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Economic Uncertainty and the Effectiveness of Monetary Policy*

Knut Are Aastveit[†] Gisle James Natvik[‡] Sergio Sola[§]

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Abstract

This paper explores if economic uncertainty alters the macroeconomic influence of monetary policy. We consider several measures of U.S. economic uncertainty, and estimate their interaction effects with monetary policy shocks as identified through structural vector autoregressions. We find that monetary policy shocks affect economic activity considerably weaker when uncertainty is high, consistently with “real-options” effects suggested by models with non-convex adjustment costs. Investment responds two to five times weaker when uncertainty is in its upper instead of its lower decile. High U.S. uncertainty is associated with lower policy influence not only domestically, but in Canada too.

JEL-codes: E30, E32, E37

Keywords: Uncertainty, Monetary Policy, Structural VAR

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1 Introduction

Is monetary policy less effective when uncertainty is high? Theory highlighting the partial irreversibility of investments, as developed by Bloom (2009), Dixit and Pindyck (1994) and Bernanke (1983), suggests that it might be. The hypothesis is that elevated uncertainty motivates agents to postpone decisions awaiting better information, and this cautiousness makes them less responsive to changes in the interest rate. During events such as the ongoing fiscal turmoil in Europe or the Great Recession in the United States, a concern has been that uncertainty holds economic activity down, and the potential relevance of the cautiousness effect is clear:¹ It implies that policy-makers must act aggressively if they aim to stabilize the economy. However, while the policy ineffectiveness proposition is well understood in theory, empirical evidence on its macroeconomic importance is limited. We therefore empirically explore how uncertainty affects the macroeconomic impact of monetary policy shocks.

We base our empirical strategy on a set of U.S.-based uncertainty measures that have been proposed in the recent literature on uncertainty shocks. As our main measure, we use stock market volatility as in Bloom (2009). In addition we follow Bachmann et al. (2013) and consider the corporate bond spread, forecaster disagreement, and a Google-based count of news articles mentioning economic uncertainty. Our final uncertainty measures are the factor-based estimates of macroeconomic uncertainty by Jurado et al. (2013) and the economic policy uncertainty index constructed by Baker et al. (2012). We then estimate how each uncertainty measure interacts with macroeconomic variables in a structural vector autoregressive (SVAR) model. To this end we utilize the interacted VAR methodology developed by Towbin and Weber (2013) and Sa et al. (2013), treating uncertainty as an exogenous interaction variable.² In order to identify monetary policy shocks we use the transparent and well-understood recursive strategy that has been extensively

¹For example, when explaining weak global growth in 2012, the IMF point to uncertainty as a primary cause and state that “uncertainty weighs heavily on the outlook” (World Economic Outlook, 2012). Baker et al. (2012) construct an index of policy uncertainty that points in the same direction. Stock and Watson (2013) find that uncertainty was one of the main contributors to the 2007-2009 U.S. recession

²Towbin and Weber (2013) study how the responses of output and investment to external shocks are affected by external debt, import structure and exchange rate regime. Sa et al. (2013) study how the effects of capital inflows change with the structure of the mortgage market and the degree of securitization in different countries. Beyond asking an entirely different question, our approach differs from these studies, as we study different countries separately, rather than using a panel.

documented elsewhere, as in for instance Christiano et al. (1999). As a robustness check, we redo the analysis using sign restrictions to identify the monetary policy shocks as in Uhlig (2005).

We start by evaluating the policy inefficiency hypothesis on U.S. data. We thereafter extend our analysis by estimating how the U.S.-based uncertainty measures interact with the transmission of monetary policy shocks in Canada, the United Kingdom and Norway.

Our main finding is that the policy ineffectiveness hypothesis has bite at the macro level. The effects of monetary policy shocks tend to be considerably *weaker* when uncertainty is high. The pattern is particularly stark for GDP and investment, and the effects are sizeable. In the United States, a monetary tightening has almost no effect when stock market volatility is in its upper decile, while the same impulse makes investment and GDP drop by approximately one percent when volatility is in its lower decile. The effect when volatility is in its lower decile is more than five times larger than when it is in its upper decile, and these differences are statistically significant. When uncertainty is measured by the corporate spread, forecaster disagreement, the Google-index, or the two alternative factor-based estimates of Jurado et al. (2013), the results are qualitatively similar, but quantitatively somewhat smaller. For these measures, the policy effect tends to be approximately halved when uncertainty is in its upper rather than in its bottom decile. The differences in policy effects remain statistically significant. It is only economic policy uncertainty that does not seem to dampen the influence of monetary policy. Notably, the qualitative pattern holds also when we use sign restrictions instead of a recursive identification scheme to identify monetary policy shocks, although the quantitative effects of uncertainty become weaker.

When we shift attention to other economies, the U.S.-pattern re-emerges for Canada, but only to a limited extent for the United Kingdom and Norway. In Canada, the investment response to a monetary policy shock is approximately halved when U.S. stock market volatility is in its bottom instead of its top decile, and this response difference is statistically significant. In the United Kingdom and Norway, the estimated investment responses to a monetary policy shocks are dampened when U.S stock market volatility is high, but this dampening statistically significant only in Norway, and it is not robust across uncertainty measures. That the interaction effects are quantitatively smaller in Canada than in the United States, and even weaker or insignificant in countries farther away, is not surprising given that we are considering economic uncertainty as measured in the United States.

Our study is closely related to the recent literature initiated by Bloom (2009),

that uses SVARs to identify uncertainty shocks and their macroeconomic effects. Bloom (2009) found that shocks to U.S. stock market volatility are followed by contractions in U.S. employment and investment. Bachmann et al. (2013) measure uncertainty by forecast disagreement and dispersion in forecast errors in business surveys from Germany and the U.S., document that the two measures are correlated, and show how innovations in these indexes are followed by economic contractions in the two countries. They also show that shocks to spreads, stock market volatility and the Google-index foreshadow similar contractions. Baker et al. (2012) construct indexes of economic policy uncertainty in the United States, Canada and Europe and find similar effects. Alexopoulos and Cohen (2009) measure uncertainty as the frequency with which news media refers to economic uncertainty, and also they find that increased uncertainty is followed by reduced economic activity. Jurado et al. (2013) reach a similar conclusion, using estimates of macroeconomic uncertainty that extract the common factors of several individual uncertainty measures. Other studies in this vein are Bachmann and Bayer (2011) and Knotek and Khan (2011). Notably, the recent strand of macroeconomic empirical research has focused exclusively on the question of how movements in uncertainty affect economic activity, while no attention has been directed to the policy-effectiveness hypothesis which we address.

The evidence that exists on policy-effectiveness and uncertainty is obtained either through micro-data (e.g. Bloom et al. (2007)), or through structural models where the implication of policy ineffectiveness is largely imposed by theory (e.g. Bloom (2009), Bloom et al. (2007)). A particularly relevant paper is Bloom et al. (2012), who build and calibrate a dynamic stochastic general equilibrium model with non-convex adjustment costs, and study how the influence of expansive policy depends on uncertainty. Related is also Vavra (2013), who constructs a model with fixed costs of price adjustment that is consistent with micro price-data, and shows that this micro-founded model predicts weaker effects of policy when firm-level volatility is high. Our contribution is to empirically evaluate with macroeconomic data if the effect of monetary policy interacts with the level of uncertainty in the economy. This relates our paper to the vast empirical literature on the transmission of monetary policy shocks, summarized at one stage by Christiano et al. (1999).³ Within this field, several studies explore how the monetary transmission mechanism has evolved over time, such as Boivin and Giannoni (2006), Canova and Gambetti (2009), Boivin et al. (2010) and Kuttner and Mosser (2002). Particularly related to our study, are the papers debating whether

³See, for example, Sims (1992), Bernanke and Mihov (1998), Romer and Romer (2004) and Bernanke et al. (2005).

policy is more or less effective in recessions, such as Smets and Peersman (2001) and Lo and Piger (2005) who find policy to be *more* influential in recessions than in booms, and Tenreyro and Thwaites (2013) and Castelnovo et al. (2013) who find policy to be *less* influential in recessions. To our knowledge, this literature has not previously addressed whether the effectiveness of monetary policy is influenced by the prevailing degree of economic uncertainty.

The remainder of our paper is organized as follows. Section 2 gives a theoretical motivation for our empirical investigation, based on a stylized model of an irreversible investment decision. Section 3 describes our data and the methodology we use. Section 4 and 5 presents our results for the United States and the other economies, respectively. We conclude in Section 6.

2 Theoretical Motivation

In this section we use a simple theoretical model to show how uncertainty influences a decision that can be postponed. The model is highly stylized, in order to allow an analytical expression of the hypothesis we want to test. The same qualitative prediction is obtained numerically in several studies using more detailed models with non-convex adjustment costs, for instance Bloom et al. (2012), Bloom et al. (2007) and Bloom (2007). The classic textbook exposition of these effects is given in Dixit and Pindyck (1994).

There are 3 periods, 0, 1 and 2. In period 0, a continuum of entrepreneurs indexed by i face the opportunity to invest in a project. The cost of undertaking this investment is γ_i , which is uniformly distributed across investors with density $1/\alpha$. If invested in, the project pays off y in periods 1 and 2, where y is stochastic. With probability p , $y = y^h$, while $y = y^l$ with probability $1 - p$. The distance between y^h and y^l captures the degree of uncertainty in this economy, and is denoted σ . Uncertainty about y is realized in period 1, and after observing this level, an entrepreneur who did not invest previously may choose whether or not to invest for period 2. We assume that after y is realized, the resale price of capital does not exceed y , and hence projects are never terminated in period 1. The alternative to investing in the project is to spend γ_i on a risk-free asset yielding the gross interest rate R .

