

On Uncertainty and Investment Rates

With Empirical Analysis of Developed Economies

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Abstract:

This thesis investigates the impact of uncertainty on investment rates. The theoretical and empirical literature on the subject is surveyed before I do an empirical analysis on investment data for 14 developed economies from 1991-2008. There are three main results from this analysis: I confirm the conclusion of most studies that uncertainty overall has a negative impact on investments. I find no evidence of non-monotonicity or even non-linearity in the effect based on the level of uncertainty. This has been found in other recent studies. On the other hand, I explain theoretically and show that there is a non-linearity in the effect of uncertainty on investment based on the direction of stock market price movements the previous year. This has not been investigated before.

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1: Introduction

The impact of uncertainty on investment is important to policy-makers and to private businesses. In the long run, investment rates are a major factor for economic growth, because they lay the foundations for future production. Investments are also strongly pro-cyclical and fluctuations in investment rates are critical drivers of business cycles. Because of this, we need to have a good understanding of the processes determining investment rates in order to lay the right framework for optimal long term investment rates and for managing the business cycle. There are many different factors affecting investments ranging from prospects for economic growth to financial market valuations to legal systems and institutions. One of the factors that are most complex and difficult to understand is uncertainty. How uncertainty regarding future economic circumstances affects investments is thus a very important question. The investment-uncertainty relationship has accordingly attracted considerable interest among economists.

The theoretical literature has identified numerous channels through which uncertainty can affect investments. It can affect expected profits, risk adjustments to required rates of return, information flow to investors and other factors. The sign of the effect through each channel and their relative magnitudes can be affected by factors such as returns to scale, risk aversion, reversibility of investments, expected future path of prices, lags between investment and generation of profits and the generating process of investment opportunities. The sum of all these factors is uncertain. No complete model exists, and partial models come up with different predictions and explanations for both the sign and the magnitude of the investment-uncertainty link. Based on what is known as the real options approach, which emphasizes investment opportunities as a valuable asset in itself and the ability of firms to time their investments optimally, most agree that uncertainty should have a negative impact on investments. However, there are theories that predict the opposite both within this framework and outside it. Uncertainty can increase expected profits through the ability of firms to adjust production, and if firms time investments optimally, the cost of waiting can increase with uncertainty if there is considerable lag from the investment decision is made to the profits start accruing. There are also new theoretical contributions that predict a non-monotonic link under certain circumstances.

A growing number of empirical studies try to answer the questions posed by the theorists. Aggregate cross-country studies and firm-level studies in individual developed economies have mostly lent support to the notion of a negative link. A few have concluded the opposite and some studies have been inconclusive. Notably, a growing literature investigates non-linearities in the link. Two recent studies (Lensink (2002) and Bo and Lensink (2005)) have confirmed the presence of a non-monotonic link that is positive for low levels of uncertainty and negative for high levels. Another study (Antoshin (2006)) has identified non-linearities connected to a number of macroeconomic variables. There are a number of problems with empirical investigations of the investment-uncertainty link. The rather complex dynamics of investments and their numerous determinants is one. Another is the measurement of uncertainty. Some studies handle these issues fairly well, while others have important flaws.

In this thesis I try to explain the link between investments and uncertainty by both surveying existing literature and investigating the link empirically on a dataset of 14 highly developed economies. I provide insight on the link between various theoretical predictions and explanations, and review existing empirical work critically. In the empirical analysis, I investigate the effect of uncertainty on aggregate national investment rates by measuring uncertainty in terms of stock market volatility, exchange rate volatility and interest rate volatility. I also incorporate recent theoretical contributions that lack sufficient testing by checking for non-monotonicities and non-linearities in the relationship between the variables.

The thesis is organized as follows. Section 2 provides an overview of selected parts of the theoretical literature on the investment-uncertainty relationship. Section 3 goes through the issues one faces when investigating the issue empirically. It deals with problems of what data to choose and how to measure uncertainty, as well as introducing the relevant theories of panel data analysis. In section 4, some earlier empirical work is presented. These studies use a variety of data and methods and represent some of the most interesting work on the subject. Section 5 presents the results from my own empirical analysis, and finally section 6 concludes.

2: Survey of the theoretical literature

There are many different theories regarding the relationship between investment and uncertainty. Most are microeconomic in nature and analyze optimal investment spending for individual firms. Some look at the firms' profits as a whole as a function of capital, while others look at the prerequisite economic conditions for investing in a single project to be optimal and a few also look at the probability of such conditions being met, and thus for a firm to invest, in a given time period. One classic strand of literature, initiated by Hartman (1972), analyzes firm profits as a whole and predicts a positive link between investment and uncertainty. The reason behind this positive link starts out with an assumption that the optimal profit function is convex in the relative prices of output to costs. This follows from an assumption that profits are linear in relative prices of inputs and outputs without adjustments, for example given by the following function, where Q denotes quantity, P is output price, C is a weighted vector of input prices and F is fixed costs:

$$\pi = Q(P - C) - F$$

I assume that the firm is a price taker, but that it can adjust quantity produced, or potentially its mix of inputs. With all else equal, if $(P - C)$ increases by Δ , profits will increase by $Q\Delta$. However, the firm is likely to find it optimal to adjust production. If the output price has increased or costs in general have decreased, it is likely to produce and sell more goods. If, in addition, the costs of some of the inputs have decreased compared to others, the firm might be able to change its mix of inputs. This optimization of production will increase profits further, so that an increase of Δ in relative prices will increase profits by more than $Q\Delta$. Conversely, a decrease in $(P - C)$ of Δ will decrease profits by $Q\Delta$ without adjustments, but optimization of production in reaction to the changed circumstances will make the decrease smaller. The profit function is thus convex. Following from Jensen's inequality¹, this makes increased uncertainty in the form of a mean-preserving spread in the distribution of either output or input prices good for expected profits. This increases expected return on capital, causing higher investments given unchanged required rates of return.

¹ For a convex function f , numbers x_i in its domain and positive weights a_i , the following is true:

$$f\left(\frac{\sum a_i x_i}{\sum a_i}\right) \leq \frac{\sum a_i f(x_i)}{\sum a_i}$$

In cases of expectations of convex functions: The expected value of a convex function of x is higher than or equal to the same convex function of the expected value of x .

One notable assumption in this literature is that firms are risk neutral. With risk averse investors, the effect predicted by Hartman seems certain to at least be moderated. Craine (1989) and Zeira (1990) simultaneously seized on this potential shortcoming and built models to incorporate risk aversion. In their models, the sign of the relationship is ambiguous. This ambiguity is intuitive and unsurprising. If expected profits are increasing in uncertainty, there will still be some level of risk aversion at which expected utility of profits start decreasing in uncertainty, and investments with it.

Another important assumption which has been made is that firms face constant returns to scale. Caballero (1991) analyses the effect of level of industry competition on the sign of the investment-uncertainty relationship. In doing so, he effectively analyses the effect of returns to scale as well. Decreasing returns to scale and imperfect competition both have the same central effect of negating convexity and making too much capital worse than too little. Caballero finds that competition level (or returns to scale) is the most important determinant of the sign of investment-uncertainty relationship. Perfect competition and constant returns to scale makes a positive uncertainty-investment relationship more likely, while imperfect competition and/or decreasing returns to scale makes a negative relationship more likely. The level of competition is more relevant to investment by individual firms and not so relevant when considering aggregate numbers. The effect of returns to scale still applies though. These effects are compared and in his model seen together with the nature of the cost of adjusting capital levels.

Hartman assumed convex and symmetric capital adjustment costs. This means that a capital adjustment that is x times larger than another adjustment will have more than x times higher costs, but positive and negative adjustments (investment or disinvestment) cost the same if they are the same size. This stands in contrast to a different strand of literature that emphasizes irreversibility of investments. This is called the real options literature, and builds on the often realistic assumptions that decisions to invest can be delayed, but once investments have been made, they are impossible or at least costly to reverse. Firms and other investors thus require additional criteria to be met before investing. Irreversibility often stem from the industry or firm specificity of capital. If you have invested in an oil tanker, but the oil price drops and you want to sell it, you're unlikely to sell close to the buying price. Another problem here is the 'lemons' problem: The seller of used equipment

knows more about the quality of the product than the buyer, and low quality products thus drive high quality ones from the market as buyers cannot tell them apart (or can only do so at a cost).

