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The Impact of Uncertainty on Investment: A Meta-Analysis

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Abstract

In this paper we perform a meta-analysis on empirical estimates of the impact between investment and uncertainty. Since the outcomes of primary studies are largely incomparable with respect to the magnitude of the effect, our analysis focuses on the direction and statistical significance of the relationship. The standard approach in this situation is to estimate an ordered probit model on a categorical estimate, defined in terms of the direction of the effect. The estimates are transformed into marginal effects, in order to represent the changes in the probability of finding a negative significant, insignificant, and positive significant estimate. Although a meta-analysis generally does not allow for inferences on the correctness of model specifications in primary studies, our results give clear directions for model building in empirical investment research. For example, not including factor prices in investment models may seriously affect the model outcomes. Furthermore, we find that *Q* models produce more negative significant estimates than other models do, *ceteris paribus*. The outcome of a study is also affected by the type of data used in a primary study. Although it is clear that meta-analysis cannot always give decisive insights into the explanations for the variation in empirical outcomes, our meta-analysis shows that we can explain to a large extent why empirical estimates of the investment-uncertainty relationship differ.

Key words: investment; uncertainty; meta-analysis
JEL-codes: C10; D21; D80; E22

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1. Introduction

The relationship between investment and uncertainty has been extensively analysed in both the theoretical and the empirical literature since the 1970s, and the concurrent debate has several central features. One of the most salient is that the theoretical literature is inconclusive about the direction of the relationship. Although many attempts have been made at resolving the issue empirically, they have only added to the existing ambiguity. Given the large number of empirical studies on this topic and the large variation in study outcomes and study characteristics, a thorough synthesis and meta-analysis of the empirical literature is warranted.

An earlier survey on the investment-uncertainty literature is given in Carruth et al. (2000). They provide an excellent overview of issues in the theoretical debate, such as the difference between the various models, the discrepancy between threshold effects and general investment effects, and the influence of market structure. Furthermore, major issues in the empirical literature are discussed, such as the possible consequences of aggregation of data in primary studies and the difference in operational measures of uncertainty. Although the Carruth et al. (2000) study is obviously useful and important in its own right, it is qualitative in nature and does not attempt to quantify the importance of the various primary-study characteristics in explaining primary-study outcomes. Therefore, in this paper we perform a meta-analysis on the relationship between uncertainty and investment spending, in order to summarise and analyse the empirical literature in a quantitative and statistically rigorous fashion. Our analysis is focused on the direction and statistical significance of the primary-study estimates. We estimate two models. The first model is an ordered probit model on a categorical dependent variable. Although this is the standard approach used in performing an analysis on direction and statistical significance (see, e.g., Mulatu et al., 2001; van der Sluis et al., 2005), a disadvantage of this approach is that it discards information on the statistical significance of empirical estimates. In order to solve this problem we estimate a second model, in which we perform a regression analysis based on p-values.

The remainder of this paper is organised as follows. Section 2 presents the theoretical background on the investment-uncertainty relationship. In Section 3 we discuss the type of primary study estimates that are used in this study, we address the sampling procedure that is used to select the estimates for our meta-analysis, and present descriptive statistics on the resulting sample. In Section 4 we discuss the operationalisation of moderator variables. These variables represent differences in primary-study characteristics that may systematically affect the outcomes of a primary study. The models and estimation procedure used for the full blown meta-analysis are presented in Section 5. Subsequently, Section 6 discusses the estimation results. Section 7 rounds off with a discussion.

2. Theoretical background

The theoretical literature on the investment-uncertainty relationship is extensive, has numerous branches and incorporates various analytical frameworks. One of the first models was developed by Hartman (1972). Using a neoclassical model without capital-stock adjustment costs, his study focuses on the relationship between capital productivity and the uncertainty variable. Under convexity of this relationship, by Jensen's inequality, the incentive to produce and invest increases when uncertainty increases, implying a positive relationship. Furthermore, his results show that both uncertainty about output prices and uncertainty about wage rates have a non-negative effect on investment, whereas investment is invariant to uncertainty concerning future investment costs. However, a weakness of this model is that it is restricted to markets with perfect competition. Moreover, it relies on assumptions of constant returns to scale and substitutability of capital for other input factors, which assures that capital productivity is convex in the uncertainty variable. Finally, adjustment costs are assumed to be symmetric, which is equivalent to assuming that capital investments are reversible. In reality, this assumption is obviously violated for most capital investments.

Pindyck (1982) uses a neoclassical model that allows for asymmetric adjustment costs. He argues that the effect of uncertainty on investment spending is dependent on the characteristics of the adjustment cost function, i.e., that uncertainty may increase (decrease) investment when adjustment costs are a convex (concave) function of investment. In contrast, using a variation on the Pindyck model, Abel (1983) suggests that increased uncertainty leads to increased investment spending regardless of the characteristics of the adjustment cost function, thereby confirming the results found by Hartman (1972). However, he also shows that adjustment costs *do* matter for the relationship between investment and Tobin's *Q*.[1] In the *Q*-model of investment (see Section 4.3 for details) the growth rate of investment under certainty is equal to the growth rate of *Q* multiplied by the elasticity of investment to *Q*, whereas under uncertainty the growth rate of capital is smaller (greater) than this quantity if adjustment costs are a concave (convex) function of investment. Uncertainty in the Abel (1983) model thereby has a direct effect on investment, but also an indirect effect through *Q*. It is clear that in this model uncertainty has a positive effect on investment spending whenever adjustment costs are convex. However, the net effect of uncertainty on investment when adjustment costs are concave is uncertain, and hence largely an empirical issue.

A crucial contribution to the investment-uncertainty literature, judged by its dominant position in contemporary thinking, is the concept of capital investment irreversibility (see Pindyck, 1991). For a neoclassical model with asymmetric capital adjustment costs, i.e., a certain degree of irreversibility of capital investment, Dixit and Pindyck show that an increase in uncertainty around future values of relevant economic variables creates an option value of waiting for information to arrive on these vari-

[1] Tobin's *Q* represents the ratio of the marginal value of capital and the market price of capital. Therefore, in this model investment takes place if *Q* is larger than one.

ables in the future. The central point of the irreversibility or real options literature is that an increase in uncertainty will, *ceteris paribus*, result in more investment projects being delayed. Note, however, that although this argument has major implications for the *timing* of investment, it does not have implications for the *level* of investment in the long run.[2] Therefore, we can distinguish between two general branches of research on the investment-uncertainty relationship; a first branch in which uncertainty is related to the timing of investment, and a second branch that analyses the impact of uncertainty on the investment level.

An interesting difference between the two branches is the importance of irreversibility. Although irreversibility is certainly a relevant factor in the second branch (see, e.g., Pindyck, 1982, 1988), it does not have such a dominant position as in the first branch. For instance, where both Pindyck (1982, 1988) and Abel (1983) claim that the characteristics of the adjustment cost function are the main explanation for the differing insights on the investment-uncertainty relationship, Caballero (1991) shows that asymmetric adjustment cost are not sufficient to explain a negative relationship. In contrast, he focuses on the before-mentioned assumptions of perfect competition and constant returns to scale technology. He shows that under decreasing marginal returns to capital, due to either imperfect competition or decreasing returns to scale, the results attained by Hartman (1972) and Abel (1983) also hold in the case of asymmetric adjustment costs. Moreover, in a highly competitive environment, the asymmetry of adjustment costs is virtually irrelevant for the direction of the relationship.