To make the investment decision interesting, we assume that the project is unprofitable if the state with low productivity materializes: $\gamma_i > y^l/R + y^l/R^2$ for all investors i . On the other hand, if the high-productivity state

materializes, the project is profitable even if it operates for one period only: $\gamma_i \leq y^h/R$.

The net present value from investing the amount γ_i in period 0 is given by $E(\pi_{i,0}^{inv}) = E(y)/R + E(y)/R^2 - \gamma_i$, while the net present value from postponing the investment decision until period 1 is $E(\pi_{i,0}^{no-inv}) = (1-p)\gamma_i + p/R^2 [y^h + (R-1)\gamma_i] - \gamma_i$. The latter expression reflects that by delaying the investment decision, the investor gains the option to invest in the risk-free asset rather than a project that has turned out to be unprofitable.

Naturally, the investment will be made in period 0 if and only if $E(\pi_{i,0}^{inv}) - E(\pi_{i,0}^{no-inv}) \geq 0$. From the two profit expressions, we can therefore express the individual investment decision in terms of the fixed investment cost. Entrepreneur i will choose to invest if $\gamma_i \leq \bar{\gamma}$, where

$$\bar{\gamma} = \frac{RE(y) + (1-p)y^l}{R^2(1-p) + (R-1)p} \quad (1)$$

Aggregate investment in period zero, I_0 , is then given by the mass of investors with $\gamma_i \leq \bar{\gamma}$. Hence, $I_0 = 1/2 + [\bar{\gamma} - E(\gamma)]/\alpha$.

We can now answer how uncertainty affects investment.⁴ First, the effect of a mean-preserving increase in uncertainty is:⁵

$$\frac{\partial I_0}{\partial \sigma} \Big|_{E(y)} = \frac{-(1-p)p}{[R^2(1-p) + (R-1)p]\alpha} < 0.$$

We see that higher uncertainty leads to lower investment. This is the “delay” effect of higher uncertainty. The effect follows from equation (1), as the mean preserving increase in uncertainty by definition reduces y^l , and thereby tightens the condition for investors to take action. Intuitively, a wider distribution of potential payoffs increases the cost of making a wrong decision and therefore raises the value of postponing the investment decision in order to gain further information. As consequence, the investment cost that triggers delay falls, and fewer invest. This delay effect has been scrutinized in the growing literature on uncertainty shocks referred to in the introduction.

Second, higher uncertainty influences how strongly movements in the interest rate R , affects the motive to invest:

⁴Notably, the key assumption behind the uncertainty effects here is that projects cannot be liquidated at a price that exceeds their productivity. This assumption makes investment irreversible in this model. If projects could be terminated and sold at prices that exceeded y , the option value of postponing investments would not be increased by higher uncertainty.

⁵Here we have utilized that $\frac{dy^l}{d\sigma} \Big|_{E(y)} = -p$.

$$\frac{\partial^2 I_0}{\partial R \partial \sigma} \Big|_{E(y)} = \frac{(1-p)p[2R(1-p)+p]}{[R^2(1-p)+(R-1)p]^2 \alpha} > 0.$$

As the partial effect of a higher interest rate on investment, $\partial I_0 / \partial R$, is negative, it follows that higher uncertainty reduces the influence of monetary policy. This reflects the “caution effect” that uncertainty creates. When uncertainty goes up, there is more at stake when deciding whether to invest or not, and hence a marginal change in investment incentives, as induced by a change in R , has a smaller impact. In terms of equation (1), the effect can be observed by noting that an interest rate hike reduces investment incentives by raising the discounting of $E(y)$ and y^l . The higher is uncertainty, the lower is y^l , and hence the smaller is the effect of R on the individual investment decision as captured by $\bar{\gamma}$. This “caution effect” is what we will explore in this paper.

3 Data and Empirical Strategy

We aim to estimate how economic uncertainty influences the transmission of monetary policy shocks. We perform our analysis first for the United States, and thereafter for Canada, the United Kingdom and Norway.⁶

We use quarterly data throughout. For the United States, we cover the period 1971Q1 to 2011Q3.⁷ For the other countries we use data from 1980Q1 to 2011Q3, since this is the longest period over which we have consistent macroeconomic series.

⁶We do not include Euro area countries in our analysis as it complicates the identification of monetary policy shocks and requires us to tackle the issue of the introduction of a single currency.

⁷We start in 1971 because this is when the firm-level uncertainty measure from Jurado et al. (2013) start. The stock market volatility index, the credit spread series and the macroeconomic uncertainty factor from Jurado et al. (2013) go further back, extending our analysis for these series does not change our results much. However, the stock market volatility index from Bloom (2009) trends steeply upward from a low level until 1970, and is therefore unlikely to treat periods of uncertainty in a symmetric way before and after 1970. For instance, while the Cuban missile crisis in 1962 cause a spike in the volatility index, this peak value still lies below the full sample average. Using dummies to capture uncertainty spikes, as in Bloom (2009), does not suffer from this problem, but this approach is not compatible with the interaction VAR strategy that we will apply.

3.1 Measuring Economic Uncertainty

As our main measure of uncertainty, we will use the series for volatility in the US stock market constructed by Bloom (2009), extended to cover the period from 2008 to 2011. From 1986 and onward, these data are taken from the Chicago Board Options Exchange VXO index of implied volatility. For the period before 1986, the implied volatility index is unavailable, and realized volatility, calculated as quarterly standard deviation of the daily S&P500, is used instead. We will refer to the stock market volatility index as the VXO-index throughout.

While financial market volatility is a natural starting point for measuring uncertainty, in the recent literature on uncertainty shocks several alternative measures have been proposed. We therefore consider a host of these. First, we use the alternative measures provided in Bachmann et al. (2013), namely the corporate bond spread, forecast disagreement, and the Google index. The corporate bond spread is the spread of the 30-year Baa-rated corporate bond yield index over the 30-year treasury bond yield, where the 20-year treasury bond has been used when the 30-year bond was missing. The forecast disagreement measure stems from the the Federal Reserve Bank of Philadelphia’s Business Outlook Survey, where large manufacturing firms in the Third Fed district are asked to give their own “evaluation of the general business activity six months from now.”⁸ Disagreement is measured as the cross-sectional dispersion in these point forecasts. The Google index is the number of articles in a given month that refer to “uncertainty” and phrases related to the economy, divided by the number of articles containing the word “today” in order to control for the overall increasing news volume. Note that this variable is only available from 1985Q1.

In addition, we utilize uncertainty measures constructed by Jurado et al. (2013) (JLN, hereafter). Rather than using one specific observable variable to proxy for uncertainty, they estimate uncertainty as factors that are common to different individual measures of uncertainty. In doing so, they consider a large set of economic time series, and pay specific attention to separating unforecastable from forecastable components in each series, as it is only unforecastable variations that should be related to uncertainty. To this end they use forecasting models with a large set of predictors. Based on the forecasting errors that result, stochastic volatility models are used to com-

⁸More precisely, according to Bachmann et al. (2013), the survey is sent to firms in Delaware, the southern half of New Jersey, and the eastern two-thirds of Pennsylvania, with voluntary participation, and monthly responses from executives in 100-125 firms.

pute the uncertainty in each times series. Uncertainty is then estimated as the common, latent “uncertainty factor” across these individual series, using principal component methodology. Two uncertainty measures result. First, based on 279 macroeconomic variables they construct a monthly measure of macroeconomic uncertainty.⁹ Second, they use 154 observations of firm-level profit growth, normalized by sales, to construct a quarterly measure of firm-level uncertainty.¹⁰

Finally, we use the economic policy uncertainty (EPU) index constructed by Baker et al. (2012). The EPU index is built on the following components: the frequency of newspaper references to economic policy uncertainty, the number of federal tax code provisions set to expire, and the extent of forecaster disagreement over future inflation and government purchases. As the Google index, this variable is only available from 1985.

The uncertainty measures are plotted in Figures 1 and 2. We see that the seven alternative measures have moved quite differently over time, and therefore should not necessarily yield the same results in our econometric analysis.

3.2 Macroeconomic variables

We include the following macroeconomic variables in our analysis: the consumer price index (CPI), real GDP, real investment, real private consumption, and the short-term interest rate. In addition we include the real effective exchange rate for the non-U.S. economies. CPI, GDP, investment and private consumption are transformed using natural logarithms.¹¹

To construct investment series which are both comparable across countries and relevant for the real-option theory, we use “gross fixed capital formation” of the private sector. These series are taken from Datastream where the original sources are the national statistical offices. For all countries, the short term interest rate is the interest rate on 3 months government bonds. It is expressed in percentage terms and is considered as an indicator of the monetary policy stance. Our measure of the real exchange rate is the “CPI real

⁹We use a quarterly version of their monthly macroeconomic uncertainty index.

¹⁰Jurado et al. (2013) construct macroeconomic and firm-level uncertainty factors for different uncertainty horizons. We use their uncertainty factors for the uncertainty horizon of 4 quarters. Results are robust to using uncertainty factors with a shorter uncertainty horizon.

¹¹For Norway we exclude the oil sector and use GDP and investments for mainland only. This is important because the oil sector is sizeable in Norway, and largely driven by other forces than the rest of the Norwegian economy.

effective exchange rate” published in the International Financial Statistics of the IMF. It is a trade weighted measure of the real exchange rate, and it is constructed so that an increase means an appreciation of the currency.