In classic theory, a firm will invest if the net present value (NPV) of the project exceeds the investment cost. The real options theory contests this by noting that the opportunity to invest has value on its own and that this value is lost when the investment is made, due to irreversibility and ability to delay. If a firm in year 0 has the opportunity to invest in an irreversible project with stochastic value X , at investment cost K , and the project cannot be delayed, it will do so if $\text{NPV} = X - K \geq 0$. However, if it can delay the project for one year and decide whether to invest then, it must take this flexibility into account. Since the project is irreversible, the flexibility is lost if the investment is made. The investment has two costs: The normal investment costs and the value of the option to invest in one year². The method to find the value of such options is available in financial derivatives theory. To find a formula, a few assumptions are necessary. First, I make the assumption that the project value varies over time and follows geometric Brownian motion (GBM) with drift:

$$dX_t = \mu X dt + \sigma X dz_t$$

where X is the project value, μ is the mean of dX , σ is the standard deviation of dX and z is the increment of a standard Wiener process such that:

$$dz_t = \varepsilon_t \sqrt{dt}, \quad \varepsilon_t \sim N(0,1), \quad E(\varepsilon_i \varepsilon_j) = 0, \quad i \neq j$$

This implies that future project values are log-normally distributed with expectation $X_0 e^{\mu t}$ and variance growing linearly with t (standard deviation growing linearly with the square root of time). This process is chosen because it is the one usually chosen for stock price when pricing stock options. Strictly, one must also assume that the project is tradable in financial markets or that it is possible to create something perfectly correlated with the project through a dynamic trading strategy. The project could for instance be an oil field, with development being the investment decision, and the value could be perfectly

² Another way of understanding this is to view the investment as being in competition with another investment: The same investment in one year. These 'two' investment projects are mutually exclusive, and one can thus only choose to invest in one of them. In this case, normal NPV rules that assume that one can accept all investments that have positive NPV do not apply.

correlated with the oil price. The firm's shareholders must also be perfectly diversified. These assumptions are unrealistic³, but are only necessary to obtain the formula, not to reach the qualitative solutions relevant to this thesis. Given these assumptions, the value of the option to invest in one year follows the well-known Black-Scholes formula (see Black and Scholes (1973)):

$$C(X) = XN(d_1) - Ke^{-rT}N(d_2)$$

$$d_1 = \frac{\ln(X/K) + (r - \delta + \sigma^2/2)T}{\sigma\sqrt{T}} \quad d_2 = d_1 - \sigma\sqrt{T}$$

where $N(\cdot)$ is the area under the standard normal distribution up to d_1 or d_2 , r is the risk free interest rate and T is the time to maturity. δ is known as the dividend yield of the underlying asset: This is the difference in return between the project and a perfectly correlated tradable asset or trading strategy. For stock options, these are the dividends stock holders receive which do not accrue to option holders⁴. The firm will invest now if $NPV = X - K - C(X) \geq 0$. Before, the only impact on uncertainty was its impact through convexity of profit function, returns to scale or discount rate due to risk aversion. Now, it also has a direct impact on the option value, which is positive, as can be seen from the formula. The firm thus requires a higher project value before investing today with higher uncertainty.

With the assumptions above, increased uncertainty can lead to investments being delayed. This means that option value considerations could lead high uncertainty to cause temporary lower investments. How long this can go on depends on how long the investments can be delayed. As T increases, the impact of uncertainty does too. If investments can be delayed infinitely, permanently lower investment rates could result from higher uncertainty. Even if investment decisions can only be delayed for a year or two, it can have important implications for business cycles.

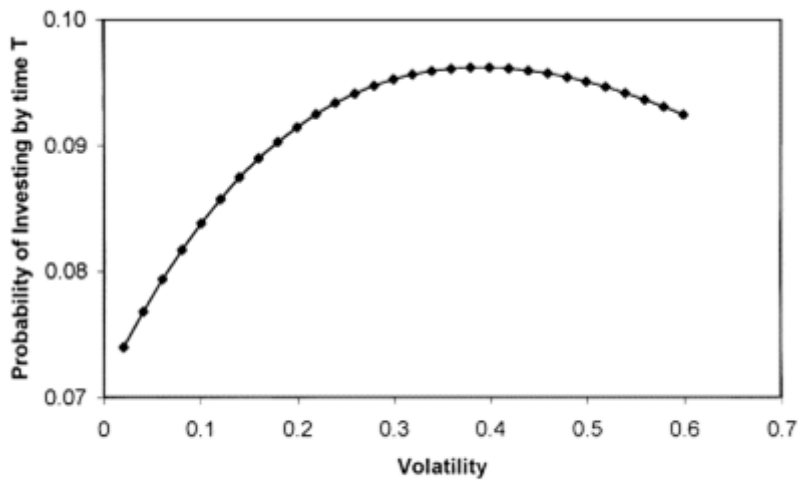
³ For a more realistic and detailed example, see for example Bjerksund and Ekern (1990).

⁴ Holders of a call stock option only receive the stock price minus the strike price (if and when the option is exercised). They only benefit from capital gains and not from dividends, which do not contribute to the stock price. The stock price will be priced to match its risk adjusted required rate of return to the sum of expected capital gains and dividends. The call option price depend on the stock prices, but a negative adjustment must be made based on dividend yield because this boosts stock price but does not increase the value of the option, for given capital gains. The paper by Bjerksund and Ekern also contains a discussion of what dividend yields amount to for investment projects. They represent any shortfall between the return the investment opportunity would have if it was traded and priced in financial markets and the return it has when the price is the investment cost.

It may seem like real options theory can only contribute to the case for a negative investment-uncertainty relationship. This seems to be the conclusion in the early literature, but it has later been challenged. Bar-Ilan and Strange (1996) note that for some projects, especially those with long lags in time between investment decision and project revenues, the option to abandon the project can be more important than the option to delay. This is because abandonment does not need to cost so much, as some or all of the cost of investment may not have been incurred yet, while investment lags also increase the opportunity cost of waiting due to extreme prices being more likely. With both very high and very low price being more likely, the option related to the adjustment that can be executed quickest to take advantage of the price movement is the most valuable. Bar-Ilan and Strange argue that abandonment often is much quicker than investment, and the abandonment option is thus much more valuable with high uncertainty.

Sarkar (2000) accepts the conventional wisdom that the option of future investment is the most important flexibility, but still questions the conventional conclusion. While it is true that increased uncertainty increases the value of the option, and with it the project value necessary for investment, it may also increase the probability of hitting any given project value. This can be illustrated easily: If the project value is 100 and there is no expected growth and no uncertainty, the known future project value is also 100. If the necessary project value to hit is 105, the probability of hitting it is zero. An increase of standard deviation from 0 to 2.5 would increase the probability to approximately 2.5% in one period (with normally distributed growth). The necessary project value will also increase though, because of the increased value of the option to invest, and the overall effect is more difficult to determine. Sarkar creates a model with a project with a perpetual revenue stream x which follows GBM with drift. Following CAPM valuation, the net present value of the project when accepted is then $x/(r + \lambda\rho\sigma - \mu) - 1$ where r is risk free interest rate, λ is market price of risk, ρ is correlation with the market portfolio and μ is mean increase in project value. $(r + \lambda\rho\sigma - \mu)$ is also the projects dividend yield δ , or return shortfall; $r + \lambda\rho\sigma$ is the theoretical required rate of return if the project was a tradable asset while μ is its actual return, leaving a shortfall of $r + \lambda\rho\sigma - \mu = \delta$. Based on normal real options analysis of investment, Sarkar derives a formula for the probability to invest in the project in a given timeframe. However, the derivative of this formula with respect to σ is ambiguous, and

numerical analysis is therefore needed. With numerical analysis, he arrives at the following relationship between uncertainty and probability to invest:



Source: Sarkar, S. (2000), *Journal of Economic Dynamics and Control* 24, page 221.

This graph expressed the probability to invest in the project with revenue stream x by time $T=5$. He has here set expected growth in project value to 0 to focus on uncertainty and not growth (an assumption that is important for his results, as we shall see). Other than that, he has set correlation with the market to 0.7, the market price of risk to 0.4, starting value of x to 0.1, interest rate to 0.1 and investment cost to 1. He finds that probability to invest increases with uncertainty when uncertainty is low, and decreases when uncertainty is high, after peaking around a standard deviation of 0.4. He reports that this result is robust when testing for other parameter values around the base case, but they do vary: The uncertainty-investment relationship is more likely to be positive when (i) the current level of uncertainty is low, (ii) λ is high, (iii) ρ is high, (iv) r is high, (v) μ is low and (vi) T is short. Note that except for the current level of uncertainty, all of these conditions reduce the present expected value of the project at time T .

Lund (2005) reviews Sarkars analysis and points out that his conclusions depend critically on assumed values of his parameters. Higher uncertainty gives higher probability of both high and low outcomes while reducing probability of outcomes close to the expected path. Thus, for a given required value to invest, x^* , the probability of investment will increase with increased uncertainty if x^* is above the expected value of the project, but decrease if it is below. Since x^* is not given, but will in fact rise if uncertainty increases, it must originally be

higher than expected value by some margin for a positive investment-uncertainty link to result from Sarkar's model. In Sarkar's base example, x_0 is 0.1 while x^* varies from 0.104 to 0.485 with σ varying from 0.01 to 0.6. With $\mu = 0$, $E(x)$ is thus 0.1 and lower than x^* for all σ , and considerably so for higher σ . Lund changes some of Sarkar's parameter values to check this and other hypotheses. Keeping Sarkar's other values but choosing $\mu = 0.01$ leads to a very different result. Probability to invest now depends strictly negatively on uncertainty, with probability going to 1 as σ goes to 0. Lund also distinguishes between increases in uncertainty that are correlated with the market portfolio and ones that are not. An uncorrelated increase in uncertainty will increase σ but decrease ρ so that δ is kept constant. This gives higher project values for given values of x , and thus reduces x^* . In a numerical case that copies Sarkar's original case but keeps δ constant, a strictly negative relationship is again obtained. Finally, Lund questions whether one can analyze the effect on investment rates overall by looking at probability of investment for one project by one firm. Projects will have different investment costs, and this introduces non-linearity in the relationship between probability to invest and aggregate investment rate. In the original case, with 3 projects with costs of 1, 2 and 3, total investment increases strictly with higher uncertainty, while the same adjustment in the fixed δ case moderates the negative relationship. In this last case too though, the main factor that affects the relationship between the probability to invest and uncertainty seems to be the difference between expected and required future project values. The new firms that are introduced have higher investments costs than the first one, increasing the required value of the project while keeping expected future values constant. The difference between these variables ($E(x_T) - x^*$) is the key factor affecting Sarkar's results.