More recent theoretical endeavours also focus on other arguments than irreversibility to show that the investment-uncertainty relationship can be negative. For instance, Nakamura (2002) shows that if the lifetime of capital is shorter than the firm's planning horizon, and under the assumption of decreasing returns to scale, increased uncertainty about the future leads to a decrease in investment spending. Furthermore, in another study by the same author it is claimed that uncertainty reduces investment spending when a firm is risk-averse (Nakamura, 1999). The result holds even under competitive conditions.[3] In a revision of the framework used in the Nakamura study, Saltari and Ticchi (2005) confirm its results but by a different line of reasoning. Their analysis also contains more detail and differentiation. The key result is that the effect of uncertainty on investment consists of two separate effects. The first effect is coined the "flexibility effect", and is basically the standard effect brought about by the convexity of marginal capital productivity in, for instance, prices. The second effect is the "risk-aversion effect" brought about by the entrepreneur's risk aversion. Since the two effects work in

[2] Although in the real options theory the long run impact of uncertainty on the level of investment is uncertain, postponing investment in an uncertain world obviously implies lower investment levels in the short run. For studies that try to unify the timing and level effects of uncertainty see Bar-Ilan and Strange (1999) and Abel and Eberly (1999).

[3] This, in turn, is in contrast to the results attained by Caballero (1991).

opposite directions, the net effect is ambiguous in their model and it depends on the relative magnitudes of both effects.[4]

In conclusion, given the ambiguity of the theoretical literature, there is no theoretical way to determine the *direction* of the relation between investment and uncertainty, let alone inferences on the *magnitude* of the effect and its economic relevance. Various explanatory factors for this ambiguity have been brought forward, some of which have already been touched upon in this section. One of the most obvious sources of heterogeneity is the degree of irreversibility of the investment itself, i.e., the smaller the possibilities to disinvest, the greater the negative impact of uncertainty on investment spending, at least in the short run. A similar argument holds for risk-aversion. The higher the risk-aversion of a decision maker, the smaller the willingness to invest under uncertain circumstances. Other factors that may affect the direction and magnitude of the relationship are underlying market structure (see Hartman, 1972; Abel, 1983; Caballero, 1991; Kulatilaka and Perotti, 2000), the discrepancy between industry-level and firm-specific idiosyncratic uncertainty (see Pindyck, 1993), and financial conditions of the firm (see, e.g., Peeters, 1997; Ghosal and Loungani, 2000). In our meta-analysis we try to control for these factors, in order to investigate whether they contribute to understanding the variation in outcomes of studies.

3. Primary study estimates, sampling procedure and sample characteristics

Empirical studies on investment behaviour generally include a wide variety of explanatory variables in their model specifications. Furthermore, some studies use a non-linear model or some sort of threshold model to investigate the impact of uncertainty on investment spending. For reasons of comparability extensively addressed below, our analysis focuses on studies that linearly relate some sort of investment measure to the level of uncertainty. When we are interested in the magnitude of the investment-uncertainty relationship, an important issue is the comparability of estimates. Specifically, the primary studies display a wide variety with respect to the model specification, i.e., double-log, semi-log and linear specifications are used. The associated problem is that we can only do a sensible meta-analysis on the magnitude of a relationship when estimates are measured in a common metric. Since estimates from double-log specifications can be directly interpreted as elasticities, this means that estimates from primary studies that use semi-log and linear models need to be transformed in order to attain comparable elasticities. For a substantial number of estimates we were not able to do so, implying that an analysis on the magnitude of the investment-uncertainty relationship would severely restrict our dataset. For this reason we decided to focus on the direction and the statistical significance of the primary-study estimates. Such an analysis does not require the transformations discussed above, because both the direction and statistical significance of empirical estimates can be sensibly compared, regardless of the model specification used in the primary study. Moreover, since the theory of investment under un-

[4] See Aizenman and Marion (1999) for an empirical analysis of this issue.

certainty is ambiguous with respect to the direction of the relationship, an analysis on direction and statistical significance provides useful insights.

The primary studies underlying our meta-analysis were collected by searching the literature using the Econlit and Picarta online search engines. Subsequently we made use of reference lists in the papers and articles obtained. Ultimately, we collected 46 studies that empirically analyse the relationship between uncertainty and investment. These studies provided a total of 967 estimates on the relationship under investigation. Although all of these estimates provide useful information on the relationship, some studies and estimates were excluded from the database for reasons discussed below.

First, as suggested by, among others, Abel and Eberly (1999), one of the potential reasons for the theoretical ambiguity on the direction of the relationship is that the relationship can best be characterised by an inverted U-curve.[5] With respect to the scarce empirical literature on this issue, two studies in our sample use a primary model specification in which uncertainty is included both linearly and quadratically (see Lensink, 2000; Bo and Lensink, 2000).[6] This is a problem, since the effect of uncertainty is conditional on the degree of uncertainty. We decided to exclude these 32 estimates from our analysis. Second, some studies use a logit or probit model to estimate the relationship. In these models the dependent variable is either binary or ordered, i.e., the analysis is concerned with estimating a change in the probability that investment actually takes place. As such, the results from these models do not provide information on the change in the level of uncertainty, as is the case with results from the regression models used in the rest of the primary studies. We therefore exclude these studies with a total of 59 estimates from our analysis as well. Third, standard errors or *t*-statistics are essential for constructing our dependent variable, since they are used to calculate the *p*-values of primary-study estimates. Therefore, 24 observations were excluded from our meta-sample, because standard errors or *t*-statistics were not given in the primary study and could not be derived with the available information either. Fourth, 32 estimates provide information on the relationship between investment and an uncertainty measure that was interacted with another variable. Since either the isolated effect of uncertainty could not be extracted, or standard errors for the isolated effect could not be obtained, these observations were excluded. Finally, some studies use alternative endogenous variables, such as the required rate of return or the investment lag (see Hurn and Wright, 1994; Favero et al., 1994). These studies are

[5] One of the arguments for such a pattern is potential risk-seeking behaviour of economic agents over the domain of small losses (see Kahneman and Tversky, 1979). Furthermore, as discussed before, an increase in uncertainty implies both an increase in the trigger value of investment and an increase in the probability of hitting this trigger value. Although it is assumed that the former effect generally dominates the latter, the reverse may be true for low levels of uncertainty. Another possibility is that firms react differently to positive and negative shocks, where the inverted U-curve stems from the notion that negative shocks are generally associated with high uncertainty (see Bo, 2001, p. 100).

[6] Main conclusion from these studies is that uncertainty indeed has a positive effect on investment spending for low levels of uncertainty, and a negative effect for high levels, thereby providing evidence for a non-linear investment-uncertainty relationship.

relevant for studying the investment-uncertainty relationship because they measure the delay of investment instead of the investment level itself. Still, since the dependent variable is the investment lag instead of the level of investment, the outcomes of these studies are incomparable to the outcomes of other empirical studies in our meta-analysis. Therefore, the 30 observations obtained from these two studies were excluded from our analysis.