3.3 Empirical model

To study how time-varying uncertainty affects the transmission of monetary policy, we estimate an interacted structural VAR model. By interacting the macroeconomic variables with an uncertainty index, we allow the impact of monetary policy to change with the degree of uncertainty. The model builds on the interacted panel VAR model developed by Towbin and Weber (2013) and Sa et al. (2013). Beyond the fact that we are studying an entirely different question, our approach differs from these two studies as they use a panel approach, while we apply a separate model to each country. Notably, with this approach time-variation in the effect of policy is directly linked to a specific determinant, uncertainty, in contrast to the studies that use VARs with stochastically time-varying coefficients, such as Canova and Gambetti (2009) and Primiceri (2005).

We will use the following interacted VAR model:

$$Y_t = A_0 + B_0 X_t + \sum_{l=1}^L (A_l Y_{t-1} + B_l Y_{t-1}^{SM} X_t) + C Z_t + E_t \quad (2)$$

where E_t is a vector of reduced form residuals at time t . The vector Y_t contains CPI, GDP, private consumption, private investments, and the short term interest rate. For the small open economies we also include the real exchange rate. Furthermore, the model allows the variables in Y_t to interact with X_t . X_t is also included as an additional regressor.¹²

The interacting variable X_t will be our uncertainty measures. Hence, uncertainty is assumed to be exogenous in the model. We use a four quarter moving average to account for a lagged reaction of consumers and investors to the level of uncertainty. Note that in our exercise we want to quantify the extent to which the response of the endogenous variables to the interest rate changes with the level of uncertainty. Therefore, in each equation we interact X_t with the interest rate only.

The vector Z_t contains additional exogenous variables. For all countries we include a linear trend in Z_t , and for the small open economies we also include

¹²This is the multivariate analog to a standard interaction term, in which the effects of Y_{t-l} on Y_t is a linear function of X_t .

the U.S. interest rate. We have also considered specifications where we include commodity prices or oil prices in Z_t , both because their inclusion has been proposed as important to identify monetary policy shocks without generating a “price puzzle”, and because oil production is important for Canada and Norway. Our results are robust to including commodity prices or oil prices in the model.

A_0 is a vector of constant terms, while B_0 , A_l , B_l and C , are parameter vectors for the interacted variable (X_t), the endogenous variables (Y_t), the interaction term ($Y_{t-1}X_t$) and the exogenous variables (Z_t), respectively.

Finally, some of the non-U.S. countries we study have changed monetary policy regime and adopted inflation targeting over our sample period. In Z_t we therefore include a dummy variable which takes the value 1 for the period after the regime change.¹³

To study the incidence of policy effectiveness in our econometric model, we need to identify monetary policy shocks. Our identification strategy is explained below.

3.4 Estimation and Identification

For the U.S. analysis we identify monetary policy shocks by imposing recursive short-run restrictions which allow the interest rate to respond within the same quarter to all the macroeconomic variables, but not vice versa. Hence, macroeconomic variables react with a lag to monetary policy shocks. This recursive structure to identify monetary policy shocks is the most conventional one in the established SVAR literature, see for instance (see Stock and Watson (2001) and Christiano et al. (1999)). As a robustness check, we also redo our analysis using sign restrictions to identify monetary policy shocks, as in Uhlig (2005). The identifying assumption here is that a monetary policy shock is associated with an increased interest rate, a fall in the price level, and a fall in GDP, for at least two quarters.

For the non-U.S. economies, we must deal with the simultaneity between the exchange rate and the interest rate. To this end we combine sign and contemporaneous zero restrictions. We allow both the interest rate and the exchange rate to respond within the same quarter to all other macroeconomic

¹³For Norway we also follow Bjørnland and Jacobsen (2010) and include three dummy variables for 1992Q3, 1992Q4 and 1993Q1 to account for episodes of extreme turbulence in the interest rate and exchange rate due to the breakdown of the fixed exchange rate regime.

variables included in the VAR, but not vice versa. In addition, we allow the interest rate and the exchange rate to react contemporaneously to each other. In order to separate a monetary policy shock from an exchange rate shock we impose two additional sign restrictions. We follow Jarocinski (2010) and impose that a positive monetary policy shock is associated with a joint increase in the interest rate and an appreciation of the exchange rate, while an exchange rate shock is associated with a decrease in the interest rate and an appreciation of the exchange rate.¹⁴ The sign restrictions are imposed to hold for two quarters.

We estimate our model using Bayesian techniques. Following Sims and Zha (1999), Uhlig (2005) and Sa et al. (2013) we impose that the priors, and hence also the posterior density, of the regression coefficients and the covariance matrix belongs to the Normal-Wishart family. We use uninformative priors, and draw all parameters jointly from the posterior (including the coefficients on the interaction terms).¹⁵ The priors and the implementation of the Bayesian estimation are discussed in more detail in appendix A. Once we have estimated the parameters of the VAR in equation (2) we identify structural shocks with the strategies explained above. When imposing sign restrictions for the small open economies we follow Rubio-Ramirez et al. (2010). For each posterior draw of the covariance matrix we compute the matrix R , obtained by orthogonalizing the variance covariance matrix¹⁶ and multiplying it by an orthonormal matrix Q . The matrix Q is constructed exactly as in Jarocinski (2010): it is an identity matrix with a lower block obtained via a QR decomposition of a 2×2 random matrix drawn from an independent standard normal. We keep the posterior draw if the matrix R generates impulse responses that satisfy the sign restrictions for both shocks. For a given parameter draw, we keep 100 impulse responses which satisfy our restrictions.

To evaluate the importance of the interaction effects, we will compute the estimated impulse responses of monetary policy shocks at two different levels of each uncertainty indicator. We will here use the 90th and 10th percentiles of the historical distribution for each uncertainty measure, denoted X^{high} and X^{low} , respectively. From the Figures 1 and 2 it is evident that the episodes of highest uncertainty in our sample correspond to the periods around the

¹⁴See Bjørnland (2009) for an alternative way to separate exchange rate shocks and monetary policy shocks using long-run restrictions.

¹⁵We start with 22,000 draws, discard the first 2,000 of them, and thereafter select only every tenth draw to avoid correlation. Consequentially, we are left with 2,000 draws of the parameters.

¹⁶We here use a standard Choleski factorization.

“Black Monday” stock market crash, the 9/11 terror attack, the collapse of the dot-com bubble, and finally the onset of the sub-prime crisis.

With the assigned values for the interaction variable X_t , the estimated VAR reduces to:

$$Y_t^{high} = \widehat{D}_0^{high} + \sum_{l=1}^L (\widehat{D}_l^{high} Y_{t-l}) + \widehat{C}Z_t + \widehat{E}_t$$

$$Y_t^{low} = \widehat{D}_0^{low} + \sum_{l=1}^L (\widehat{D}_l^{low} Y_{t-l}) + \widehat{C}Z_t + \widehat{E}_t$$

where $\widehat{D}_0^{high} = \widehat{A}_0 + \widehat{B}_0 X^{high}$ and $\widehat{D}_0^{low} = \widehat{A}_0 + \widehat{B}_0 X^{low}$. Similarly, $\widehat{D}_l^{high} = \widehat{A}_l + \widehat{B}_l X^{high}$ and $\widehat{D}_l^{low} = \widehat{A}_l + \widehat{B}_l X^{low}$. These are standard reduced form VAR-models, and there is therefore no further complication associated with using the restrictions discussed above to identify a monetary policy shock and analyze its effects at high and low levels of uncertainty.

3.5 A Test Statistic for the Interaction Effect

Because the impulse responses for low and high levels of uncertainty are correlated, the confidence bands around each response alone give a distorted impression about the statistical significance of their difference. To assess the difference more formally, we therefore compute a test statistic using the impulse responses based on draws of the posterior parameters. For each of the 2,000 saved draws we compute the differences between the response of the variables to a monetary policy shock under high and low uncertainty, respectively. This provides us with an empirical distribution of the difference between the responses, which we can then use to compute a probability band. The two impulse responses can be considered statistically different from each other if the interval between the probability bands lie above or below zero.

We will report these probability bands in figures. Each figure will display the distribution of the the difference between the impulse response under high and low uncertainty. For example, a positive value for investment will mean that a monetary tightening causes a greater drop in investment when uncertainty is low than when uncertainty is high. For each variable, we will report 68% and the 90% probability bands, respectively.

4 Results for the United States

We first estimate how economic uncertainty interacts with the transmission of monetary policy shocks in the United States.

4.1 Interaction with Stock Market Volatility

Our starting point is to estimate the effects of monetary policy shocks using stock market volatility as our measure of uncertainty. Figure 3 displays the effects of a one percentage point unanticipated increase in the policy rate. The impulse responses with circles are estimated for the case where volatility is in its upper decile, while the curves with marks give the estimated responses when volatility is in its lower decile. The figure plots responses for the first 20 quarters after the shock.

We see that when volatility is low, the responses of GDP, investment and consumption, are significant, and in line with conventional monetary theory. In contrast, when stock market volatility is high, the same variables respond negligibly. Investment falls by less than 0.5 % when volatility is in its upper decile, while it falls by more than 1 % when volatility is in its lower decile. This difference is consistent with the cautiousness effect explained above. Consumption displays a similar pattern, and it falls by a maximum of almost 3 percentage points when volatility is low, which contrasts with a fall of less than 1 percentage point when uncertainty is high. The GDP response is consistent with the investment and consumption movements, and it falls by at most 1 percentage point when volatility is low, versus less than 0.5 percentage points when volatility is high.

For the price level, we see that in both the high and low volatility scenarios, there is a “price puzzle” as prices initially increase in response to the monetary tightening. In terms of inflation, this would translate into an increase for the first quarters, and a decline only several periods later. This puzzle is a well-known by-product of using a structural VAR with recursive ordering to identify monetary policy shocks, see for instance Sims (1992) and Christiano et al. (1999). More interestingly for our purposes, we see that this initially positive inflation response is practically insensitive to the level of stock market volatility.