There is also the issue of historical prices and the process generating investment opportunities. If an investment opportunity has just been discovered, historical prices will not matter. However, since investment will be made once a price (output price for instance, or project value) breaks through a barrier from beneath, historical prices matter for the stock of existing opportunities. If prices are far below a recent peak, new investments are less likely to take place. Opportunities were not taken when prices were high, and they will not be taken unless prices rise above the previous level, which is unlikely. In this case, high uncertainty is likely to increase probability of investment, as they make extreme price

movements more likely. There is, in other words, a path dependency in the relationship between investment and the growth and volatility of prices. Historical prices matter, but how far back in history one must go is a question of how and when opportunities are generated and how long they can be delayed for, which is a very tough question to answer. This will complicate any analysis.

The theories mentioned above are mostly based on firm-level decision-making. Since my empirical analysis is based on aggregate macroeconomic data, the issue of whether the conclusions are valid for the investment rates of the economy as a whole is important. A theoretical model that takes all the microeconomic theories into account and analyzes their effect on aggregate investment is likely to become too complex to work with. Other empirical studies on the investment-uncertainty link do indicate that there are aggregate effects, but most do not test the theories directly. Bertola and Caballero (1994) construct a hypothetical desired aggregate investment rate for the US from 1954 to 1986 under the assumption of reversible, frictionless investment and compares this to the actual investment data. They find that the frictionless investment data displays far more volatility than the actual data, with a standard deviation of 0.046 compared to 0.017. The smooth nature of US investments can thus only be explained by assuming irreversible investments. The irreversibility of investment means that even though optimal capital levels have big fluctuations from year to year, the capital stocks firms keep have much smaller fluctuations, because it would cost too much to adjust to new optimal levels every period. This study illustrates the importance of irreversibility for aggregate investments as well. In fact, irreversibility could be more important if there are big changes to aggregate optimal capital levels than if these changes happen to individual firms. The reason for this is that it will be much more difficult to sell plants, equipment and other capital goods if everyone else is trying to do the same.

3: Empirical issues

3.1: Data and uncertainty measures

The first empirical issue that comes up is whether to analyze aggregate or firm-specific data. Disaggregate studies have the advantage of more precision and more straightforward applications of most theoretical models. As an example, the real options model with output-price uncertainty can be easily translated to firms in industries with one output with an easily observable stochastic price process, like mining or oil extraction. Aggregate studies can have the advantage of answering important macroeconomic questions more directly. An aggregate slump in investment rate is simply much more important for business cycles and economic growth than industry or firm-specific slumps. Disaggregate studies test theoretical models directly, while aggregate studies test whether conclusions from disaggregate studies stand the test of aggregation. Both types of studies are necessary to investigate the investment-uncertainty relationship.

Since uncertainty is inherently unobservable, any empirical study must decide on which variable it will use as a proxy. This is not an easy question. One must decide what variable one is interested in the uncertainty of and how to actually measure this uncertainty. There is also the question of what is meant by uncertainty; whether total volatility matters or only the part that cannot be predicted.

Many theoretical models deal with output price uncertainty, but firms often have many different outputs, so using this approach empirically can be hard even in firm-level studies. As mentioned above though, there are examples of industries where analysis of output price uncertainty becomes relatively straightforward (oil, mining). In aggregate studies, one would need to find variables that are related to large numbers of output prices. Exchange rates are possible to use, and have been used in many cases. They directly affect output prices for all exports and also have an impact on prices on goods that are produced at home but can be imported. Most theoretical models that deal with output price uncertainty can also deal with cost uncertainty. Interest rate is one cost that applies to most investments, so interest rate uncertainty can also be used. Exchange rates can obviously also directly affect costs of firms that import inputs. Output prices, exchange rates and interest rates each only deal with part of the uncertainty a firm is facing. Stock prices are based on firms' entire future earnings stream. They should thus in theory incorporate all relevant prices and can be

a good variable to use. One problem is that it does not translate easily to theoretical models. The prediction of a theoretical model of increased uncertainty in stock market prices can often be unclear, if the model is based on output prices or costs. In aggregate studies, where the link to microeconomic theory is less direct anyway, it might be seen as the best variable to use. This requires well-functioning, liquid stock markets, though. Another problem is that stock prices do not just fluctuate because of fluctuations in expected profits, but also as a result of fluctuating risk adjusted discount rates for stock market investments. It is unclear whether these fluctuations should have the same effect as expected profit fluctuations. Related is the issue of stock market bubbles and volatility connected to this. In general, when using stock market volatility as a proxy for uncertainty instead of prices that directly affect firms' profit, a broad scope is gained at the cost of a clear causal link.

There are many approaches to measuring the uncertainty of relevant variables. These can be split in two categories: Measurements based on historical data and forward-looking market-based measures. Starting with historical data based measures; the most straightforward is the standard deviation or variance of the variable. If one analyzes annual investment data, the monthly, weekly or daily standard deviation of the variable within the year can be used as a proxy for uncertainty. Alternatively, recursive estimation can be used to measure the volatility up to each point in the time-series. The GARCH-model (Generalized AutoRegressive Conditional Heteroscedasticity) presented by Bollerslev (1986) is a more sophisticated method for measuring changing volatility. The variable, be it stock price, output price or exchange or interest rate, is in the GARCH-model explained by the following equation:

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \varepsilon_t$$

$$\sigma_t^2 = \gamma_0 + \gamma_1 \varepsilon_{t-1}^2 + \gamma_2 \sigma_{t-1}^2$$

where σ_t^2 denotes the variance of ε_t . It is conditional on previous conditional variances and actual errors up to period t. The equations above constitute a normal GARCH (1, 1) model. Further lags of y , σ and ε can be added, as well as a time trend and other extensions. The GARCH-model is very popular for explaining volatility in financial data, because it displays the common phenomenon of volatility clustering. It is useful for creating an uncertainty proxy because it estimates how much historical variance influences future variance. One can use the conditional variance from this model as a proxy for uncertainty. One potential

problem is that GARCH-models work best on high-frequency data (daily or weekly), while investment data are quarterly or annual. If one uses the same frequency of data for the uncertainty variable as the investment variable, as is ideal, the GARCH-model will not fit that well. If one uses higher frequency data of the uncertainty variable to estimate the GARCH-model, the conversion to a quarterly or annual uncertainty measure is not straightforward. A third way to use historical data is to create a model to explain the variable in question and using the forecast errors as uncertainty measures. This captures the notion that only unpredictable volatility should be considered uncertainty. If one is not willing to take great care in creating such models however, they can suffer from misspecification. If superfluous explanatory variables are included, they might still explain some random fluctuation and reduce volatility when they should not. There is also the question of whether it matters if an independent variable contains information about the dependent variable or not; it might have to be included in the predictions of decision-makers to matter. Otherwise, the variation it explains might be perceived as uncertainty.

Forward-looking measures based on market prices take care of both this problem and the problem that historical data do not necessarily reflect the future. An example of a market based measure is the implied volatility derived from option pricing formulae. In its normal application, the Black-Scholes formula mentioned earlier takes stock price, strike price, time to maturity, risk free interest rate, dividend yield and volatility as inputs, and gives the price of the option. Stock price, strike price, time to maturity and risk free interest rate are observable variables (though which interest rate to choose is debatable). Dividend yield can also often be estimated fairly accurately. Volatility on the other hand is harder to measure, as is currently being discussed. Since the price of a stock option is readily observable in the market, one can use that as an input instead of volatility, and compute the implied volatility. This theoretically gives the market perception of the volatility of the stock price and should thus be a good measure of uncertainty. There are a few issues with this too though. The Black-Scholes model is just a model and does not describe reality perfectly. Its assumption of stock prices following GBM is unrealistic: Stock return distributions are not normal, but have negative skewness and excess kurtosis. This deviation of reality from the model is clear when looking at the implied volatilities from stock options with different strike prices. Options that are deep in the money or far out of the money have considerably higher implied volatilities

than options that are at the money⁵. This is a well established property of implied volatilities from the Black-Scholes model and is called a 'volatility smile'. It occurs mainly because of the excess kurtosis, or fat tails, in the actual stock return distributions, that make extreme movements much more likely than modeled by Black and Scholes. The assumption of continuous and costless trading that is strictly necessary to make the Black-Scholes arbitrage arguments work is also unrealistic. Another issue is that, just like for stocks, part of the fluctuations in price is caused by trading, not by changing fundamentals. Black-Scholes derived measures are just examples of implied volatilities. Ferderer (1993) employs the term premium embedded in the term structure of interest rates to measure uncertainty. The risk premium stems from the higher duration of long rates. Duration is the weighted average time until maturity of a bond, but also a measure of the sensitivity of bond price to interest rate change. Thus, longer rates mean higher risk. Ferderer's method of extracting the term premium is based on the term premium theory of the term structure of interest rates. Long rates are assumed to be a weighted average of future short rates plus a risk premium:

$$i_L = (w_1 i_{s1} + w_2 i_{s2} + w_3 i_{s3} \dots) + \theta_L$$

If one can find the expectations of future short rates, one can find the term premium.

