195)
$F_{i,t-2} / K_{i,t-3}$	0.0014 (0.0119)	0.0055 (0.0086)
$F_{i,t-3} / K_{i,t-4}$	-0.0018 (0.0130)	
$\sum F_{i,t-n} / K_{i,t-n-1}$	0.0282 (0.1295) P=0.828	0.1040 (0.0575) P=0.071
U_t^S	-0.0872 (0.0360)* P=0.015	-0.0785 (0.0350)* P=0.025
No. obs.	22979	22979
No. firms	6053	6053
R^2	0.0753	0.0662

Further regressors: year dummies, constant. In parentheses: robust standard errors allowing for autocorrelation within firms and heteroscedasticity in general. R^2-values relate to overall variation. P-values use robust standard errors. Instruments: first differences of real sales (lag 1 to 3), of cash flow per unit of capital (lag 1 to 3), of the uncertainty indicator and of cluster averages for contemporaneous real sales and cash flow per unit of capital. ** significant at 1% level; * significant at 5% level.

Table 3: LSDV and First Difference Estimation with Cost Uncertainty. Dependent variable: I_t / K_{t-1}				
Variable	**(1) LSDV**	**(2) First Diff.**	**(3) LSDV**	**(4) First Diff.**
$\hat{S}_{i,t}$	0.1128** (0.0095)	0.0628** (0.0109)	0.1133** (0.0095)	0.0629** (0.0108)
$\hat{S}_{i,t-1}$	0.0807** (0.0091)	0.0427** (0.0106)	0.0817** (0.0091)	0.0429** (0.0106)
$\hat{S}_{i,t-2}$	0.0387** (0.0086)	0.0153 (0.0099)	0.0395** (0.0086)	0.0151 (0.0099)
$\hat{S}_{i,t-3}$	0.0085 (0.0087)	0.0030 (0.0095)	0.0093 (0.0087)	0.0038 (0.0096)
$\sum \hat{S}_{i,t-m}$	0.2407** (0.0250) P<0.0005	0.1237** (0.0303) P<0.0005	0.2437** (0.0250) P<0.0005	0.1248** (0.0304) P<0.0005
$F_{i,t} / K_{i,t-1}$	0.0747** (0.0084)	0.0982** (0.0096)	0.0743** (0.0084)	0.0994** (0.0096)
$F_{i,t-1} / K_{i,t-2}$	0.0415** (0.0072)	0.0414** (0.0074)	0.0415** (0.0072)	0.0423** (0.0074)
$F_{i,t-2} / K_{i,t-3}$	0.0162** (0.0057)	0.0139* (0.0059)	0.0163** (0.0057)	0.0151* (0.0060)
$F_{i,t-3} / K_{i,t-4}$	0.0035 (0.0044)	0.0051 (0.0046)	0.0035 (0.0045)	0.0058 (0.0046)
$\sum F_{i,t-n} / K_{i,t-n-1}$	0.1358** (0.0129) P<0.0005	0.1586** (0.0149) P<0.0005	0.1356** (0.0130) P<0.0005	0.1626** (0.0151) P<0.0005
U_t^S			-0.0425* (0.0173) P=0.014	-0.0698** (0.0225) P=0.002
U_t^C	-0.1693** (0.0464) P<0.0005	-0.2324** (0.0588) P<0.0005	-0.1612** (0.0465) P=0.001	-0.2250** (0.0590) P<0.0005
Joint significance			P<0.0005	P<0.0005
No. obs.	29724	23005	29724	22979
No. firms	6745	6053	6745	6053
R^2	0.0795	0.0326	0.0798	0.0333

Further regressors: year dummies, constant. In parentheses: robust standard errors allowing for autocorrelation within firms as well as heteroscedasticity in general. P-values use robust standard errors. R^2-values relate to variation within firms. ** significant at 1% level; * significant at 5% level.

Table A1: Industry Composition of the Sample

Industry Classification (SYPRO)	No. of Firms	No. of Observations
Petroleum Raffineries	16	132
Manufacture of Coke and Quarrying	222	1,645
Iron and Steel Production	118	859
Nonferrous Metals	64	495
Foundries	100	724
Metal Forming	284	2,087
Steel Structures	236	1,680
Machinery	1,169	8,726
Road Vehicles	166	1,255
Ships	8	63
Aeronautical Industry	4	32
Electrical Products	385	2,921
Precision and Optical Goods	285	2,119
Ironware and Sheet Metal	526	3,967
Music and Toys	134	944
Chemicals	349	2,629
EDP	19	130
Ceramic Products	70	523
Glassware	75	546
Wood	257	1,813
Wood Products	196	1,406
Cellulose	193	1,444
Paper and Paperboard	50	391
Printing and Duplication	268	1,998
Plastic	444	3,282
Rubber Products	59	455
Leather and Leatherwear	56	453
Textiles	327	2,410
Apparel	208	1,528
Food and Tobacco	448	3,302
Total	**6,745**	**49,959**

Table A2: Size Distribution of Firms by Mean Employment			
n < 20	**20 <n = 100**	**100 < n = 500**	**n > 500**
675	2622	2547	901
10.01%	38.87%	37.76%	13.36%

Table A3: Summary Statistics for Principal Variables							
Var.	**No. of Obs.**	**Mean**	**Std. Dev. Levels**	**Std. Dev. Mean Dev.**	**25%-Percentile**	**Median**	**75%-Percentile**
I_t/K_{t-1}	49959	0.18632	0.22111	0.19255	0.06007	0.12003	0.22303
$\hat{S}_t$	49959	0.02443	0.15581	0.14349	-0.06037	0.02577	0.10963
F_t/K_{t-1}	49959	0.30481	0.52616	0.33850	0.11098	0.19369	0.34507
U_t^S	36500	0.17962	0.11207	0.06250	0.09915	0.15370	0.23250
U_t^C	41774	0.04847	0.03957	0.02191	0.02206	0.03817	0.06261

Table A4: Correlations of Principal Variables					
Variable	I_t/K_{t-1}	$\hat{S}_t$	F_t/K_{t-1}	U_t^S	U_t^C
I_t/K_{t-1}	1				
$\hat{S}_t$	0.1764	1			
F_t/K_{t-1}	0.2197	0.1751	1		
U_t^S	0.0388	0.0166	0.0016	1	
U_t^C	-0.0358	0.0031	-0.0056	0.1674	1