The test statistic for each difference in impulse response is reported in Figure 4. As we would expect from the large effects discussed above, we see that for

the real variables, the 90% probability bands all lie above zero. For inflation the difference seems insignificant.

4.2 Interaction with Alternative Uncertainty Measures

The first alternative uncertainty measure we consider is the corporate bond spread. Figure 5 report impulse responses and the test statistic. We see that the pattern is very similar to what we obtained using stock market volatility. GDP, investment and consumption all fall more when uncertainty is low. The test statistic shows that these differences are statistically significant. For prices, the price puzzle seems somewhat stronger under low uncertainty.

Next, we use forecaster disagreement. Figure 6 shows that the effect of a monetary tightening on the three real variables is two to three times stronger when forecaster disagreement is in its upper decile rather than its lower decile. The test statistics show that these differences are significant above the 68% level, but not at the 90% level.

The results using the Google-index are given in Figures 7 Note that the sample behind these results is considerably shorter, as the Google-index goes back only to 1985. Once again we see lower effects of policy on real activity when uncertainty is high. Quantitatively, the influence of uncertainty is similar to what we found using the credit spread and forecaster disagreement: the responses of real variables are roughly halved when uncertainty is in its upper rather than in its lower decile. The 68% bands consistently lie above zero, whereas the 90% bands at some point exceed zero for all three real variables. For inflation, the influence of uncertainty is negligible.

Figures 8 and 9 show the results when the two JLN factor-based measures are applied. For both indicators we see a dampened effect of monetary policy shocks when uncertainty is high. The dampening is particularly stark when we use the firm-level uncertainty factor, in which case the peak response of investment is about one third as strong with high rather than low uncertainty. The test statistic indicates that the response differences are significant at the 68% and 90% levels for the macro and firm-specific factors respectively.

Finally, we consider the EPU-index, which also starts in 1985. Figure 10 shows that this uncertainty measure paints a very different picture than the other six. The initial effect of the monetary policy shock on the real economy is greater when the EPU-index is high, the direct opposite effect of what we saw for the other indices. While not shown here, when we decompose the

EPU-index into its four subcomponents, and run our analysis on each separately, we find that it is the forecaster disagreement over future government purchases which causes the positive interaction between the EPU-index and policy effectiveness. The remaining three sub-components yield zero or negative interaction effects.

4.3 Identification by Sign Restrictions

As a robustness check, we assess the interaction effects of uncertainty on the impact of monetary policy shocks when the latter are identified via sign restrictions. We here follow the approach proposed by Uhlig (2005), and impose the restrictions that monetary policy shocks are followed by reduced prices and lower GDP. We impose that the sign restrictions must hold for two quarters.¹⁷

Figure 11 displays our results using sign restrictions. To conserve on space, we report only impulse responses for investment, and we restrict attention to only 6 uncertainty measures. The one we ignore is the JLN firm-level uncertainty measure. Further results are available upon request.

The main pattern from Figure 11 is consistent with the results from the recursive strategy, in that the investment responses to monetary policy shocks are weaker under high than under low uncertainty. As with the recursive identification strategy, it is only for the EPU-index that the results are overturned. On the other hand, the uncertainty bands are wide, and overlap for all uncertainty measures. Hence, although the main qualitative patterns with the two identification schemes are consistent, the evidence using sign restrictions is considerably weaker than what we observed with the recursive identification scheme.¹⁸

5 Results for 3 non-U.S. Economies

We next extend our analysis to Canada, the United Kingdom and Norway. We will estimate the interaction effects between monetary policy shocks and the same U.S.-based uncertainty measures as we utilized above. Partly, this

¹⁷Imposing the sign restrictions to hold for longer horizons does not have substantial effects. Results are available upon request.

¹⁸These results are robust to specifications of the model in first differences. Results are available upon request.

can be seen as an extension to gauge the influence of U.S. uncertainty on policy effectiveness in other countries. In addition, by studying how small open economies are affected by uncertainty measured in the United States, our results are less prone to any potential biases from treating uncertainty as exogenous. The extension can thus be considered as a robustness check to deal with this specific endogeneity problem.

Figures 13 to 18 display our results for the three non-U.S. economies. For space considerations, we leave the JLN firm-level uncertainty measure aside. We also present the impulse responses of investment only, as this is the variable closest tied to our motivation from real-option theory. In short, the other variables respond roughly as expected to the monetary policy shock, only with a price puzzle similar to that in the United States. Further results are available upon request.

In Canada, Figure 13 shows that the effect of the policy shock is dampened by uncertainty when the latter is measured by stock market volatility, the credit spread or the JLN macro-uncertainty measure. Consistently with the uncertainty bands in the figure, the test statistic in Figure 14 also indicates that the dampening is statistically significant for these three uncertainty measures. In contrast, for the three other uncertainty measures the effects of the policy shock seems unaffected by the degree of uncertainty.

For the United Kingdom, we see from Figures 15 and 16 that there is little or no evidence of interaction effects with the U.S. uncertainty measures. The impulse responses are weaker under high uncertainty as measured by stock market volatility, the credit spread or forecaster disagreement, but these differences are not significant. With the JLN macro uncertainty measure, the interaction effect is overturned in the short run, and with the remaining two uncertainty measures the investment responses are positive, casting doubt over whether monetary policy shocks are properly identified.

Finally, when we consider the investment responses in Norway, we see that high stock market volatility is associated with a somewhat weaker investment response. This dampening is modest, however, and the five other uncertainty measures do not indicate a link between U.S.-uncertainty and policy effectiveness in Norway.

Overall, there is some evidence that economic uncertainty in the U.S. interacts with the influence of monetary policy in Canada, but less so in the two other economies that are farther away. To the extent that there are interaction effects there, it is with the financial uncertainty-measures only. A likely reason why financial uncertainty measures interact more strongly, is

that financial markets are internationally integrated, and therefore tend to reflect aspects of the economic environment that are relevant across countries, whereas the non-financial measures are more specific to the United States, and less relevant elsewhere.

6 Conclusion

Over the last years economic uncertainty has been given much attention, both by policymakers and in the academic literature, as a potential influence in business cycle fluctuations. Much of the debate has been motivated by concerns that elevated uncertainty might motivate firms and households to delay decisions that are costly to reverse. This paper contributes here. Our empirical findings indicate that monetary policy is less effective when uncertainty is high. In the United States, consumption, investment and GDP-responses to a monetary policy shock are approximately halved when economic uncertainty measures are in their upper rather than their lower deciles. This qualitative pattern holds for 6 out of 7 uncertainty measures that we consider. There is also evidence that uncertainty measured in the United States dampens the influence of monetary policy in Canada. This implies that when uncertainty is high, monetary policymakers may face a trade-off between acting decisively and acting correctly, as policy must be more aggressive than otherwise in order to stabilize economic activity.

Our results are consistent with the “cautiousness” effects suggested by economic theory which emphasizes the role of fixed adjustment costs. However, two of our findings may imply that alternative mechanisms are also at play. First, non-convexities should be more important for investment than consumption, which conflicts somewhat with the finding that in the United States uncertainty dampens consumption responses as much as investment responses. Second, the pattern of reduced policy effect is particularly stark, and the effects particularly large, when uncertainty measures from financial markets are utilized. This could indicate that financial channels are playing a role. Further research on the exact mechanism behind the policy ineffectiveness effects we find seems warranted. Moreover, while our methodology treats economic uncertainty as exogenous, it makes conceptually more sense to think of uncertainty as endogenous. Developing econometric and theoretical models that endogenize economic uncertainty seems a highly fruitful avenue for future research.

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Appendices

Appendix A Bayesian estimation and priors

We use an uninformative version of the natural conjugate priors described in Kadiyala and Karlsson (1997) and Koop et al. (2007). For simplicity, assume we can rewrite equation 2 in the following form:

$$Y = X\beta + \epsilon \quad (3)$$

where X now includes all regressors in equation 2, i.e. lagged endogenous, exogenous and interacted variables, and ϵ has a variance-covariance matrix Σ .

We apply the general Matricvariate Normal - Wishart priors for β and Σ^{-1} .

$$p(\beta, \Sigma^{-1}) = p(\beta)p(\Sigma^{-1}), \quad (4)$$

where

$$(\beta|\Sigma) \sim \mathcal{MN}(\underline{\beta}, \underline{V}) \quad (5)$$

and

$$(\Sigma^{-1}) \sim \mathcal{W}(\underline{H}, \underline{\nu}) \quad (6)$$

Noninformativeness is then achieved by imposing that $\underline{\nu} = 0$ and $\underline{H}^{-1} = 0 \times I$. By using the prior, we can derive the following conditional posteriors for $p(\beta|Y, \Sigma^{-1})$

$$(beta|Y, \Sigma^{-1}) \sim \mathcal{MN}(\bar{\beta}, \bar{V}) \quad (7)$$

where

$$\bar{V} = (\underline{V}^{-1} + \sum_{t=1}^T X' \Sigma^{-1} X)^{-1} \quad (8)$$

and

$$\bar{\beta} = \bar{V}(\underline{V}^{-1} + \sum_{t=1}^T X' \Sigma^{-1} Y) \quad (9)$$