Though they do not represent perfect measures of expectations, interest rate surveys can be used for this purpose. The term premium is not the equivalent of any conventional measure of volatility, like the implied standard deviations from the Black-Scholes formula, but is used as a proxy for uncertainty.

Antoshin (2006) suggests that a criterion for choosing between historical and implied volatility could be their relative informational powers. Literature investigating this has mixed results. Canina and Figlewski (1993) study daily call options prices on the S&P 100 index from 1983 to 1987 and find virtually no correlation between subsequently observed volatility and implied volatility. On the other hand, Day and Lewis (1992) and Lamoureux and Lastrapes (1993) find that implied volatility is valuable for prediction, but not necessarily better than GARCH-models. Meanwhile, analyzing currency options, Jorion (1995) finds that implied volatility dominates GARCH and other historical volatility models in predictive power, but also that implied volatility is a biased measure. This bias is contested in several later papers

⁵ A stock option that is 'at the money' has a strike price that is equal to the current stock price. A call option that is 'in the money' has a strike price far below the current stock price and the opposite, a call option with a strike price above the current stock price, is called 'out of the money'.

(Christensen and Prabhala (1998), Ederinton and Guan (2002) and others) which find that implied volatility is an efficient and unbiased predictor of volatility. These studies are all done on daily or weekly data, and on options in deep, liquid markets. As mentioned, GARCH-models are best fitted to high-frequency data. Comparisons on lower-frequency data could thus favor implied volatility, but this is mere speculation. The lack of research on monthly, quarterly or yearly data means that no conclusion can be drawn on whether implied or historical volatility is the best predictor in these cases. In a recent study, Li and Yang (2009) investigates the informational power of the implied volatilities of S&P/ASX 200 index options traded on the Australian stock market from 2001 to 2006. These are traded infrequently and in low volumes. Their finding that implied volatility is a better predictor of subsequent volatility than historical volatility thus provides a defense for their use in relatively illiquid markets.

3.2: Panel data analysis

When modeling investment, one usually wants to analyze data for several countries or firms and across time. There is considerable variation both between firms and countries and over time. Pure time-series or cross-sectional studies thus ignore a lot of information. Time-series analysis of just one country or one firm can hardly lead to general conclusions, while pooled time-series of different countries or firms can potentially lead to considerable bias and loss of efficiency due to heterogeneity of coefficients. If one does not suspect any time or country/firm specific effects, one might simply pool all the data and run a normal regression. Generally though, estimation methods designed for panel data are needed. Panel data analysis can be quite complex, and a short primer on panel data analysis⁶ therefore follows, which is necessary to understand my study and other empirical work. My study will use relatively simple methods, partly as a result of the time-series dimension of my data being greater than the cross-section dimension, but most other studies have large N, small T panels and use complex instrumental variables techniques that will also be presented here. This is done to make the other empirical studies that are presented in section 4 more accessible to readers that do not specialize in econometrics.

A general static panel data model may look like this:

⁶ Parts of this primer follow lecture notes by Øyvind Anti Nilsen from the course 'Topics in Empirical Analysis' at the Norwegian School of Economics and Business Administration (NHH), in 2009.

$$y_{i,t} = \beta_0 + \beta_1 x_{i,t} + a_i + \varepsilon_{i,t}$$

i denotes group (i.e. country or firm) while t denotes time. Both a_i and $\varepsilon_{i,t}$ are error terms. ε is the idiosyncratic error term used in normal regressions, while a is a time-invariant, group-specific error term. It is usually this error term that causes the added complexity in panel data models. There may also be a group-invariant, time-specific error term. A big problem is that there may be correlation between a and x , rendering OLS biased and inconsistent.

A class of models called fixed effects models has several ways of dealing with this. One solution is to first difference the equation.

$$y_{i,t} - y_{i,t-1} = (\beta_0 - \beta_0) + \beta_1(x_{i,t} - x_{i,t-1}) + (a_i - a_i) + (\varepsilon_{i,t} - \varepsilon_{i,t-1})$$

$$\Delta y_{i,t} = \beta_1 \Delta x_{i,t} + \Delta \varepsilon_{i,t}$$

This removes the constant term and the time-invariant error term. There are thus no endogeneity problems as long as the explanatory variables are not correlated with the idiosyncratic error.

Another solution is to introduce $N-1$ group dummy variables (with N groups).

$$y_{i,t} = \beta_0 + \beta_1 x_{i,t} + \delta_1 D^{i=1} + \dots + \delta_{N-1} D^{i=N-1} + a_i + \varepsilon_{i,t}$$

This parameterizes all the variation of a and thus removes it. The third solution is to subtract the mean of each variable.

$$y_{i,t} - \bar{y}_i = (\beta_0 - \beta_0) + \beta_1(x_{i,t} - \bar{x}_i) + (a_i - \bar{a}_i) + (\varepsilon_{i,t} - \bar{\varepsilon}_i)$$

$$y_{i,t}^* = \beta_1 x_{i,t}^* + \varepsilon_{i,t}^*$$

This is called the within group estimator. These three estimation techniques remove the problem created by the time-invariant error term, but also remove a lot of information in the variation between groups.

The explanatory variables and the time-invariant error term do not necessarily correlate. One should still include the unobserved group-effects in the model, but part of the variation between groups can contribute to parameter estimation. The random effects model subtracts part of the mean of each variable:

$$y_{i,t} - \theta \bar{y}_i = \beta_0(1 - \theta) + \beta_1(x_{i,t} - \theta \bar{x}_i) + (a_i - \theta \bar{a}_i) + (\varepsilon_{i,t} - \theta \bar{\varepsilon}_i)$$

$$0 < \theta < 1$$

The percentage of the mean subtracted, the value of θ , increase with the number of time periods T and with the proportion of error variance contributed by the time-invariant term, through the following relationship:

$$\theta = 1 - \sqrt{\frac{1}{1 + T \sigma_a^2 / \sigma_u^2}}$$

As T gets larger, the difference between the random and fixed effects models gets smaller.

Under some additional assumptions, a Hausman test (Hausman (1978)) can be used to test whether a fixed or random effects model is appropriate. The test computes the statistic

$$H = NT(b_0 - b_1)' \text{var}(b_0 - b_1)^{-1} (b_0 - b_1)$$

where b_0 and b_1 are vectors of the coefficients of the fixed and random effects models respectively. The statistic is chi-squared distributed under the null hypothesis that both estimators are consistent. The alternative is that one or both are inconsistent. The idea is that the fixed effects model is consistent, and if one cannot reject the null hypothesis, the random effects model is consistent as well. If so the random effects model should likely be used, as it is more efficient because it has more degrees of freedom (fewer parameters estimated).

Dynamic panel models present additional problems. These contain a lagged dependent variable, contemporaneous and lagged explanatory variables or autocorrelated error terms. The problems arise in the first and third case, and can be illustrated with the simplest model, a simple autoregressive (AR (1)) panel model:

$$y_{i,t} = \beta y_{i,t-1} + a_i + \varepsilon_{i,t}$$

To explore the properties of this model I solve backwards:

$$y_{i,t} = \beta(\beta y_{i,t-2} + a_i + \varepsilon_{i,t-1}) + a_i + \varepsilon_{i,t}$$

$$= (1 + \beta + \beta^2 + \dots)a_i + \varepsilon_{i,t} + \beta\varepsilon_{i,t-1} + \beta^2\varepsilon_{i,t-2} + \dots$$

From this, it is clear that the explanatory variable $y_{i,t-1}$ is correlated with a_i and with $\varepsilon_{i,t-1}$, $\varepsilon_{i,t-2}$ and so on. Maybe the estimation techniques used in the static panel case still work here? I first difference the equation

$$\Delta y_{i,t} = \beta_1 \Delta y_{i,t-1} + \Delta \varepsilon_{i,t}$$

Then I check the correlation between the explanatory variable and the error term:

$$\begin{aligned} \text{Cov}(\Delta y_{i,t-1}, \Delta \varepsilon_{i,t}) &= E(y_{i,t-1} \varepsilon_{i,t}) - E(y_{i,t-1}, \varepsilon_{i,t-1}) - E(y_{i,t-2}, \varepsilon_{i,t}) + E(y_{i,t-2}, \varepsilon_{i,t-1}) \\ &= 0 - \sigma_u^2 - 0 + 0 = -\sigma_u^2 \neq 0 \end{aligned}$$

This clearly does not fix the problem. It is of interest to see what kind of bias this creates:

$$p \lim_{N \rightarrow \infty} \hat{\beta} = \frac{\text{cov}(\Delta y_{t-1}, \Delta y_t)}{\text{var}(\Delta y_{t-1})} = \beta + \frac{\text{cov}(\Delta y_{i,t-1}, \Delta \varepsilon_{i,t})}{\text{var}(\Delta y_{t-1})} = \beta - \frac{\sigma_u^2}{\text{var}(\Delta y_{t-1})}$$

The endogeneity creates a negative bias for the coefficient. Importantly, this bias does not depend on T , and is thus not reduced in panels with large T .