Ultimately, we arrive at a sample of 790 observations from 39 different studies.[7] Table 1 presents some descriptive statistics on the sample. This table shows that 64% of the estimates is negative. When a further distinction is made between significant and insignificant results, with a critical significance level of 5%, the number of insignificant negative results is approximately equal to the number of insignificant positive results. However, a large difference exists between significant negative and positive results (29% versus 6%).

Table 1: Descriptive statistics on direction and 5% statistical significance (N = 790)

		Count	Percentage	Count	Percentage
Negative:	significant	230	29 %	509	64 %
	insignificant	279	35 %		
Positive:	insignificant	234	30 %	281	36 %
	significant	47	6 %		
Total		790	100 %	790	100 %

4. Operationalisation of moderator variables

In this section we discuss the operationalisation of factors that may affect the investment-uncertainty relationship, most of which have been identified in Section 2. Below we subsequently discuss differences in the measurement of investment (Section 4.1), differences in the measurement and sources of uncertainty (Section 4.2), differences between empirical studies that may have important theoretical implications (Section 4.3), and various remaining empirical differences between primary studies (Section 4.4). Finally, it is clear that there are some sources of heterogeneity in the sample of estimates that we cannot control for. In Section 4.5 we discuss the most important ones and their potential impact on the meta-analysis results.

[7] In Appendix A we provide details on the characteristics of these 39 studies.

4.1 Measures of investment

In primary studies investment is measured at an aggregate level, i.e., no distinction is made between different types of investment. In this respect the measurement of investment is fairly homogeneous across primary studies, with some exceptions. Some studies use a very specific type of investment, such as investment in producer durables or investment in fixed machinery, but across studies the variation along this line is small and too diverse to control for in a meta-analysis. As such, some heterogeneity in the sample, for instance due to the fact that some of these measurement differences represent differences in degree of irreversibility, is not accounted for. However, considering the limited variation in this respect, the impact is likely small in any case. In contrast, there are four distinct ways in which investment is specified in primary studies, i.e.:

- Investment (*I*);
- Investment scaled by capital (*I*/*K*);
- Investment scaled by some measure of income, such as sales or GDP (*I*/*S*);
- Investment measured by the capital to labour ratio (*K*/*L*).

A priori, it is not always clear why and in what way differences in the specification of investment affect primary study estimates. However, one issue stands out. Looking at the partial correlations between estimates and the investment measure, it appears that when investment is measured by the capital to labour ratio, a predominantly positive relationship emerges, in comparison to other investment measures. The interpretation of this result is not straightforward. Although the reported coefficient $\partial(K/L)/\partial U$ is positive in most cases, this does not mean that $\partial I/\partial U$ is positive. If indeed $\partial I/\partial U$ is negative, implying a slower growth or a decline in capital *K*, but $\partial L/\partial U$ is even more negative, then $\partial(K/L)/\partial U$ is positive, disguising a negative investment-uncertainty relation.

Therefore, a positive relationship between uncertainty and the capital-labour ratio may reflect the possibility that labour is affected by uncertainty as well. In the part of the theoretical literature that predicts a positive relationship between investment and uncertainty, capital and labour are assumed to be substitutes, and labour is assumed to be a flexible input factor. However, if hiring of labour is irreversible to some extent as well, for instance as a result of legislative protection of employees, the framework changes. In this case labour investment may be affected by uncertainty too. Although increased uncertainty may still lead to a decrease in investment in this case, relative factor demand may show a relative increase in demand for capital. Therefore, although these studies do not provide direct evidence on the investment-uncertainty relationship, they provide valuable information on relative factor demand under uncertainty. In our meta-analysis we therefore distinguish between the four measures of investment discussed above.

4.2 Measures of uncertainty

The source of uncertainty in primary studies is not as homogeneous as is the case for investment. We distinguish seven sources of uncertainty, i.e., uncertainty regarding sales/demand/output, profit, output prices, input prices, inflation, exchange rates, stock prices and a rest category with variables such as uncertainty on government expenditures. It is interesting to investigate whether differences in the relationship appear along this line, since according to the theoretical literature uncertainty from different sources should have a similar impact on investment spending.[8]

Furthermore, there is no clear consensus in the literature on how to construct a good proxy for uncertainty. The main reason is that underlying the method of measuring uncertainty are assumptions regarding the expectation formation process of decision-makers. As a consequence, several measures are used in primary studies. Most of the empirical studies on the investment-uncertainty relationship use historical data on the variable under investigation to create an uncertainty proxy. They either take the unconditional standard deviation of a series or they use a more complicated prediction model in order to take out the ‘predictable’ part of a time series.[9]

An important criticism with respect to using historical data to measure uncertainty is that uncertainty is essentially a forward-looking phenomenon. Since historical data are by definition backward looking, they are not optimal for measuring uncertainty. A first option to create a more forward-looking uncertainty measure is to use market measures of risk, such as the risk premium embedded in the term structure of interest rates (see, for instance, Ferderer, 1993a). Another, more popular approach is to ask entrepreneurs or economists for their subjective evaluations of uncertainty. Six of the articles in our database use such a subjective uncertainty measure, thereby avoiding the inherent theoretical problems with historical data, and having to make assumptions on the expectations formation process. For example, Guiso and Parigi (1999), Pattillo (1998) and Lensink et al. (2000) use a survey in which entrepreneurs are asked to give a probability distribution of the development of expected sales over some period.[10] Obviously, such a measure comes closest to the ideal of individual perceived uncertainty.

Ultimately, we create a dummy variable to account for the difference between studies using historical data and studies using subjective evaluations of uncertainty. For a second dummy variable on the measurement of uncertainty a further distinction of studies using historical data is made. It ac-

[8] For empirical analyses on the differential impact of different sources of uncertainty, see Koetse et al. (2006) and Huizinga (1993).

[9] In the latter case, usually an ARCH (see, e.g., Episcopos, 1995) or a GARCH (see, e.g., Huizinga, 1993) model is applied to take out the ‘predictable’ autoregressive part of a series. A third option is to estimate an ARMA model (see, for instance, Goldberg, 1993). Ultimately, the choice for a specific model depends on the assumptions of the expectation formation process by investment decision makers.

[10] See Ferderer (1993b) and Driver and Moreton (1991) for alternative approaches to measure subjective uncertainty.

counts for differences between studies using the unconditional variance of a series, and studies that use some form of prediction model to take out the predictable part of a series and subsequently use the conditional variance as their proxy for uncertainty.