and likewise for $p(\Sigma^{-1}|Y, \beta)$

$$(\Sigma^{-1}|Y, \beta) \sim \mathcal{W}(\bar{H}, \bar{\nu}) \quad (10)$$

where

$$\bar{\nu} = T + \underline{\nu} \quad (11)$$

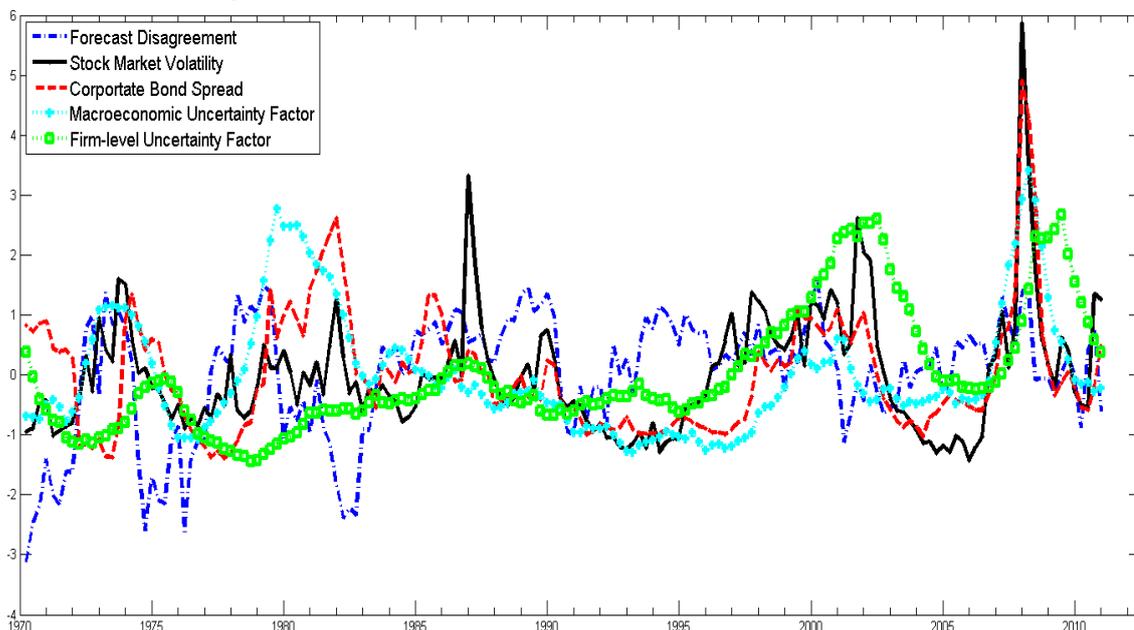
and

$$\bar{H} = [\underline{H}^{-1} + \sum_{t=1}^T X' \Sigma^{-1} (Y - X\beta)(y - x\beta)']^{-1} \quad (12)$$

We then use the Gibbs sampler to sequentially draw from the normal $p(\beta|Y, \Sigma^{-1})$ and the wishart $p(\Sigma^{-1}|Y, \beta)$.

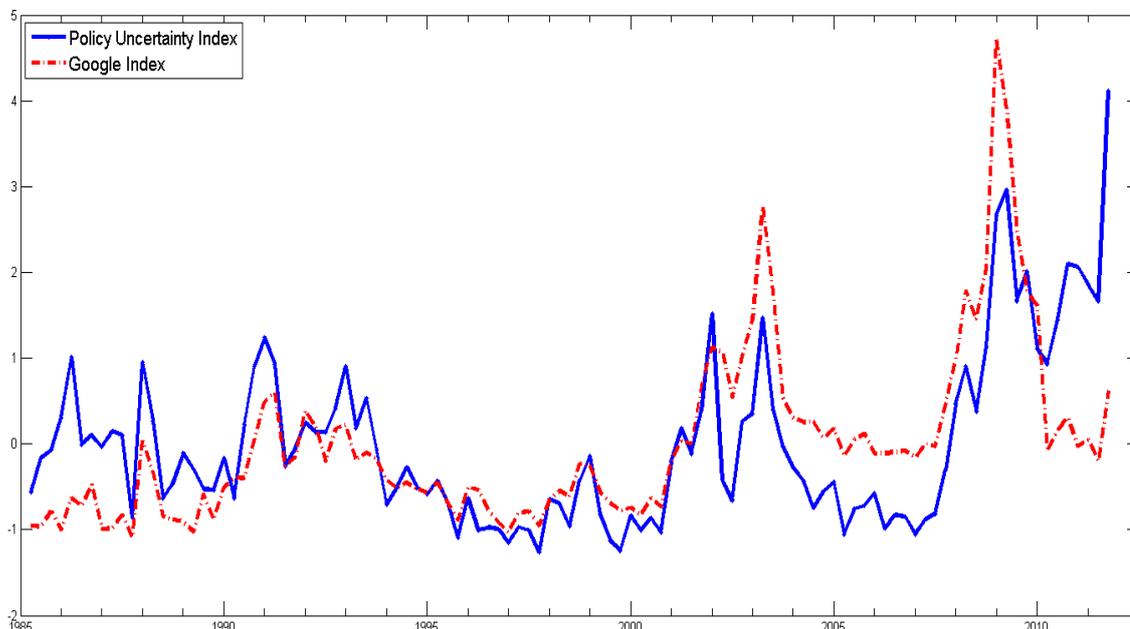
Appendix B Figures

Figure 1: Uncertainty Measures Since 1970



Note: The quarterly average of the stock market volatility index from Bloom (2009) extended to 2011, a corporate bond spread and the forecast disagreement measure used in Bachmann et al. (2013) for the period 1970Q1-2011Q3. Each series has been demeaned and standardized by its standard deviation.

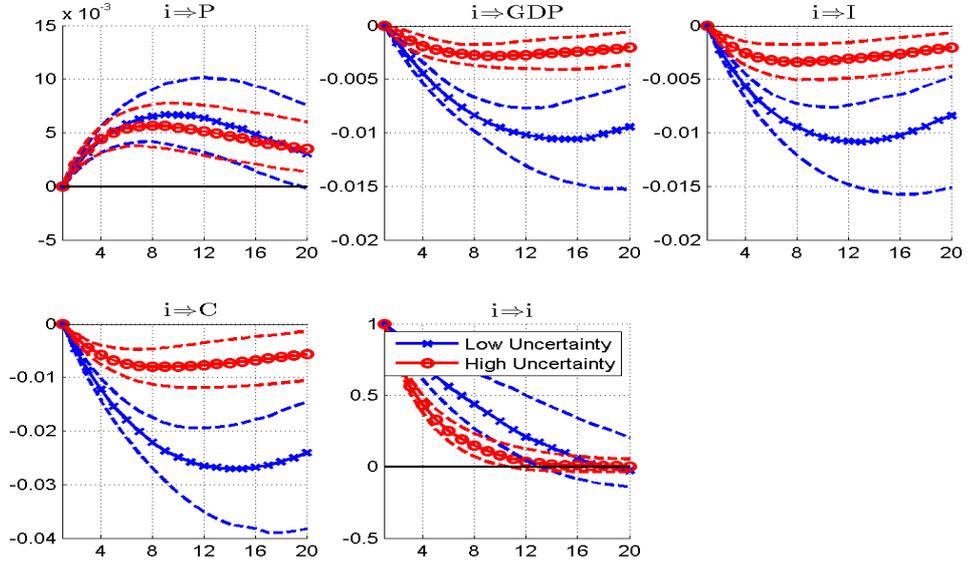
Figure 2: Uncertainty Measures Since 1985



Note: The quarterly average of the policy uncertainty index in Baker et al. (2012) and the Google index used in Bachmann et al. (2013). The series have been demeaned and standardized by their standard deviation.