Neither the within group estimator nor the dummy variable approach solve the problem either. The within group estimator is also biased, as there is correlation between the mean and lag of y and the mean of u . Nickell (1981) and Anderson and Hsiao (1981) derive the expression for this bias. It is always negative for $|\beta| < 1$, increases in absolute value when β increases, but it is reduced with higher T , and goes to zero when T goes to infinity. The variable is asymptotically unbiased but can be considerably biased for low values of T and can retain bias for higher T with strong dependence on lagged dependent variables.

Anderson and Hsiao (1982) propose an instrumental variables approach to fix the problems with dynamic panel data. They first difference the equation to get rid of a_i , and then use $y_{i,t-2}$, or alternatively $\Delta y_{i,t-2}$, as an instrument for $\Delta y_{i,t-1}$. These instruments are correlated with the explanatory variable:

$$\Delta y_{i,t-1} = \beta \Delta y_{i,t-2} + \Delta \varepsilon_{i,t-1} = \beta(y_{i,t-2} - y_{i,t-3}) + \Delta \varepsilon_{i,t-1}$$

They are also not correlated with the error term:

$$E(y_{i,t-2}, \Delta \varepsilon_{i,t}) = E(y_{i,t-2} \varepsilon_{i,t}) - E(y_{i,t-2} \varepsilon_{i,t-1}) = 0$$

$$E(\Delta y_{i,t-2}, \Delta \varepsilon_{i,t}) = E(y_{i,t-2} \varepsilon_{i,t}) - E(y_{i,t-2} \varepsilon_{i,t-1}) - E(y_{i,t-3} \varepsilon_{i,t}) + E(y_{i,t-3} \varepsilon_{i,t-1}) = 0$$

This assumes no second order autocorrelation in the error term, as this would introduce correlation between $y_{i,t-2}$ and $\Delta \varepsilon_{i,t}$.

Arellano and Bond (1991) build on the Anderson-Hsiao model by exploiting that $\Delta y_{i,t-1}$ is not just correlated with $y_{i,t-2}$, but also with $y_{i,t-3}$, $y_{i,t-4}$ and so on. They thus use all lagged levels of the dependent variable as instruments for its first difference. They use a generalized method of moments (GMM) approach to achieve this. In GMM, the first stage is a system of linear regressions of the endogenous variables on the instruments. Just like with ordinary method of moments, the sample moments are matched to the moment conditions, but here this is done for a whole system of regressions. The use of more instruments can give the Arellano-Bond model higher efficiency than the Anderson-Hsiao model. The estimators do not only work on the lagged dependent variable, but also on other explanatory variables with serial correlation.

One important problem with many empirical applications of the Arellano-Bond model is that the instruments can be weak. They are based on the correlation between lagged dependent and explanatory variables and the first difference of explanatory variables. If this correlation is low, the instruments are weak, and the estimator is biased. This problem is especially common for variables that are close to random walk. Another potential problem occurs when there are too many instruments and they overfit the endogenous variables. If the instruments fit the endogenous variables too well, they will not cease to be endogenous⁷. This can be a big problem if T is large. The model works best in large N, small T panels. Its efficiency has been proven in simulations when N goes to infinity.

⁷ Even if instruments are not correlated with error terms, they will still predict an explanatory variable that is correlated with the error term if there are enough instruments, if that explanatory variable is correlated with the error term in the first place. Intuitively, if there are as many instruments as observations, the first stage regression predictions will match the endogenous variables perfectly and the final estimators will match those of OLS.

4: Survey of the empirical literature

The number of empirical studies on the investment-uncertainty link was low but has been growing more rapidly since the late 1990's. Most share the main finding that uncertainty affects investment negatively, but they find different effects of uncertainty from different sources, and some identify non-linearities in the link. There are also interesting variations in investment models, estimation techniques, and particularly in the choice of uncertainty measures.

Servén (1998) and Byrne and Davis (2004) investigate the effect on aggregate investment of uncertainty stemming from many different sources (expressed by the volatility of different macroeconomic variables). Servén analyzes data from a large number of developing countries, while Byrne and Davis analyze data from the G7 group of large rich countries. Both create measures of uncertainty from GARCH-models of exchange rates, cost of capital measures, inflation and production growth, while Servén includes terms of trade and Byrne and Davis include stock market prices. They use slightly different estimation techniques and investment models (they differ in which other explanatory variables they include besides uncertainty), which seems warranted due to their different data. Servén, for example, uses a measure of credit flow to the private sector, which is necessary because capital markets in developing economies cannot be assumed to function well. Despite different data and models, they reach two common conclusions: The main conclusion is that uncertainty generally affects investment negatively. The second conclusion is that exchange rate uncertainty has a particularly strong negative effect.

Following up on Sarkar's theoretical work, Lensink (2002) and Bo and Lensink (2005) study non-linearity and non-monotonicity in the investment uncertainty link. To do this, both include their uncertainty measures both as a simple and a quadratic term in their investment equations. The first article studies aggregate data from 17 developed countries while the second studies firm-level data from the Netherlands. They both find that the effect of uncertainty on investment fits Sarkar's model: At low levels of uncertainty the effect of more uncertainty is more investment, but this effect is reversed at higher levels. The models used are a bit different. Bo and Lensink use GARCH-measures of uncertainty, while Lensink uses within-period daily volatility, and while Bo and Lensink use the GMM methods presented by Arellano and Bond among others, Lensink uses more standard methods designed for static

data in his first article. The second paper seems more sophisticated in its estimation techniques and investment models, but there are some potential weaknesses in both articles. In the first, lagged levels of the independent variables are not included, nor is it differenced, even though the variable, investment to GDP ratio, is likely to be strongly autocorrelated. In the second article, the uncertainty measure for year $t+1$ is used to explain investment rate in year t . However, the uncertainty measure is constructed by fitting a GARCH-model to daily data, and then averaging daily conditional variances to get yearly measures. To use conditional variance from GARCH-models one must either measure uncertainty on data with the same time interval as the investment data, or exploit the fact that the conditional variances have autocorrelation and thus that period t conditional variance (which is known when the investment takes place), is a good proxy for conditional variance in period $t+1$. The problem with Bo and Lensinks approach is that daily conditional variances for next year cannot possibly be known now, and thus have no relevance for investment decisions.

The studies described above all use uncertainty measures based on historical data. As briefly mentioned towards the end of section 3.1 of this thesis, Ferderer (1993) employs the risk premium embedded in the term structure of interest rates as his uncertainty measure. The risk premium is isolated by comparing current long interest rates with the consensus forecasts of short interest rates from the Goldsmith-Nagan survey. Ferderer cites two advantages of this uncertainty measure. First, it is forward-looking, so they do not suffer from the “peso” problems associated with backward-looking measures⁸. Second, it may help shed some light on the countercyclical behavior of the term premium, by connecting this with the role uncertainty plays in the business cycle. He also notes that there is empirical evidence of the connection between risk measures based on historical data his measure. For example, Engle, Lilien and Robbins (1987) show a positive relationship between ARCH⁹ measures of interest rate uncertainty and the risk premium embedded in the term structure for US treasury bills. Studying US firm-level investment, he includes his uncertainty measure

⁸ “Peso” problem is a term that stems from the devaluation of the Mexican peso in 1976. Mexican interest rates had curiously been consistently higher than American rates even though the exchange rate was fixed. Holders of pesos seemingly got a free lunch, when their investments were analyzed with historical data. However, the devaluation in 1976 and the losses suffered showed that historical data analysis was not sufficient.

⁹ Engle (1982). GARCH, presented earlier in the thesis is a generalization of the ARCH model.

in two different investment models. One is based on user cost of capital, the other on Tobins Q. He finds a significant negative relationship between uncertainty and investment.

Interestingly, the effect of uncertainty is higher than that of the cost of capital or average Q.