4.3 Theoretical issues

The empirical studies on investment can roughly be classified in two groups on the basis of the underlying theoretical models. The first model, discussed extensively in Jorgenson (1971), is the accelerator model of investment. In this model investment spending is driven by income or sales. These models include sales or GDP as an explanatory variable (depending on the level of data aggregation). The second distinctive model is the *Q*-model of investment. In this model an investment opportunity is related to Tobin's *Q* (see Tobin, 1969; Cuthbertson and Gasparro, 1995). Investment takes place if marginal *Q*, the ratio of the marginal value of capital and the market price of capital, is larger than one. Since Tobin's *Q* is a marginal quantity, and it is therefore difficult if not impossible to measure, most empirical studies use the average *Q*, which is measured as the ratio of the market value of a firm to the replacement costs of its assets. Since stock prices, and therefore *Q*, reflect expected future profits, the *Q*-model has an additional feature above and beyond the standard neoclassical investment model in that it incorporates expected future profits into current investment decisions. However, the main issue of interest for our purposes is that, as *Q* represents the market value of capital, it should incorporate uncertainty. Therefore, an important remaining question is whether explicitly accounting for uncertainty has power in explaining investment behaviour above and beyond *Q*.[11]

Apart from these distinctive investment models, there are various variables, such as factor prices, that may be important explanatory variables in investment models. Furthermore, the theoretical models used by Abel (1983) and Caballero (1991) imply that there is a positive relationship between investment and 'idiosyncratic' uncertainty for firms with constant returns to scale technology operating in a competitive environment. Conversely, Pindyck (1993) notes that if uncertainty is identical for all firms in an industry, it will be more difficult to disinvest than if only a single firm experiences increased uncertainty. He subsequently shows that industry-wide uncertainty has a negative impact on investment spending, even under perfect competition and constant returns to scale. However, under alternative assumptions, idiosyncratic uncertainty may be just as important for investment decisions. In fact, in an empirical investigation using firm-level data, the results in Bo (2002) suggest that idiosyncratic uncertainty has a negative impact on investment and is more important than aggregate uncertainty measures. Since it is difficult to distinguish between the two sources of uncertainty in empirical research, mainly due to data-related constraints, empirical studies that distinguish explicitly between industry-wide and idiosyncratic uncertainty are scarce. However, in our meta-analysis the differential effect of these two uncertainty measures will largely be picked up by the distinction between different

[11] See, among others, Bo (2001) for an extensive discussion and empirical investigation of this issue.

levels of data aggregation. Unfortunately, this distinction may reveal other effects of data aggregation on the estimates as well, thereby obscuring the effect of the differences mentioned above.

4.4 Operational issues

This section describes the operational differences between the studies included in our meta-database that may influence the outcome of the study. Some of these differences may reflect numerous issues. For instance, regional differences may reflect differences in sector composition, degree of competition, institutional settings, etc. The potentially most important operational differences between primary studies are:

- Time period: We include the mid year of the primary data sample;
- Location: Studies using data from the USA, Europe, developing countries and other countries;
- Data type: Cross-section, time-series and panel data;
- Data period: Annual, quarterly and monthly data;
- Estimation method: OLS, GMM, IV, and other estimation methods;
- Joint estimation: Multiple uncertainty sources were included in the primary model specification.

Empirical studies explaining investment behaviour generally include a wide variety of explanatory variables in their model specifications. Among these are capacity utilisation – the argument being that investment will only take place when capacity utilisation is high – human capital, a time trend, tradeflows, a lagged dependent variable to control for autocorrelation, government expenditures, and the financial position of the firm. For each of these variables there are good arguments to include them as explanatory variables in investment models, and most primary studies do. Because we cannot distinguish between well-defined empirical models, we include dummies in our meta-model specification for each of the explanatory variables.

4.5 Remaining sources of variation

It is clear that some sources of heterogeneity cannot be accounted for in our meta-analysis. First, among the moderators of the investment-uncertainty relationship are the degree of irreversibility of investment, the degree of risk-aversion, and assumptions on production factor substitution. Unfortunately, on these issues the empirical literature does not provide explicit information. Investment is generally an aggregate measure, making a direct distinction between different levels of irreversibility impossible. The degree of risk-aversion and the level of factor substitution are also unobservable. The only possible way to account for these sources of heterogeneity is by including fixed effects for specific sectors, or even countries, with different characteristics on the above mentioned dimensions. The problem here is that a sector-specific fixed effect measures the impact of all three sources of heterogeneity. The effect may obviously be caused by various other sources of heterogeneity as well, important ones being differences in the underlying market structure and differences in firm size. Although we would pick up part of the heterogeneity in the sample by including fixed effects, we would not be able to attribute it to a specific source. Moreover, a practical difficulty is that very few studies actually distinguish between sectors at a low level of aggregation. Most studies that use sector level data do so for the entire manufacturing sector, implying that very little sectoral variation is present in the underlying set of primary studies. Because of the latter argument, sector-specific fixed effects are not included in our analysis. Therefore, part of the heterogeneity in the sample of estimates is likely to be left unexplained. However, the fact that primary studies generally use manufacturing data has a potential upturn as well. Within a primary study the differences with respect to the three above mentioned sources of heterogeneity may be substantial. However, since a large part of the studies use similar data, differences between primary studies on these issues are likely small when the number of observations in primary studies are large (which they generally are).

5. Models and estimation procedure

This section discusses the models and the estimation procedure used for our meta-analysis on the direction and statistical significance of estimates from primary studies on the investment-uncertainty relationship. We estimate two different models. The first model is an ordered probit model for which we distinguish between three estimate categories, i.e., negative significant estimates, insignificant estimates, and positive significant estimates. In meta-analyses on the direction and statistical significance of the effect under investigation, using a probit or an ordered probit is standard practice (see, for instance, Mulatu, 2001; Van der Sluis et al., 2005). Although estimation of an ordered probit model has some distinct advantages in terms of clarity of interpretation, we propose an alternative model that does not discard relevant information on the degree of statistical significance of the estimates. This model produces results that we can compare to the results from the ordered probit model. This second model is a regression model in which the dependent variable is again constructed from the *p*-values of the estimates of primary studies, but is kept in a continuous form rather than that is transformed into a categorical variable, as is the case with the ordered probit model. In the next two subsections we discuss these two models. Subsequently, in Section 5.3 we address the estimation procedure used for our model estimations.

5.1 Ordered probit model on a categorical dependent variable

As mentioned above, most meta-analyses in which information on the magnitude of the estimated effect is absent, or in which estimates are simply incomparable in magnitude, deal with this situation by creating a categorical variable that includes the direction and the statistical significance of the estimated effect. We follow this procedure, distinguishing between three estimate categories, i.e., negative significant estimates (y = 0), insignificant estimates (y = 1), and positive significant estimates (y = 2). The model suited for analysing the variation in a categorical variable with more than two ordered categories is the ordered probit model. This model assumes, as does the standard probit model, that there is a latent variable y^* that can be explained by a set of explanatory variables x_i, which may include a constant, such that:

$$y^* = \sum_i \beta_i x_i + \varepsilon , \tag{1}$$

where ε is an error term assumed to be normally and i.i.d. distributed. Assuming y^* itself is unobserved, we only have information on the categorical variable y. In our case y consists of the three categories discussed above. The observed variable y has the following structure:

$$\begin{aligned} y &= 0 \quad if \quad y^* \leq \mu_1 \\ y &= 1 \quad if \quad \mu_1 < y^* \leq \mu_2 , \\ y &= 2 \quad if \quad \mu_2 < y^* \end{aligned} \tag{2}$$

where the parameters μ_1 and μ_2 are estimated by the model. For reasons of simplicity and efficiency, μ_1 is standardised at 0, and the model only estimates μ_2. For notational clarity, let μ_2 be represented by μ from now on. Furthermore, an important assumption is that the underlying latent variable y^* is normally distributed, so that the probability distribution of the observed variable y becomes:

$$\begin{aligned} \text{Prob}(y=0) &= \Phi\left(-\sum_i \hat{\beta}_i x_i\right) \\ \text{Prob}(y=1) &= \Phi\left(\hat{\mu} - \sum_i \hat{\beta}_i x_i\right) - \Phi\left(-\sum_i \hat{\beta}_i x_i\right). \\ \text{Prob}(y=2) &= 1 - \Phi\left(\hat{\mu} - \sum_i \hat{\beta}_i x_i\right) \end{aligned} \tag{3}$$