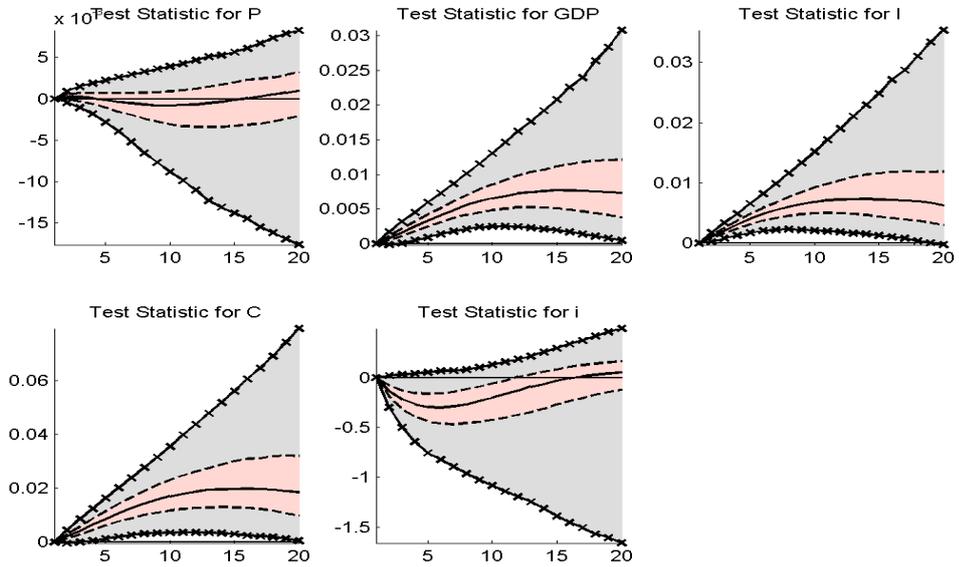
B.1 Results for the United States

Figure 3: Monetary Policy Shock - USA - Stock Market Volatility



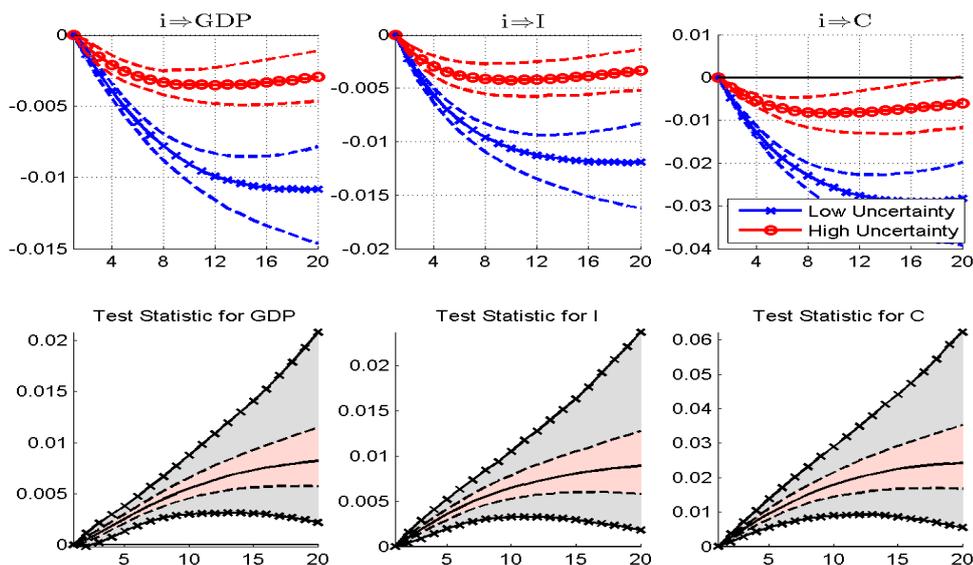
Note: Impulse responses to a one percentage point increase in the interest rate, when the stock market volatility index is in its upper and lower decile.

Figure 4: Test - USA - Stock Market Volatility



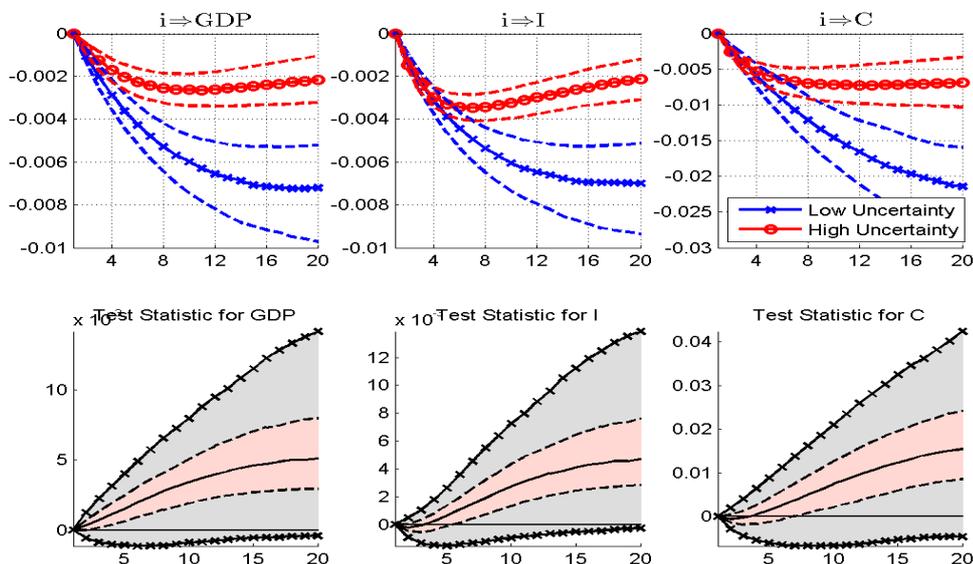
Note: The distribution of the difference between the impulse responses under 90th and 10th percentile levels of stock market volatility. The shaded areas represent the 68% and the 90% probability bands.

Figure 5: Monetary Policy Shock - USA - Credit Spread



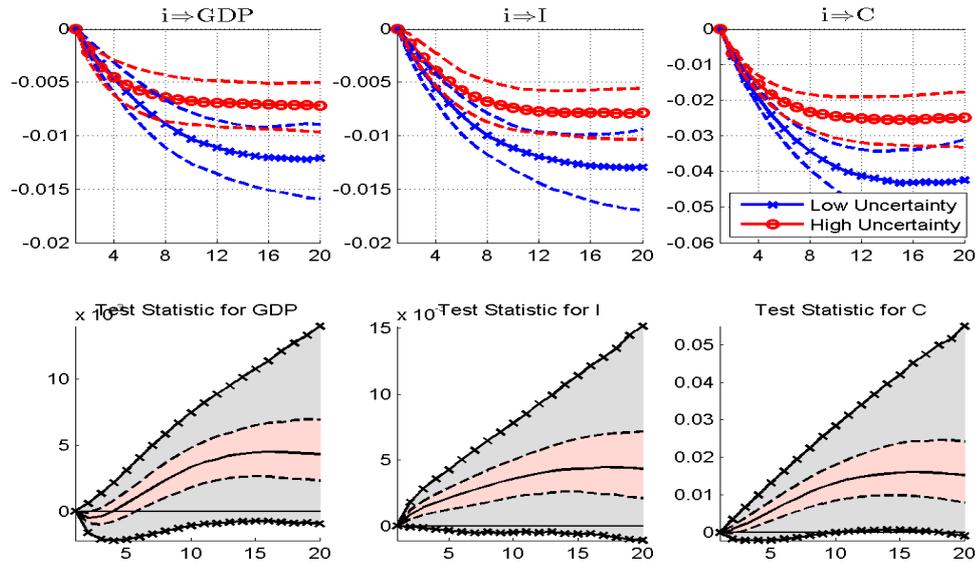
Note: The upper panel shows impulse responses to a one percentage point increase in the interest rate, when the credit spread is in its upper and lower decile. The lower panel shows the distribution of the difference between the impulse responses under 90th and 10th percentile levels of the credit spread. The shaded areas represent the 68% and the 90% probability bands, respectively.

Figure 6: Monetary Policy Shock - USA - Forecaster Disagreement



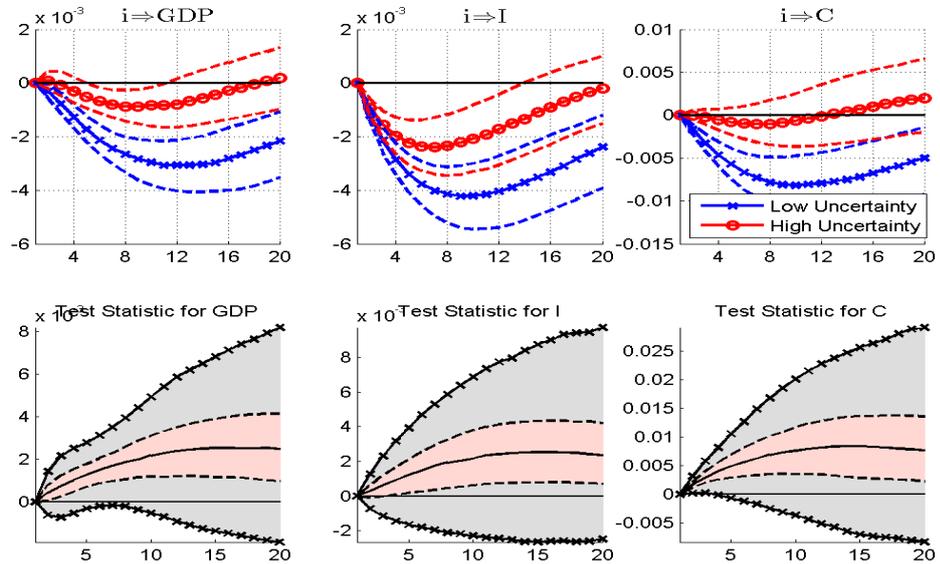
Note: The upper panel shows impulse responses to a one percentage point increase in the interest rate, when the forecaster disagreement index is in its upper and lower decile. The lower panel shows the distribution of the difference between the impulse responses under 90th and 10th percentile levels of the forecaster disagreement index. The shaded areas represent the 68% and the 90% probability bands, respectively.

Figure 7: Monetary Policy Shock - USA - Google



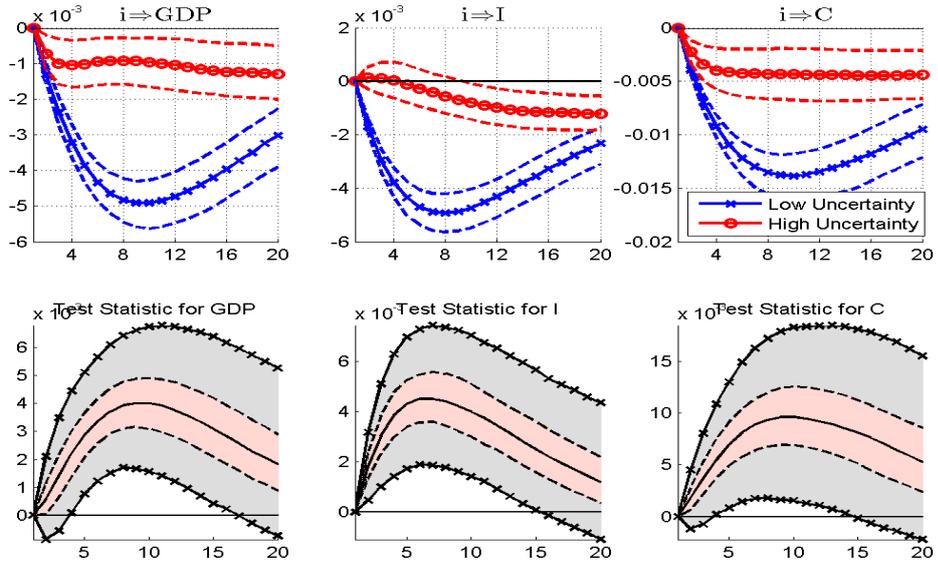
Note: The upper panel shows impulse responses to a one percentage point increase in the interest rate, when the Google index is in its upper and lower decile. The lower panel shows the distribution of the difference between the impulse responses under 90th and 10th percentile levels of the Google index. The shaded areas represent the 68% and the 90% probability bands, respectively.