In a particularly interesting paper, Antoshin (2006) studies the effect on investment of uncertainty stemming from different sources. He also studies non-linearities in the investment-uncertainty link, though these are different kinds of non-linearities from the specific one analyzed by Sarkar, Lensink and Bo. In addition, Antoshin's is the only study on investment rates that I am aware of that use implied volatilities from options as uncertainty measures. To achieve all this, he carefully constructs a dataset of 77 publicly traded companies in the US oil sector from 1983 to 2004. As previously noted, the oil sector lends itself to analysis as it has one clear observable output price. He uses implied volatilities from oil futures options as his measure of industry-wide uncertainty. He also creates an economy-wide uncertainty measure from implied volatilities from Treasury bill interest rate futures and a firm-specific uncertainty measure from implied volatilities from stock options. The general effect of these uncertainties is negative, though the effects are not all significant in all empirical specifications. The economy-wide interest rate uncertainty measure has a stronger effect than the others and is always significant. To analyze non-linearities, Antoshin estimates empirical measures of investment-uncertainty sensitivity by dividing change in investment by change in uncertainty measures, for example as given by the following equation: $s_{i,t} = (\text{capex}_{it} - \text{capex}_{i,t-4}) / \text{capex}_{i,t-4} * 100 / (\sigma_{t-1} - \sigma_{t-5})$, where σ is the oil price volatility and capex is capital expenditure. He then studies the effect of a number of industry-wide and firm-specific factors on these sensitivities. He finds strongly significant effects of most industry-wide variables, but mostly insignificant effects of firm-specific variables. High GDP, CPI, and oil prices, as well as lagged oil price volatilities, are found to weaken investment sensitivity to oil price volatility, while high interest rates and lagged interest rate volatilities are found to strengthen the sensitivity.

A natural question arising after reading these and other studies on the investment-uncertainty links is whether the various conclusions from studies using different methods on different data hold in general. If they don't, the follow up questions becomes: When do they hold? More empirical investigation is needed to properly understand this topic. I will try to contribute in the next section.

5: Empirical analysis

5.1: The data

I analyze the effect of uncertainty on investment spending in 14 developed economies from 1991 to 2008. The countries analyzed are Australia, Canada, Denmark, Finland, France, Germany, Italy, the Netherlands, New Zealand, Norway, Sweden, Switzerland, the UK and the US. I choose this category of countries and this time period to get a somewhat homogeneous group. These countries have been relatively similar economically, politically and culturally in the time period chosen. This means that there are fewer unobservable differences in the data that will disturb the correlations I am interested in. The exact choices of years and countries (for instance, why include the Netherlands and France but not Belgium, and why start in 1991 and not 1990) are due to availability of data. For the stated countries and time period, I have managed to create a balanced panel.

To estimate the effect of uncertainty on investment, I estimate investment as a function of uncertainty as well as other relevant variables. The variables I include are real interest rates, GDP growth rates and stock market returns. Real interest rates are included because they are closely related to cost of capital for firms, and are thus closely related to the required rate of return for investment projects. High interest rates thus lead to lower investments. GDP growth rates and stock market returns are included to explain the cyclical variation in investment rates. High stock market returns indicate optimism for the future, while GDP growth has positive autocorrelation and high GDP growth in the recent past makes high growth in the future more likely. Both these factors should induce higher investments.

For investment and GDP, quarterly and yearly data are available. These frequencies are thus my available choices, as well as slower frequencies created by summing yearly data. I choose to analyze quarterly data. This is because most previous aggregate studies have focused on yearly data, leaving quarterly aggregate investment dynamics relatively unexplored. Apart from this, the relative merits of analyzing quarterly or yearly data are debatable. Quarterly investment data are characterized by strong inertia, which will need to be accounted for and reduces variability and thus informational content. However, there is four times more data to make up for this, and there is the added benefit of being able to analyze short term fluctuations that are lost in annual data.

I have used OECDs databases on quarterly national accounts to find investment and GDP data. Gross fixed capital formation (GFCF) is the variable chosen for investment. Quarterly GDP data are utilized to get GDP growth. All of these data are seasonally adjusted and at constant prices. The seasonal adjustments are appropriate, because seasonal growth should not affect investments significantly, as these usually have much longer horizons.

For real interest rates, I have used 3-month interbank rates for all countries, along with expected inflation, both variables taken from Thomson Datastream. Quarterly 3-month interbank data were constructed by taking the average of rates on the first day of each month in the quarter. For expected inflation, adaptive expectations were assumed: The expected inflation rate is the inflation rate in the previous year. Which interest rate to choose is not straightforward. Interbank rates are admittedly not the interest rates most relevant for investments, as firms do not borrow at these rates. Commercial paper rates, investment grade bond rates or bank lending rates might be more relevant. The appeal of 3-month interbank rates are the availability of data and similarity of use in all countries (all countries in question have similar interbank markets, but lending to firms happen through different channels in different countries). The connection from interbank rates through cost of funds for banks to lending and bond rates make them relevant, if not perfect.

Stock market returns are based on the Morgan Stanley Country Indices (MSCI) for all countries, downloaded from Thomson Datastream. Quarterly returns are computed.

I have constructed uncertainty measures from stock market prices, exchange rates and interest rates. I have chosen these variables because of their relevance to investment decisions. Stock market uncertainty reflects uncertainty regarding the general future state of the economy. Interest rates are, as mentioned earlier, a direct cost of most investments, so it's applicability to theory is straightforward. The same is true for exchange rate uncertainty for industries where exports or imported inputs are important. These measures are not completely separate. There is considerable overlap, especially between stock market uncertainty and the other measures, as stock market uncertainty encompasses every factor relevant to the future profitability of firms and also for investments. So theoretically, the effect of uncertainty in the other variables should be captured in the effect of the stock market measure. However, this is unlikely to hold in practice, and I have included the others

because they are important factors that can affect general profitability to a very large extent. The uncertainty connected to interest and exchange rates do in fact have a more direct effect on most firms, and seeing which type of uncertainty – general all-encompassing but indirect stock market uncertainty or direct but narrow interest rate and exchange rate uncertainties – have a larger effect is interesting in itself.

For the stock market measure, the MSCI are again used for all countries. For the exchange rate measure, real effective exchange rates are used. These are trade-weighted measures of the real inflation-adjusted value of a country's currency, and are theoretically what should matter for exports and imports. They might understate the uncertainty though. Individual firms are often exposed to one single currency or a few currencies, and will be vulnerable to the uncertainty of these. A measure of the national currency's overall value might lose some of this relevant uncertainty in aggregation. If the euro has appreciated 10% against the American dollar but depreciated 10% against both the British pound and the Japanese Yen, there may not be much change in the overall trade weighted value of the euro, but important changes have happened for many firms. The European firm importing mobile phone components from Japan and exporting the phones to the US will certainly feel the pinch. For the interest rate measure, the aforementioned 3-month interbank rate data are used. These data are all found on Thomson Datastream. I chose to construct measures using the GARCH-model. Specifically, I estimated GARCH (1, 1)-models on monthly data on all the time series, saved the conditional variances, summed these over the quarter to get quarterly measures of conditional variance and got their square roots to have conditional standard deviations. This is an admittedly ad-hoc procedure, but there is no theoretically perfect alternative, so one has to try and do the best possible. There is a trade-off between getting GARCH-models to fit the data and avoiding irrelevant short-term noise created by trading. The GARCH (1, 1) models fit the monthly data reasonably well, with significant coefficients and explanatory power in all cases. While monthly fluctuations can be influenced by speculative bubbles, they are clearly not driven primarily by trading noise.

I believe implied volatilities from options can be better measures of uncertainty than conditional variances from GARCH-models. I still choose not to use them. Part of the reason for this is that I have a large data set, and finding data and then creating implied volatilities for all my data requires a lot of work. The quality of the implied volatilities would also differ

in different countries and time periods. In the countries with deep liquid option markets, most of all the US, there are ample data available and they are not plagued by trading creating too much of the fluctuation. However, in the smaller countries, especially in the start of the time period, implied volatility data are likely to be of poor quality. In the only study on this topic that uses implied volatilities (that I am aware of), Antoshin (2006) seems to have chosen his data set specifically in order to maximize the amount and quality of implied volatility data. He analyzes firm-specific data in the US, and then only publicly traded companies. In an aggregate cross-country study like mine, implied volatilities become much more problematic to use. Li and Yang (2009), mentioned earlier, show that there may still be benefits, but they were thought to be too small to justify the extra work.

5.2: The investment function

I will analyze a linear investment function on the aforementioned variables. To get comparable investment data for the different countries, I divide investment by GDP to get investment rates. To start out, I want to find out to what order the investment rates are autocorrelated, in order to know how many lags of the dependent variable to include in my model. Because there is no readily available autocorrelation test for panel data beyond the first order¹⁰, I simply regress investment rates on their own lags. The specific coefficients are not relevant, only the general picture of number of significant lags. I include six lags in the regression:

Reg on investment rates	Coefficient (St.err)
Investment rate lag 1	0.8167 (0.0337)
Investment rate lag 2	0.2123 (0.0435)
Investment rate lag 3	0.1023 (0.0426)
Investment rate lag 4	-0.1023 (0.0419)
Investment rate lag 5	-0.0394 (0.0414)
Investment rate lag 6	-0.0181 (0.0327)

Table 1: Exploratory regression to find autoregressive function of investment rates. A standard random effects model is used. A bold font means that the coefficient is significant at the 5% level.