Note that the interpretation of coefficients from an ordered probit model is not straightforward. A coefficient only conveys information on changes in the probability of finding an estimate in the extreme left and extreme right category. For instance, a positive coefficient implies that the entire distribution has shifted to the right, i.e., the probability of finding a ‘negative significant’ estimate has decreased while the probability of finding a ‘positive significant’ estimate has increased. Therefore, there are two problems in interpretation. First, the coefficients do not convey information on the exact change in the probability of finding a certain estimate. Second, the coefficients do not present direct information on the change in the probability of finding an insignificant estimate. This is the reason why our analysis focuses on the calculation of marginal effects. In our situation a marginal effect represents a change in the probability of finding an estimate in one of the three categories.

5.2 Regression analysis based on p-values

When using an ordered probit approach some of the information on the statistical significance of the relationship is discarded. To see this, note that the assumption that y^* itself is unobserved is not true, since underlying the categories defined for the ordered probit analysis are the *p*-values of the estimates. Therefore, although an analysis on a categorical variable is common practice in economic meta-analysis, it is suboptimal because it discards information on the degree of statistical significance of the estimates. Therefore, in order to make optimal use of the information present in our database, we propose to perform a regression analysis in which the dependent variable is again based on the underlying *p*-values of the primary-study estimates, but which is now defined continuously rather than categorical. Specifically, the basis for our analysis are the one-sided *p*-values of the primary-study estimates, which are restricted to values between zero and one by definition. Compared to our ordered probit analysis, estimates with *p*-values below 0.05 are negative significant, estimates with *p*-values between 0.05 and 0.95 are insignificant, and estimates with *p*-values larger than 0.95 are positive significant. As such, the dependent variable that is based on these one-sided *p*-values contains information that is similar to the information contained in the dependent variable for the ordered probit model.

Not surprisingly, the problems in interpreting the coefficients from the ordered probit analysis are encountered with an analysis on *p*-values as well. Note that estimates from an analysis on *p*-values do not tell us much themselves. Although the estimated coefficients represent changes in average *p*-values, a transformation is needed to get information on changes in the probability of finding a positive or negative, or of finding a significant or insignificant estimate. For the ordered probit model we solved this problem by looking at the marginal effects implied by the model estimates. Therefore, in order to make the results from the two models comparable, we need to transform the estimates from our regression analysis to marginal effects as well. Several steps are needed for this.

First, observe that (one-sided) *p*-values are truncated at zero and one by definition. Therefore, if we estimate a regression model on *p*-values, a potential problem is that the model produces estimated *p*-values that are outside this range. To avoid this problem, we transform the *p*-values to *z*-values. In comparison to the situation for *p*-values, estimates with a *z*-value below –1.96 are negative significant, while estimates with a *z*-value larger than 1.96 are positive significant. Estimates with *z*-values in between these values are insignificant. Ultimately, we perform a regression analysis on the obtained *z*-values.

Second, the coefficients from the regression analysis represent marginal effects on the *z*-values of changes in primary-study characteristics. For instance, the estimated constant is the estimated average *z*-value for a study for which all dummy variables are equal to zero, i.e., the reference case. This may, for example, be a study that uses time-series data, with investment as the dependent variable, and a simple standard deviation of sales in previous periods as the measure of uncertainty. In this situation, the estimated coefficient on, for instance, cross-section data represents the difference between the average *z*-value for the reference study, and a study that is similar but uses cross-section instead of time-series data. In order to obtain the estimated average *z*-value for the latter type of study, we have to add the estimated coefficient on cross-section data to the estimated coefficient for the reference study, i.e., the constant. By applying this procedure we obtain estimated average *z*-values for changes in the primary-study characteristics that we distinguish in our meta-analysis.

The third step consists of transforming the estimated average *z*-values into marginal effects that are comparable to the marginal effects from the ordered probit analysis.[12] For this, we assume that these *z*-values are normally distributed around their estimates. This is in line with the assumptions made in estimating an ordered probit model, which also assumes that the estimated parameters are normally distributed around an estimated parameter with variance equal to one. Using a normal distribution that is centred around the estimated average *z*-values, we can calculate the probability of obtaining a negative significant (y = 0), an insignificant (y = 1), and a positive significant estimate (y = 2), for each of the study characteristics distinguished in the meta-analysis. Identical to the ordered probit analysis we use a 5% critical significance level to calculate these probabilities. In this case the probabilities for the three categories are given by:

$$\begin{aligned} \mathrm{Prob}(y=0) &= \Phi(-1.96-\hat{z}) \\ \mathrm{Prob}(y=1) &= \Phi(1.96-\hat{z})-\Phi(-1.96-\hat{z}), \\ \mathrm{Prob}(y=2) &= 1-\Phi(1.96-\hat{z}) \end{aligned} \tag{4}$$

with $\hat{z}$ being a *z*-value derived from the model estimates. The values –1.96 and 1.96 represent, respectively, the left hand side and the right hand side critical values of the *z*-distribution for a two-sided critical significance level of 5% (remember that the dependent variable in this analysis is the z-value of the primary-study estimates). The marginal effects for a specific study characteristic are now obtained by calculating the change in the probabilities in equation (4) associated with the change in $\hat{z}$ for that study characteristic.

Finally, a difficulty associated with the regression analysis discussed in this section is that standard errors of the computed marginal effects are not readily available. Within the ordered probit analysis the standard errors of marginal effects are obtained by linear approximation using the delta method

[12] Note that the marginal effects of both models are calculated at the mean values of the explanatory variables. For a dummy variable D this means that the marginal effect is a change in the estimate probabilities due to a shift from D = 0 to D = 1, keeping other variables constant at their respective means.