Figure 8: Monetary Policy Shock - USA - JLN Macro



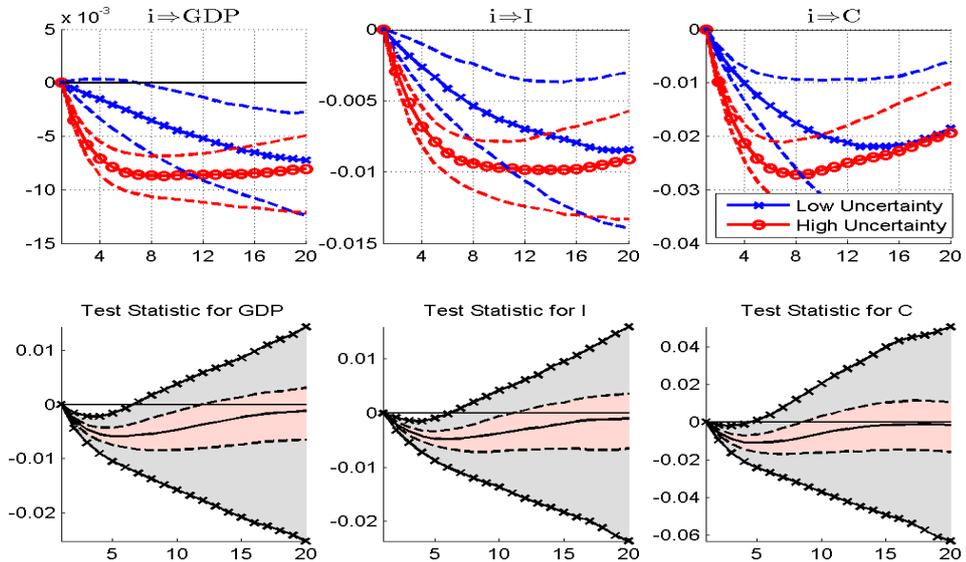
Note: The upper panel shows impulse responses to a one percentage point increase in the interest rate, when the macroeconomic uncertainty index of Jurado et al. (2013) is in its upper and lower decile. The lower panel shows the distribution of the difference between the impulse responses under 90th and 10th percentile levels of the macroeconomic uncertainty index of Jurado et al. (2013). The shaded areas represent the 68% and the 90% probability bands, respectively.

Figure 9: Monetary Policy Shock - USA - JLN Firm



Note: The upper panel shows impulse responses to a one percentage point increase in the interest rate when the firm-level uncertainty index of Jurado et al. (2013) is in its upper and lower decile. The lower panel shows the distribution of the difference between the impulse responses under 90th and 10th percentile levels of the firm-level uncertainty index of Jurado et al. (2013). The shaded areas represent the 68% and the 90% probability bands, respectively.

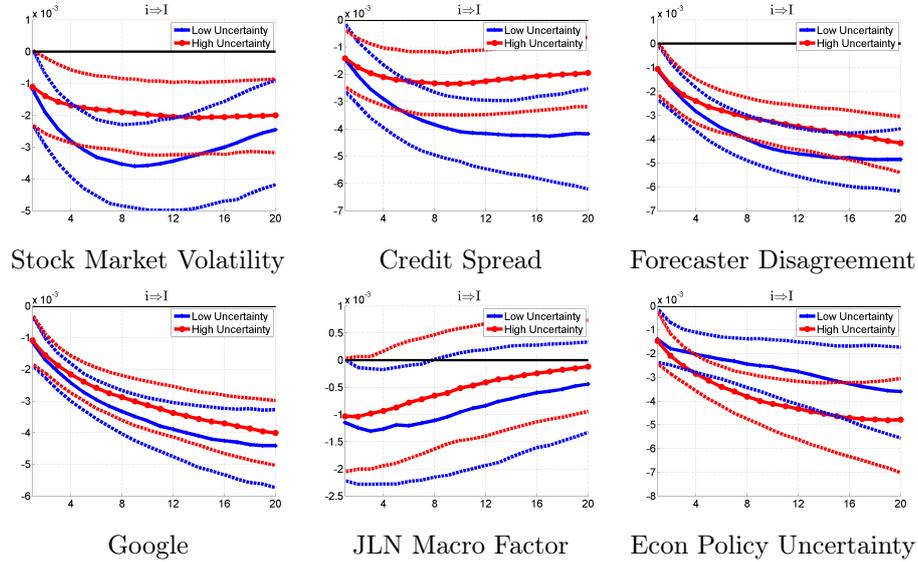
Figure 10: Monetary Policy Shock - USA - Economic Policy Uncertainty



Note: The upper panel shows the impulse responses to a one percentage point increase in the interest rate when the EPU-index is in its upper and lower decile. The lower panel shows the distribution of the difference between the impulse responses under 90th and 10th percentile levels of the EPU-index. The shaded areas represent the 68% and the 90% probability bands, respectively.

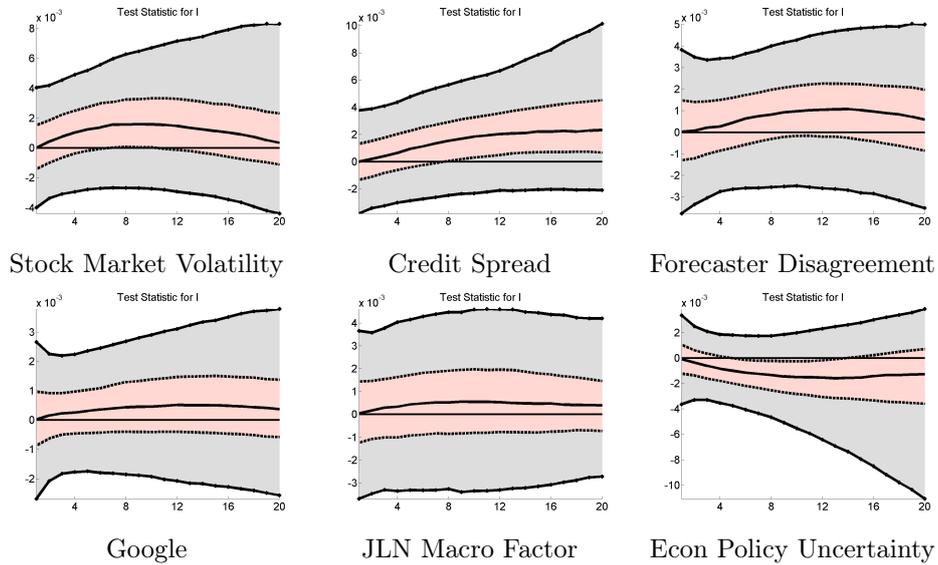
B.2 Results for the United States - Sign Restrictions

Figure 11: Monetary Policy Shock - USA - Investment responses



Note: Investment responses to a one percentage point increase in the interest rate, when uncertainty measures are in their upper and lower deciles. Monetary policy shock identified by sign restrictions.

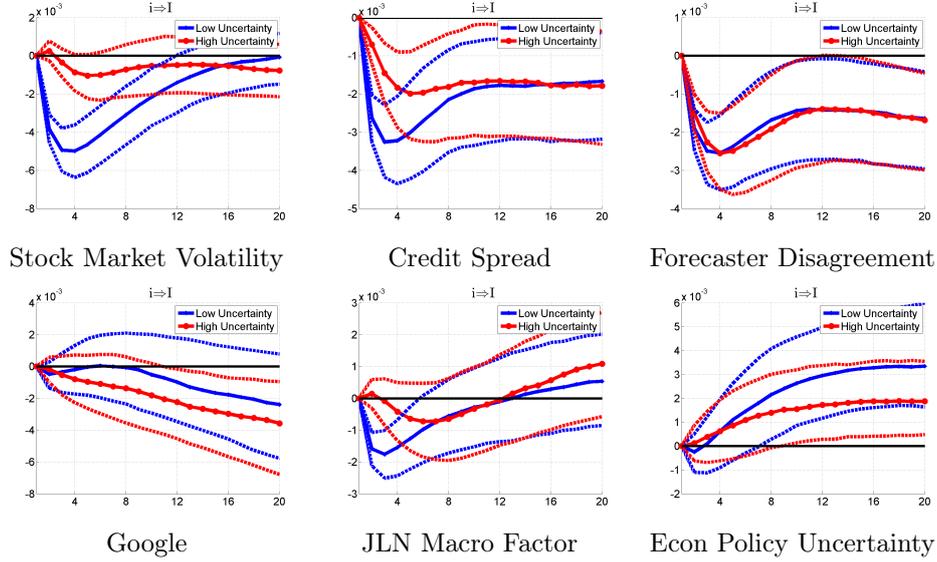
Figure 12: Test - U.S. Investment responses



Note: The distribution of the difference between the investment responses under 90th and 10th percentile levels of the uncertainty-indices. The shaded areas represent the 68% and the 90% probability bands, respectively.