¹⁰ Fu et al (2002) and Okui (2008) propose tests for respectively random and fixed effects models. As these tests are not available in Stata, they were thought to be prohibitively complex to implement when considering the limited benefit.

There seems to be autocorrelation of up to and including the fourth order. Four lags of the dependent variable may thus have to be included in the model. I will start out with that but may adjust if there is residual autocorrelation or if some of the lags' coefficients turn out to be insignificant.

I include all explanatory variables lagged once. This is because there is often a lag between investment decision and actual investment. It also has the added benefit of added certainty of the direction of causation between the explanatory and dependent variable. This is especially true of GDP growth and stock market returns, which can clearly be influenced by the investment rate: Investments are a part of GDP and therefore influence GDP growth, while they also add to future GDP growth and therefore to stock market returns as well. Assuming that investment rate does not influence GDP growth and stock market returns one quarter before seems reasonable. I thus get the following equation:

$$\begin{aligned} IR_{i,t} = & \beta_0 + \beta_1 IR_{i,t-1} + \beta_2 IR_{i,t-2} + \beta_3 IR_{i,t-3} + \beta_4 IR_{i,t-4} + \beta_5 GG_{i,t-1} + \beta_6 SR_{i,t-1} \\ & + \beta_7 RI_{i,t-1} + \beta_8 SU_{i,t-1} + \beta_9 EU_{i,t-1} + \beta_{10} IU_{i,t-1} + a_i + \varepsilon_{i,t} \end{aligned}$$

Where IR is investment rate, GG is GDP growth, RI is real interest rate, SR is stock market return, SU is stock market uncertainty, EU is exchange rate uncertainty and IU is interest rate uncertainty. As mentioned in section 3.2, a_i represents country-specific time-invariant effects that are not picked up by the explanatory variables. This could for instance be a cultural, political or institutional inclination to save and invest more in one country than in another. ε is of course the normal idiosyncratic error found in all regressions.

My investment function is not an attempt to create the best model for explaining and predicting investment. My goal is only to investigate the sign of the investment-uncertainty relationship. The reason for including other variables is to make sure that the effect of uncertainty on investment is not a result of effect from uncertainty through these other variables to investment, nor a correlation as a result of one variable, like very high economic growth, influencing both investment rates and uncertainty. This goal is adequately achieved without creating a complete structural model of investment and without testing a number of different models to see which predicts investment better.

Before proceeding to estimate my investment equation, I check the correlations between my explanatory variables (excluding the lagged dependent variables). This is summarized in the table below:

	GG	SR	RI	SU	EU	IU
GG	1					
SR	0.0441	1				
RI	-0.0970	0.0411	1			
SU	-0.0718	-0.0678	0.0908	1		
EU	0.0309	-0.0415	0.2632	-0.0761	1	
IU	-0.1895	0.1180	0.5418	0.1500	0.0872	1

Table 2: Correlations between explanatory variables of investment function. GG: GDP Growth, SR: Stock market return, RI: Real interest rate, SU: Stock market uncertainty, EU: Exchange rate uncertainty, IU: Interest rate uncertainty.

Interestingly, the correlations between the uncertainty measures are very small, and even negative in the case of stock market and exchange rate uncertainty. There seems to be a general perception that the level uncertainty in different markets is related, often strongly, making this result rather odd. The low correlations may be peculiarities of my data or the general wisdom might be wrong to some extent (high correlation of financial market volatilities might for instance only happen in crises). The level of multicollinearity (correlation between explanatory variables) in my data is generally low, though real interest rates are highly correlated with interest rate uncertainty and clearly also correlated with exchange rate uncertainty. This is not a major problem, but it means that the effects of these variables will be a bit harder to measure. It also means that it is very important to include the level of interest rates in the equation, as the uncertainty variables could otherwise 'steal' the effect on investments of interest rates, which would be a bias and might make the coefficients significant when they should be insignificant.

5.3: Econometric results

I estimate my investment equation with both a normal random effects method and a within group (fixed effects) estimation method:

Reg on investment rates	RE Coeff (St.err)	FE Coeff (St.err)
GG (β_5)	0.4535 (0.1154)	0.3360 (0.1182)
SR (β_6)	0.0071 (0.0077)	0.0094 (0.0077)
RI (β_7)	-0.0013 (0.0005)	-0.0022 (0.0005)
SU (β_8)	-0.0438 (0.0226)	-0.0842 (0.0321)
EU (β_9)	0.1296 (0.0898)	-0.0058 (0.1281)
IU (β_{10})	-0.0023 (0.0012)	-0.0028 (0.0013)

Table 3: Regressions of investment equation. GG: GDP Growth, SR: Stock market return, RI: Real interest rate, SU: Stock market uncertainty, EU: Exchange rate uncertainty, IU: Interest rate uncertainty. Standard random effects and fixed effects (within group) models are used. A bold font means that the coefficient is significant at the 5% level.

For reasons of conciseness, I have not included the coefficients on the lagged dependent variables in the table. They were all significant with the same signs as in the first exploratory regression. Before discussing results, I do a Hausman test to find out which of the random or fixed effects methods should be used. It rejects the null hypothesis of both models being valid, with a P-value of this reported at 0.0001. So, if I can assume that the fixed effects model is efficient, then the Hausman test clearly recommends using this model. As shown in section 3.2, normal random effects and fixed effects models will be biased when estimating a dynamic model. For the fixed effects approach however, I have used a within groups estimation technique. The bias will then be reduced with a large T. Mine is very large, at 66, reducing the bias significantly. This should mean that my fixed effects regression is reasonably well specified and that the results can be trusted. I have chosen not to apply Arellano-Bond or other models specifically designed for dynamic panel data because the problems with the fixed effects method are largely mitigated by a large T, and the other methods have many other potential biases which can be much harder to identify.

Looking at the fixed effects results in the above table, the most interesting is that stock market uncertainty and interest rate uncertainty have significant negative effects at the 5% level. In the case of the effect of stock market movements, it is interesting to note that there is a much clearer effect of stock market uncertainty than of stock market returns. While the positive future expectations indicated by high stock market returns intuitively should induce higher investments, this effect could be dwarfed by negative impacts of higher volatility. One could suspect that the weak effect of stock market returns could be due to high correlation

with the GDP growth variable, but this turns out not to be important; the correlation is only 0.044 and stock market returns only have a slightly larger coefficient when leaving out GDP growth from the regressions. For interest rates, both the level and the volatility matters. The stronger effect of real interest rates as opposed to stock market returns could be a result of it having a much more direct effect on investment decisions through cost of capital. For exchange rate uncertainty, on the other hand, no significant effect is visible in any specification. This is somewhat puzzling, but exchange rate uncertainty is likely to affect fewer investments than interest rate uncertainty and stock market uncertainty. While all investments depend on the cost of capital and on the general future state of the economy, not all of them depend on foreign trade. Lastly, as explained in section 5.1, the use of trade-weighted exchange rates could be flawed, as they underestimate the uncertainty faced by individual firms significantly. These arguments aside, my results are even more puzzling when considering that they are inconsistent with other similar studies. As mentioned earlier, Serven (1998) and Byrne and Davis (2004) find that exchange rate uncertainty has a particularly strong effect on investment (and that it is significantly negative). My explanations for the lack of effect of exchange rate uncertainty in my own data do not explain this difference, as both these papers estimate exchange rate uncertainty in the same way that I do. I do have a different data set of course, which likely explains the difference. My results thus sow doubt over earlier conclusions that exchange rate uncertainty has a particularly strong effect on investment. This is clearly not a universal phenomenon. They confirm the overall negative effect of uncertainty on investment, though. With the clearest effect being that of stock market uncertainty, they indicate that uncertainty in stock prices may be the best proxy for the uncertainty facing a firm and affecting its investment decisions.

To test for potential non-monotonic effects of uncertainty on investment, as theoretically explained by Sarkar and empirically tested by Lensink and Bo, I square the uncertainty terms and add the squares to the original investment equation, and estimate the following equation:

$$\begin{aligned}
 IR_{i,t} = & \beta_0 + \beta_1 IR_{i,t-1} + \beta_2 IR_{i,t-2} + \beta_3 IR_{i,t-3} + \beta_4 IR_{i,t-4} + \beta_5 GG_{i,t-1} + \beta_6 SR_{i,t-1} \\
 & + \beta_7 RI_{i,t-1} + \beta_8 SU_{i,t-1} + \beta_9 EU_{i,t-1} + \beta_{10} IU_{i,t-1} + \gamma_1 SU_{i,t-1}^2 + \gamma_2 EU_{i,t-1}^2 \\
 & + \gamma_3 IU_{i,t-1}^2 + \alpha_i + \varepsilon_{i,t}
 \end{aligned}$$

This time, I leave out the random effects model. Only uncertainty measures are included in the table this time, as nothing dramatic happen to the other variables:

Reg on investment rates	FE Coeff (St.err)
SU (β_8)	-0.0139 (0.0966)
SU ² (γ_1)	-0.2357 (0.3139)
EU (β_9)	0.5446 (0.4114)
EU ² (γ_2)	-7.24 (5.15)
IU (β_{10})	-0.0043 (0.0032)
IU ² (γ_3)	0.00015 (0.0003)

Table 4: Regression on investment equation including squared uncertainty terms. SU: Stock market uncertainty, EU: Exchange rate uncertainty, IU: Interest rate uncertainty. Other variables in investment equation are included in regression but not reported. Standard fixed effects (within group) model is used. A bold font means that the coefficient is significant at the 5% level.