(see Greene, 2003, pp. 674-675). We apply a similar procedure to compute the standard errors of marginal effects that are obtained from the regression analysis on *z*-values. A difference with the ordered probit model is that cut-off values for the three estimate categories are known for the regression analysis, since we know the distribution of the dependent variable.[13]

5.3 Estimation procedure

In analysing the direction and statistical significance of the investment-uncertainty relationship we use a meta-model specification with dummy variables in order to identify potential sources of estimate variation. As is the case for most meta-analyses in economics we will furthermore have to deal with the fact that multiple estimates are gathered from a single study. As shown by Bijmolt and Pieters (2001), a good way to deal with this multiple sampling issue is to estimate a hierarchical level model. However, this model deals specifically with meta-analyses on the size of the effect, and is not applicable to our meta-analysis on direction and statistical significance. We therefore take a different approach and estimate a model with equal weights per study, in which each observation is weighted with the inverse of the total number of estimates that is drawn from the same study (see Bijmolt and Pieters, 2001). This procedure prevents that studies with a large number of estimates have a large influence on the estimation results. The standard errors in our model are estimated using the sandwich estimator (see Williams, 2000; Wooldridge, 2002, Section 13.8.2). This estimator corrects for between-cluster heteroskedasticity by allowing for different error variances of the clusters. Furthermore, it corrects for dependence between observations within a cluster. To account for dependence due to multiple sampling, each study represents a separate cluster.

6. Results

The marginal effects derived from our model estimations are presented in Table 2. With a few exceptions, the signs of the marginal effects from the two models are identical. Furthermore, estimated changes in the probabilities of finding negative significant and insignificant estimates are larger in the second model. Although the model estimates convey comparable information, the marginal effects from second model should be preferred to the first model on a statistical basis, because the model incorporates all available information on the degree of statistical significance of the estimates.

[13] Compare, for instance, the model in equation (3) with the model in equation (4). A detailed description of the procedure applied for computing standard errors of marginal effects from the regression analysis on *z*-values is available upon request from the corresponding author.

Table 2: Marginal effects from an ordered probit analysis on a categorical dependent variable and from a regression analysis on *z*-values (standard errors in parentheses)

	Marginal effects from ordered probit analysis on a categorical variable			Marginal effects from regression analysis on *z*-values		
	$y = 0$	$y = 1$	$y = 2$	$y = 0$	$y = 1$	$y = 2$
			Investment measures			
Investment to capital ratio	.019	–.015	–.004	.100	–.097	–.002
	(.155)	(.124)	(.031)	(.133)	(.130)	(.003)
Investment to sales ratio	–.273**	.158**	.115	–.111	.105	.006
	(.109)	(.052)	(.091)	(.079)	(.072)	(.008)
Capital to labour ratio	–.288**	–.268	.555	–.171**	–.477	.647*
	(.042)	(.410)	(.415)	(.036)	(.393)	(.393)
			Sources of uncertainty			
Input price uncertainty	.003	–.003	–.001	.172	–.170	–.002
	(.170)	(.135)	(.034)	(.426)	(.424)	(.002)
Sales uncertainty	.237	–.205	–.032	.607	–.601	–.006
	(.232)	(.212)	(.022)	(.394)	(.391)	(.004)
Stock price uncertainty	–.004	.003	.001	.265	–.262	–.003
	(.256)	(.202)	(.054)	(.395)	(.393)	(.002)
Profit uncertainty	–.119	.080	.039	.196	–.194	–.002
	(.187)	(.098)	(.091)	(.561)	(.559)	(.002)
Inflation rate uncertainty	–.040	.031	.009	.114	–.112	–.002
	(.187)	(.136)	(.051)	(.344)	(.342)	(.003)
Exchange rate uncertainty	.062	–.050	–.012	.276	–.271	–.005
	(.244)	(.203)	(.042)	(.382)	(.377)	(.005)
Other uncertainty sources	.195	–.170	–.025	.537	–.534	–.003*
	(.235)	(.218)	(.019)	(.396)	(.395)	(.002)
			Uncertainty measures			
Subjective uncertainty	.366**	–.334*	–.032**	.054	–.053	–.001
	(.182)	(.176)	(.011)	(.112)	(.110)	(.002)
Uncertainty with prediction	–.144	.120	.025	–.054	.052	.001
	(.178)	(.153)	(.026)	(.150)	(.147)	(.003)
			Theoretical aspects			
Tobin's *Q* included	.090	–.076	–.014	.139	–.137	–.002
	(.118)	(.104)	(.015)	(.224)	(.222)	(.002)
Accelerator variable included	.116*	–.085*	–.031	.106*	–.101*	–.005
	(.069)	(.047)	(.025)	(.060)	(.055)	(.006)
Wages included	–.259**	.078	.181	–.170**	.114**	.056
	(.082)	(.109)	(.169)	(.042)	(.055)	(.054)
Capital price included	.109	–.092	–.017	.073	–.071	–.001
	(.166)	(.147)	(.020)	(.107)	(.106)	(.002)
Industry level data	–.171	.132	.039	–.115	.111	.004
	(.140)	(.105)	(.038)	(.126)	(.121)	(.006)
Firm level data	–.295**	.178**	.117	–.134*	.126*	.007
	(.119)	(.050)	(.102)	(.076)	(.070)	(.007)

Table 2: *Continued*

	Marginal effects from ordered probit analysis on a categorical variable			Marginal effects from regression analysis on *z*-values		
	$y = 0$	$y = 1$	$y = 2$	$y = 0$	$y = 1$	$y = 2$
Other explanatory variables in primary models						
Time trend included	–.088	.067	.021	–.111*	.106*	.005
	(.108)	(.080)	(.029)	(.065)	(.062)	(.004)
Debt position included	–.170**	.101**	.069	–.149**	.120**	.029
	(.079)	(.036)	(.061)	(.055)	(.038)	(.039)
Stock price included	.422**	–.392**	–.029**	.342	–.340	–.002**
	(.184)	(.179)	(.009)	(.228)	(.228)	(.001)
Size of firm included	.025	–.020	–.005	.163	–.162	–.002
	(.261)	(.215)	(.046)	(.222)	(.221)	(.001)
Governmental expenditures	.235	–.210	–.026*	.214	–.212	–.002**
	(.208)	(.195)	(.015)	(.182)	(.182)	(.001)
Dependent lag included	.117	–.096	–.021	.164	–.161	–.003
	(.126)	(.109)	(.018)	(.130)	(.128)	(.002)
Tradeflows included	–.150	.109	.042	–.038	.037	.001
	(.158)	(.098)	(.062)	(.121)	(.116)	(.005)
Remaining issues						
Cross-section data	.189	–.155	–.034	.129	–.126	–.003
	(.134)	(.114)	(.023)	(.090)	(.087)	(.003)
Panel data	.252	–.217	–.034*	.275**	–.272**	–.004*
	(.166)	(.151)	(.018)	(.125)	(.124)	(.002)
Average year of primary sample	–.021*	.020*	.001**	–.020	.020	.00004
	(.011)	(.011)	(.0004)	(.013)	(.013)	(.00003)
GMM estimation	.102	–.086	–.016	.150	–.148	–.002
	(.156)	(.137)	(.020)	(.122)	(.121)	(.001)
Other estimation techniques	–.225**	.076	.150	–.166**	–.006	.173
	(.082)	(.103)	(.167)	(.037)	(.130)	(.132)
Instrumental variables estimation	.077	–.061	–.016	–.050	.049	.001
	(.152)	(.121)	(.031)	(.138)	(.134)	(.004)
Joint estimation	–.178**	.136**	.042**	–.198**	.189**	.009
	(.064)	(.053)	(.017)	(.071)	(.068)	(.005)

*, ** implies coefficient is significant at 10% and 5%, respectively.