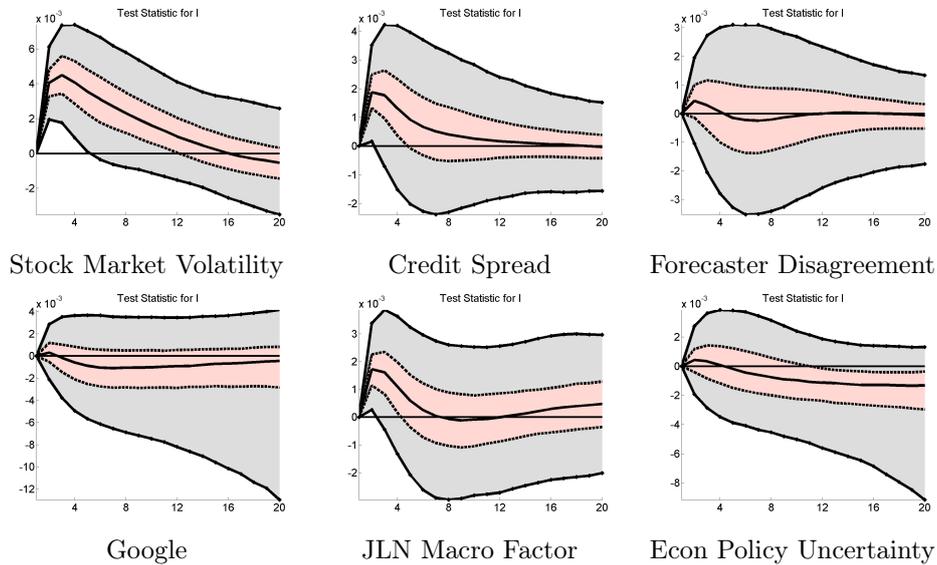
B.3 Results for Canada, the United Kingdom and Norway

Figure 13: Monetary Policy Shock - Canada - Investment responses



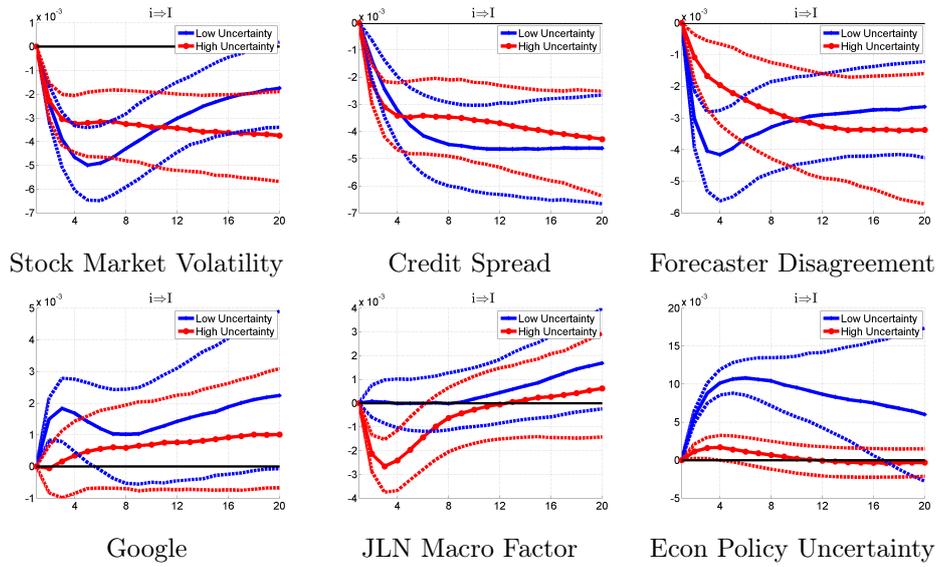
Note: Investment responses to a one percentage point increase in the interest rate, when uncertainty measures are in their upper and lower deciles. Monetary policy shock identified recursively.

Figure 14: Test - Canada - Investment



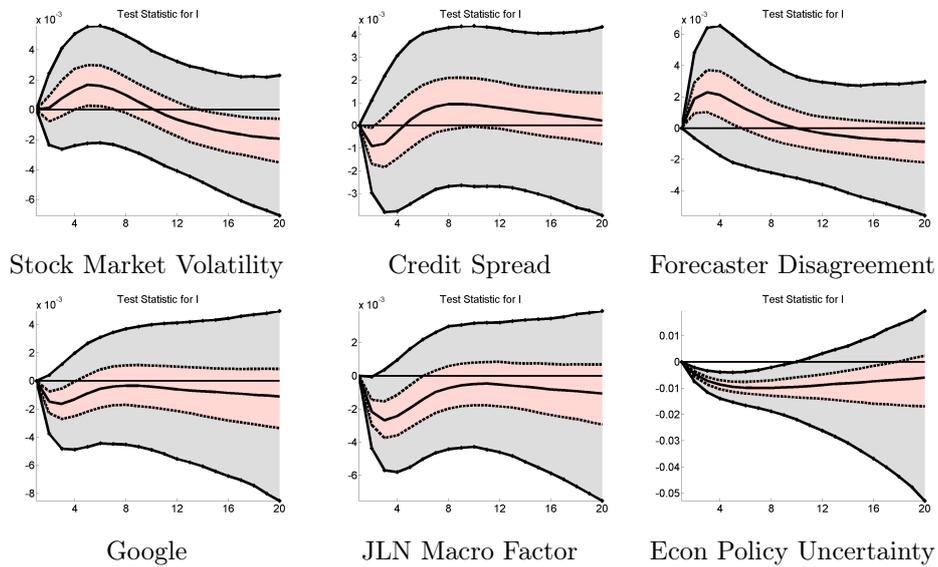
Note: The distribution of the difference between the investment responses under 90th and 10th percentile levels of the uncertainty-indices. The shaded areas represent the 68% and the 90% probability bands, respectively.

Figure 15: Monetary Policy Shock - UK - Investment responses



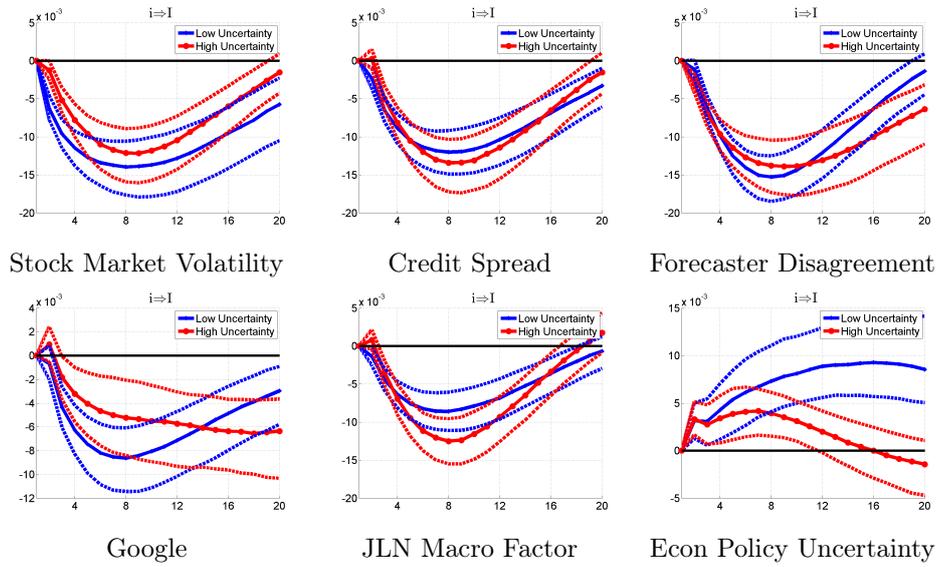
Note: Investment responses to a one percentage point increase in the interest rate, when uncertainty measures are in their upper and lower deciles. Monetary policy shock identified recursively.

Figure 16: Test - UK - Investment



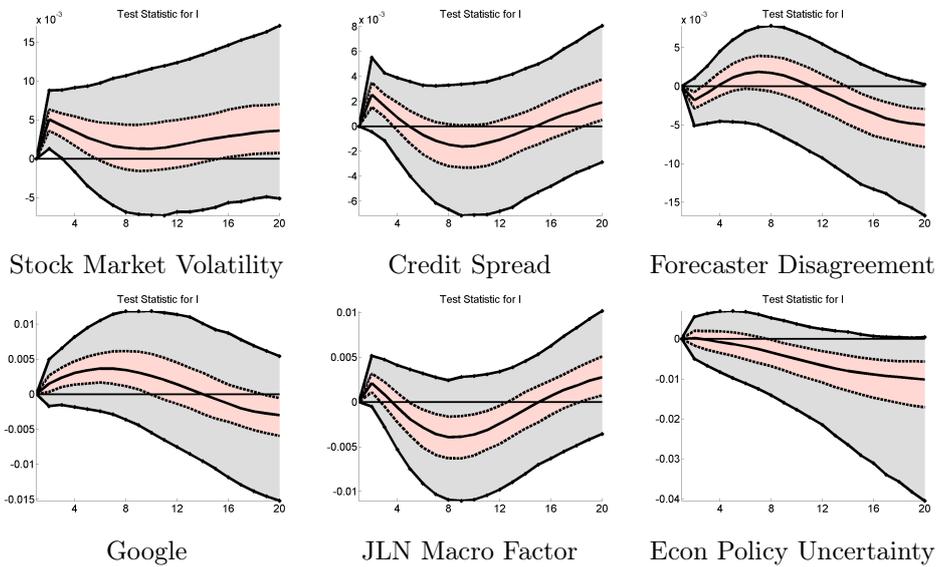
Note: The distribution of the difference between the investment responses under 90th and 10th percentile levels of the uncertainty-indices. The shaded areas represent the 68% and the 90% probability bands, respectively.

Figure 17: Monetary Policy Shock - Norway - Investment responses



Note: Investment responses to a one percentage point increase in the interest rate, when uncertainty measures are in their upper and lower deciles. Monetary policy shock identified recursively.

Figure 18: Test - Norway - Investment



Note: The distribution of the difference between the investment responses under 90th and 10th percentile levels of the uncertainty-indices. The shaded areas represent the 68% and the 90% probability bands, respectively.