None of these coefficients are significant. The interdependence between uncertainty measures and their squares disturb the original coefficients sufficiently to make them insignificant, while the squares themselves have insignificant coefficients of varying signs. There are no indications of a stable non-monotonic link between investments and uncertainty in these results. Detecting such effects may demand more data or more detailed data than detecting simple linear effects, or such effects may not be present. As can be recalled from the theoretical section, Sarkar's prediction of non-monotonicity relies heavily on economic circumstances. The main factor was the difference between expected future project value and the value required for investment to take place. With required values higher than expected values, investment was likely to depend positively on uncertainty for low levels of uncertainty. This means that all else being equal, a positive trend in prices will mean uncertainty is more likely to have a strictly negative effect instead of a non-monotonic first-increasing-then-decreasing effect. If his theory can be translated to the aggregate case, it could mean that uncertainty is more likely to have a strictly negative effect when economic growth, stock market returns and demand growth is high, as investment thresholds in terms of expected project value may be below the mean future project value. These conditions have been prevalent in Western Europe and the Anglo-Saxon

world from 1991-2008. This is a drawback of analyzing a relatively heterogeneous dataset: Conclusions drawn only really apply to the analyzed group and time period.

The dynamics just mentioned may need further explanation and investigation. As suggested above, they could be the result of economic agents extrapolating the recent past into the future. Positive development in stock markets could induce them to think positive development is more likely in the future. Stability will then be seen as very positive, as the expectation is that project values will make investment profitable, and stronger chance of deviation from this expectation is unwanted. This intuitive explanation builds on a number of assumptions regarding formation of expectations. A more robust explanation looks at the investment opportunities in existence at any given time. The ones that have existed for a while exist now because they have not been taken, but been delayed. When there has been a recent decline in expected future project values, they will have been rejected at higher expected future values than the present expected values. Thus, the difference between required value to invest and expected future value is greater, and uncertainty can be positive for investment rates by increasing the probability of extreme changes in value. In the aggregate case, with my dataset, a recent decline in project values can be connected most clearly with negative stock market returns or higher interest rates. To test for path-dependency of the investment uncertainty link on these two variables, I create dummy variables related to stock market returns and movement in real interest rates in the year up to the start of the decision quarter (the quarter before investment). If the return in the year has been negative, the dummy variable takes a value of 1, and it takes the value of 0 otherwise. I do the same with real interest rates, except here the value is 1 with positive change. I then multiply the dummy variable with the uncertainty measures connected with the same variables, to create a new variable which can be interpreted as 'uncertainty measure of a variable if the variable has had development that is negative for investment in the previous year'. This means that the effect of stock market (interest rate) uncertainty on investment will be measured by two variables when stock market returns (changes in interest rates) have been negative (positive) and only the original variable when returns (interest rate changes) have been positive (negative). The hypothesis is that the coefficients of the uncertainty measures multiplied with the dummy variables will be positive, and maybe that the total effect in the cases of negative development will be positive. The first

would show a non-linearity in the investment-uncertainty relationship, the second a non-monotonicity. In addition to the multiplied dummy variables, I need to include stock market returns and interest rate changes for the previous year as variables to control that any effect of the dummy variables are a result of changing effects of the uncertainty measures and not direct effects of stock market returns or interest rate changes. The following equation is estimated:

$$\begin{aligned} IR_{i,t} = & \beta_0 + \beta_1 IR_{i,t-1} + \beta_2 IR_{i,t-2} + \beta_3 IR_{i,t-3} + \beta_4 IR_{i,t-4} + \beta_5 GG_{i,t-1} + \beta_6 SR_{i,t-1} \\ & + \beta_7 RI_{i,t-1} + \beta_8 SU_{i,t-1} + \beta_9 EU_{i,t-1} + \beta_{10} IU_{i,t-1} + \delta_1 DS_{i,t-1} SU_{i,t-1} \\ & + \delta_2 DI_{i,t-1} IU_{i,t-1} + \delta_3 SRY_{i,t-1} + \delta_4 ICY_{i,t-1} + \alpha_i + \varepsilon_{i,t} \end{aligned}$$

Reg on Investment rates	FE Coeff (St.err)
SU (β_8)	-0.1126 (0.0346)
IU (β_{10})	-0.0030 (0.0017)
DS*SU (δ_1)	0.0515 (0.0234)
DI*SI (δ_2)	0.0005 (0.0020)
SRY (δ_3)	0.0048 (0.0035)
ICY (δ_4)	0.0008 (0.0006)

Table 5: Regression of investment equation including dummy variables for stock market declines and positive interest rate movements. SU: Stock market uncertainty, IU: Interest rate uncertainty, DS: Dummy variable takes value of 1 if stock market has had negative return previous year, DI: Dummy variable that takes value of 1 if interest rate change has been positive previous year, SRY: Stock market return previous year, ICY: Interest rate change previous year. Other variables in investment equation are included in regression but not reported. Standard fixed effects (within group) model is used. A bold font means that the coefficient is significant at the 5% level.

Once again, variables that have not changed in any meaningful way are not included in the table. The most interesting result of this last regression is that stock market uncertainty multiplied by the dummy variable has a significantly positive coefficient. This indicates that stock market uncertainty has a non-linear effect on uncertainty, and that the effect is less negative when stock market returns have been negative. It does not indicate non-monotonicity, as the coefficient seems to be smaller in absolute value than the normal stock market uncertainty coefficient (even if this difference is not significant at a 5% level¹¹).

¹¹ A quick glance at the coefficients and their standard errors reveal that they are not significantly different. Go 1.96 standard errors up from the stock market uncertainty coefficient to arrive at -0.045. This is smaller than 0.0515 in absolute value. Add in the fact that both variables and not only one contain errors, and the insignificance is even clearer.

Similar conclusions cannot be drawn from looking at the interest rate data; there is no evidence of any non-linearity. The significance of the normal interest rate uncertainty measure is a little more doubtful in these results, but this seems to be a result of disturbance from the non-significant dummy variable. When I do the same regression but leave out the interest rate dummy variable, the normal uncertainty measure is significant again. It is also interesting to note that including a second stock market return variable did not really impact the first one at all. Together, the two variables are almost significant, and this seems to justify their inclusion in the investment equation.

6: Concluding remarks

After an overview of previous theoretical and empirical literature I have analyzed the relationship between investment rates and various uncertainty measures in 14 modern economies from 1991 to 2008. This empirical analysis indicates that uncertainty impacts investment rates negatively. The majority of recent theoretical literature and almost all empirical research share this main finding. According to a theoretical model of the probability of investment in a single project presented by Sarkar (2000), the investment-uncertainty link may be non-monotonic. This is a possibility that had largely been ignored in empirical work. Two recent studies (Lensink (2002) and Lensink and Bo (2005)) confirms this hypothesis: Investment was shown to increase with uncertainty at low uncertainty levels and then start decreasing at higher levels. This thesis does a similar analysis and contradicts these findings. There is no clear sign of non-linearities based on the level of uncertainty in my data. The previous studies might suffer from bias because of omitted lagged dependent variables in the first and dubious use of daily conditional variances for the following year in the second. Their conclusions might also be correct, and the investment-uncertainty link may be non-monotonic in certain economic circumstances and strictly negative in others.

Based on further analysis of Sarkar's model by Lund (2005), there is reason to believe that potential non-monotonicities or non-linearities depend on the difference between the expected future net present values of projects and the required values necessary for firms to invest. In the aggregate case, it is reasonable to assume that project values are correlated with stock market prices. If stock market prices have recently declined, project values have probably done the same. Because a large portion of investment opportunities have existed for a while, expected future values have thus been higher earlier in the lifespan of the opportunities than they are now. Thus, the opportunities that have not been taken earlier have required expected values that are much higher than the present expected values. Higher uncertainty can therefore have a positive effect by increasing the probability of extreme positive changes in project values. In an empirical analysis of this theory, I show that negative stock market returns in the recent past have a significant impact on the effect of stock market uncertainty on investment. The total effect of uncertainty becomes non-linear, but not non-monotonic: When stock market returns have been negative, uncertainty still has a negative effect on investment, but it is significantly smaller than when returns

have been positive. The significance of this conclusion is somewhat weakened by the fact that there was no sign of this effect when real interest rate changes and real interest rate uncertainty was analyzed. Non-linearities in the investment-uncertainty link are topics for further research. Lensink and Lensink and Bo found non-monotonicity related to the level of uncertainty, Antoshin (2006) found non-linearities related to several macroeconomic variables like CPI and GDP, and I have found non-linearities related to stock market returns. A thorough empirical investigation of all of these is needed.

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