6.1 Measurement of investment and uncertainty

The results show that measurement of investment may have an effect impact on the outcome of a study, although the two models differ with respect to the degree to which this is the case. Most striking in this respect is that the results confirm that for studies using investment measured as the *K*/*L* ratio there is a substantial increase in the probability of finding a positive significant estimate. Although this result tells us little about the direction and significance of the investment-uncertainty relationship itself, it does suggest that hiring of labour is affected by uncertainty as well. We therefore have to consider the possibility that substitution between capital and labour takes place in periods of increased uncertainty. Although the direction of substitution is unclear from our results, it is likely that the source of uncertainty is an important moderator in this respect.

The two models differ regarding the impact of specific uncertainty sources, with the second model producing substantially higher marginal effects. However, in both models the magnitude of the impact of sales uncertainty and other uncertainty sources stands out. Using sales uncertainty in primary models substantially increases the probability of finding a negative significant result than using other sources of uncertainty, *ceteris paribus*. This finding may be explained by realising that sales are generally a more important indicator of economic circumstances, and may therefore have a more substantial impact on investment decision making in firms.[14] The models also differ rather substantively regarding the effect of uncertainty proxy. Whereas the first model finds a large difference between studies that use a backward-looking uncertainty proxy and those that use a forward-looking or subjective uncertainty proxy, the effect found in the second model is substantially smaller.

6.2 Theoretical implications

It has been argued that uncertainty may be captured by Tobin's *Q* (i.e., the shadow value of capital) making it unnecessary to explicitly account for uncertainty in investment models. In contrast, our findings suggest that using a *Q*-model actually increases the probability of finding a negative significant impact of uncertainty on investment spending. Hence, our results suggest that Tobin's *Q* not only fails to incorporate the full impact of uncertainty on investment spending, its omission from primary model specifications may even obfuscate a negative relationship. The magnitude of this effect appears to be relatively limited, however. Furthermore, not including wages, capital prices and an accelerator variable in primary model specifications may cause the estimated effect of uncertainty on investment to be substantially off the mark.

The ordered probit marginal effects show that primary models that use industry- and firm-level data produce more insignificant and positive significant results than studies that use country-level data. Moreover, the effect is stronger for firm-level data. Although the marginal effects are somewhat smaller in the second model, the direction of the probability changes are identical. This finding is in contrast with a claim made in Pindyck (1993), who argues that under industry-wide uncertainty the possibilities to disinvest are smaller than under idiosyncratic or firm-level uncertainty, implying a stronger negative impact of uncertainty on investment spending under firm-level uncertainty. A possible explanation for the discrepancy between our findings and this theoretical claim is that differences in the level of data aggregation may affect study outcomes in ways that cannot be disentangled from

[14] In a monopolistic market, output prices are set by the monopolist and therefore endogenous. In more competitive markets, output prices are close to their marginal cost levels in any case, and therefore less sensitive to external shocks, especially in the short and medium run. Since sales reflect changing preferences and/or general economic changes, they may be of more direct importance in investment decision making.

the effect mentioned above. For example, differences in the degree of irreversibility may average out in aggregate data, leading to different insights on the relationship than those obtained from studies that use disaggregate data. The precise effects of these aggregation issues are therefore unclear.

6.3 Primary-model specification and impact of data type

Next to accelerator variables and factor prices, various other explanatory variables appear to be important in primary model specifications as well. Among others, stock prices, the debt position of firms – providing evidence that financial position of a firm is indeed important for investment decisions – and a time trend appear to be relevant sources of estimate variation. Also, when more than one source of uncertainty is included in the primary model specification the probability of finding an insignificant result increases. This result is plausible if the uncertainty proxies are correlated, in which case including each measure in isolation would produce, on average, more statistically significant estimates of the relationship under investigation.

The type of data used has a strong impact on the outcome of a study. Studies that use cross-section data produce more negative significant and less insignificant results than studies that use time-series data. This holds *a fortiori* for studies that use panel data. There are several possible explanations for this result. An intuitive one is that cross-section data measure the long run impact of uncertainty on investment, whereas time-series data measure short run investment reactions to uncertainty. The argument is that cross-section data incorporate structural changes across countries or industries, whereas the period in time-series data is not large enough to incorporate these changes. Using this line of reasoning, our findings suggest that the impact of uncertainty on investment spending is negligible in the short run, but becomes increasingly negative as time progresses. Another possible explanation is that cross-section data measure changes in investment spending in reaction to more permanent changes in uncertainty. This would also explain the strong impact of panel data, since panel data contain more detailed information on whether changes in uncertainty are permanent or only temporary. Our results give no decisive insight on either explanation.

7. Discussion and conclusions

The impact of uncertainty on investment spending has been heavily debated since the early 1970s. The many theoretical insights developed over the years provide an ambiguous picture on the direction of the effect, and many moderators of the relationship have been suggested. In this paper we investigate the heterogeneity in outcomes of empirical studies by means of meta-analysis. We focus on the direction and statistical significance of the estimated coefficients. The standard approach for such an analysis is to estimate an ordered probit model on a categorical variable. However, a disadvantage of this approach is that it discards some of the available information on the statistical significance of the estimates. We propose an alternative approach in which we estimate a regression model on the z-values of the estimates. For both models we provide marginal effects, or changes in the probabilities of finding a negative significant, an insignificant and a positive significant estimate. Although qualitative results of the two models are similar, the sign and magnitude of the estimated coefficients differ substantially in some cases.

With respect to the theoretical ambiguity regarding the direction of the investment-uncertainty relationship, our results do not provide direct evidence on the question whether the relationship between investment and uncertainty is negative or positive. However, it is clear from the exploratory analysis that very few studies actually find positive results that are statistically significant. This finding is confirmed by our regression analysis. The estimated marginal effects show that the probability of finding a positive significant estimate in primary studies is small. Moreover, with few exceptions, most primary-study characteristics do not have a substantial impact on this particular probability. In contrast, regarding the estimated probabilities on obtaining a negative significant and an insignificant estimate, our results show that there are several relevant sources of variation in empirical estimates.

Although a meta-analysis generally does not allow for strong rejections of theories, or allow for inferences on the correctness of primary model specifications, our results give clear directions for model building in empirical investment research. Not including factor prices in investment models may seriously affect the model outcomes. Furthermore, it has been argued that including uncertainty in *Q* models of investment is unnecessary because *Q* already incorporates uncertainty. We find, however, that *Q* models produce more negative significant estimates than other models, *ceteris paribus*. Failing to include Tobin's *Q* in investment models may therefore obfuscate a negative relationship. The outcome of a study is also affected by the type of data used in a primary study. The difference between cross-section and time series data may reflect differences between the short and long run effects of uncertainty, but may also hint at differences between the effects of permanent and temporary uncertainty.

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Appendix A: Characteristics of the studies included in the meta-analysis

Table A.1: Detailed characteristics of the studies included in the meta-samples

Study	NOBS	Period	Location	Aggregation level	Data type	Data frequency	Tobin's *Q*
Dorfman and Heien (1989)	1	1970-1985	USA	F	C	O	N
Driver and Moreton (1991)	2	1978-1987	UK	I	T	Q	N
Ghosal (1991)	5	1968-1977	USA	C	C	O	N
Aizenman and Marion (1993)	8	1970-1985	Developing countries	C	C	O	N
Ferderer (1993a)	15	1978-1991	USA	F	T	Q	N
Ferderer (1993b)	16	1969-1989	USA	C	T	Q	Y
Goldberg (1993)	174	1970-1989	USA	I	T	Q	N
Huizinga (1993)	73	1954-1989	USA	I	T , C	Q	N
Pindyck and Solimano (1993)	36	1960-1990	Developing countries, Other	C	T , C	A , O	N
Serven and Solimano (1993)	4	1976-1988	Developing countries	C	P	A	N
Aizenman and Marion (1995)	7	1970-1993	Developing countries	C	C	O	N
Episcopos (1995)	5	1947-1992	USA	C	T	Q	N
Ghosal (1995)	12	1959-1986	USA	C	T,C	A , O	N
Price (1995)	3	1961-1992	UK	C	T	Q	N
Bleaney (1996)	8	1980-1990	Developing countries	C	C	O	N
Ghosal and Loungani (1996)	35	1972-1989	USA	I	C	Y	N
Leahy and Whited (1996)	64	1981-1987	USA	F	C	O	Y
Price (1996)	3	1963-1994	UK	C	T	Q	N
Bell and Campa (1997)	15	1977-1989	USA, other	I	C	O	N
Glezakos and Nugent (1997)	4	1960-1990	USA	C	T	Q	Y
Peeters (1997)	50	1983-1993	Spain, Belgium	F	P	A	N
Serven (1997)	16	1970-1990	Developing countries	C	P	A	N
Brunetti and Weder (1998)	3	1974-1989	Various	C	C	O	N
Pattillo (1998)	3	1994-1995	Ghana	F	P	A	N
Serven (1998)	36	1970-1995	Developing countries	C	T , C , P	A , O	N

Table A.1: *Continued*

Study	NOBS	Period	Location	Aggregation level	Data type	Data frequency	Tobin's *Q*
Aizenman and Marion (1999)	6	1970-1992	Developing countries	C	C, P	A , O	N
Darby et al. (1999)	3	1976-1996	USA, Germany, France	C	T	Q	Y
Goel and Ram (1999)	12	1974-1992	12 OECD countries	C	C	M	N
Bo and Lensink (2000)	8	1984-1996	Netherlands	F	C	M	Y
Calcagnini and Saltari (2000)	11	1970-1995	Italy	C	T	Q	N
Ghosal and Loungani (2000)	42	1958-1991	USA	I	C	Y	N
Lensink (2000)	1	1970-1997	Various	C	T , P	A	N
Lensink et al. (2000)	21	1999	Netherlands	F	C	O	N
Ogawa and Suzuki (2000)	36	1984-1993	Japan	F	P	A	N
Goel and Ram (2001)	6	1981-1992	9 OECD countries	C	T , P	A	N
Green et al. (2001)	6	1992-1996	Poland	F	C	M	N
Temple et al. (2001)	16	1972-1992	UK	I	P	A	N
Bo (2002)	16	1984-1995	Netherlands	F	P	A	Y
Henley et al. (2003)	8	1975-1995	UK	F	P	A	N

NOBS: Number of estimates provided by a study
Period: Time period to which primary study applies
Location: Country to which primary study applies
Aggregation level: C = country, I = industry, F = firm
Data type: T = time-series data, C = cross-section data, P = panel data
Data frequency: Frequency of data measurement; A = annual, Q = quarterly, M = monthly, O = one year only or average of multiple years
Tobin's Q: Tobin's *Q* is included in the primary model; Y = Yes, N = No

Appendix B: Meta-model estimates

Table B.1: Estimates from an ordered probit analysis on a categorical dependent variable and a regression analysis on *z*-values (standard errors in parentheses)

	Analysis on a categorical variable (Ordered probit)	Analysis on *z*-values (WLS)
Constant	–.620	–1.097
	(.899)	(1.491)
	Measurement of Investment	
Investment to capital ratio	–.056	–.411
	(.464)	(.522)
Investment to sales ratio	1.008**	.561
	(.511)	(.460)
Capital to labour ratio	2.146**	3.351**
	(1.056)	(1.064)
	Sources of Uncertainty	
Input price uncertainty	–.010	–.592
	(.510)	(1.236)
Sales uncertainty	–.655	–1.889
	(.608)	(1.244)
Stock price uncertainty	.012	–.863
	(.779)	(1.056)
Profit uncertainty	.407	–.663
	(.739)	(1.587)
Inflation rate uncertainty	.126	–.419
	(.606)	(1.097)
Exchange rate uncertainty	–.182	–.989
	(.706)	(1.195)
Other uncertainty sources	–.534	–1.595
	(.606)	(1.114)
	Measurement of Uncertainty	
Subjective uncertainty	–.971**	–.214
	(.481)	(.420)
Uncertainty with prediction	.418	.222
	(.496)	(.600)
	Theoretical Issues	
Tobin's *Q* included	–.257	–.496
	(.318)	(.697)
Accelerator variable included	–.375	–.533
	(.242)	(.354)
Wages included	1.160*	1.428**
	(.630)	(.499)
Capital price included	–.310	–.284
	(.449)	(.383)

Table B.1: *Continued*

	Analysis on a categorical variable (Ordered probit)	Analysis on *z*-values (WLS)
	Theoretical Issues	
Industry level data	.528	.512
	(.448)	(.589)
Firm level data	1.066*	.677
	(.570)	(.420)
	Other Explanatory Variables in Primary Model	
Time trend included	.277	.543*
	(.348)	(.325)
Debt position included	.625*	1.093*
	(.368)	(.616)
Stock price included	–1.114**	–1.025*
	(.523)	(.574)
Size of firm included	–.073	–.560
	(.761)	(.638)
Governmental expenditures	–.632	–.708
	(.533)	(.499)
Dependent lag included	–.343	–.635
	(.350)	(.444)
Tradeflows included	.491	.172
	(.572)	(.578)
	Remaining Issues	
Cross-section data	–.551	–.521
	(.383)	(.364)
Panel data	–.699	–.949**
	(.439)	(.378)
Average year of primary sample	.053*	.054**
	(.028)	(.030)
GMM estimation	–.290	–.536
	(.426)	(.393)
Other estimation techniques	.995	2.020**
	(.643)	(.546)
Instrumental variables estimation	–.232	.220
	(.457)	(.617)
Joint estimation	.558**	.916**
	(.194)	(.304)
R^2 (adjusted)	--	.42
NOBS (DOF)	790 (757)	790 (757)
Log-Likelihood	–523.0	–1582.4
Log-Likelihood restricted	–637.9	–1814.5

*, ** = Statistically significant at 10% and 5%, respectively

Note: Both models are estimated with equal weights per study. Robust standard errors are obtained by applying the sandwich estimator to correct for within-study dependency and between-study heteroskedasticity. For this, each study is defined as a separate cluster.