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Tesi di Dottorato di Silvia Delrio, matricola 956078

Coordinatore del Dottorato
Prof. Giacomo Pasini

Supervisore del Dottorando
Prof. Giovanni Caggiano

Co-supervisore del Dottorando
Prof. Roberto Casarin

Empirical Essays on Uncertainty and Fiscal Shocks

Silvia Delrio

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Summary

This thesis empirically investigates the macroeconomic effects of uncertainty and fiscal shocks, particularly focusing on the role of nonlinearities in the transmission mechanisms of shocks.

Chapter 1 investigates the effects of global uncertainty shocks in open economies and explores the role that different levels of country risk exposure might have in the transmission of the shock. We employ an Interacted VAR model and examine the dynamic responses of output and exchange rate to a global uncertainty shock for a group of developed economies. The I-VAR model allows to account for time variation in country relative riskiness and for the possible presence of nonlinearities in the transmission mechanism, through the computation of state conditional impulse response functions. As a measure of global uncertainty, we take the realized volatility of the MSCI World Index log returns. Taking the U.S. as the reference country, we consider the spread between each country's interbank rate and the Federal Funds rate as our measure of relative riskiness. Following Gourio, Siemer, and Verdelhan (2013), we define a country as being in high risk regime when its interbank rate is lower than the FFR (negative spread), whereas we define the country in low risk regime when its interbank rate is higher than the FFR (positive spread). The spread reflects different levels of precautionary savings in the two countries. The country which is more exposed to aggregate risk experiences a higher level of precautionary savings, which implies a higher demand for safe assets and a lower (risk-free) rate. The country with lower exposure to risk has a lower level of precautionary savings, and a higher interest rate, since the demand for risk-free assets would be lower. Our results show that countries' relative risk exposure to aggregate risk plays a relevant role in the transmission of a global

uncertainty shock and provide evidence for the presence of nonlinear effects in the transmission of the shock to economic activity. Indeed, the dynamic responses of output in high risk state are estimated to be negative and statistically larger than those in low risk. Concerning the exchange rate, we find that it appreciates on impact in response to a global uncertainty shock in both riskiness regimes, but we find little evidence in favor of the presence of nonlinearities in the transmission of the shock to the exchange rate.

Chapter 2 estimates time-varying spending multipliers, to assess the evolution of U.S. fiscal policy effectiveness over time. We ask whether and how the monetary policy stance affects the transmission of fiscal policy shocks and devote special attention to the size of spending multipliers when the economy is at the zero lower bound (ZLB). To this aim, we model a set of standard macro-fiscal variables over the period 1954Q3-2015Q3 by using a time-varying parameter VAR model with stochastic volatility, which allows both shocks and the fiscal transmission mechanism to change over time. Unconventional monetary policy in the last part of the sample is explicitly accounted for by including the shadow rate estimated by Wu and Xia (2016), which captures relevant information about the monetary policy stance from movements in the term structure of interest rates. The distinction between active and passive monetary and fiscal policies proposed in Leeper (1991) and the estimated joint monetary-fiscal regimes in Davig and Leeper (2011) offer an interesting framework to interpret our results. Estimates obtained from our quarterly TVP-VAR show that government spending multipliers considerably vary over the investigated period, and are larger during periods in which monetary policy does not strongly react to inflation movements, like times of passive monetary policy regime and at the ZLB. Moreover, spending multipliers display an increasing trend over time. This result, jointly with the increasing variability of output accounted for by spending shocks over the investigated period suggested by our FEVDs, point to increasing relevance over time of fiscal policy in explaining output fluctuations.

Chapter 3 is based on joint work with Giovanni Caggiano, Efrem Castelnuovo and Tim Robinson. It estimates time-dependent finance-uncertainty multipliers in the post-WWII U.S. sample. An uncertainty multiplier captures the response of a measure of real activity (industrial production, employment, unemployment) to an uncertainty shock. Following Alfaro, Bloom, and Lin (2016), we aim at understanding to what extent financial conditions affect this multiplier. Indeed, it has been shown that financial frictions play an important role in the transmission of uncertainty shocks (e.g., Caldara, Fuentes-Albero, Gilchrist, & Zakrajšek, 2016). Moreover, Beetsma and Giuliodori (2012) and Mumtaz and Theodoridis (2016) show that the effects of uncertainty shocks vary over time. For these reasons, we model a number of macroeconomic indicators with a time-varying parameter VAR along with measures of financial uncertainty and credit spreads, to isolate exogenous variations in uncertainty and assess their real impact conditional on financial markets' stance. Uncertainty shocks are identified by relying on the measure of financial uncertainty recently constructed by Ludvigson, Ma, and Ng (2016). Gilchrist and Zakrajšek (2012)'s credit spread measure is decomposed in two orthogonal components - the exogenous excess bond premium and the endogenous part of the spread - to control for credit supply shocks while considering the amplification effect due to financial frictions following an uncertainty shock. Our results point to substantial variations in the finance-uncertainty multipliers over the investigated period. Uncertainty shocks always have recessionary effects, although with time-varying persistence, and those effects are amplified in periods of financial distress.

Chapter 1

Estimating the Effects of Global Uncertainty in Open Economies

1.1 Introduction

In recent years the role of uncertainty in driving business cycle fluctuations has received a great deal of attention in the policy debate (e.g., FOMC, 2008; Blanchard, 2009), and since the seminal work of Bloom (2009), macroeconomic research has increasingly focused on the investigation of the mechanisms linking uncertainty to economic activity, as well as tried to empirically estimate its effects on the economy. It has been claimed that the increased level of macroeconomic uncertainty was one of the main causes of the Great Recession of 2008-2009 (e.g., Stock & Watson, 2012) and that heightened uncertainty also played an important role in the slow recovery that followed thereafter (e.g., Leduc & Liu, 2015). Moreover, Bloom et al. (2014) among others highlight the fact that uncertainty can also affect economic policy effectiveness. Indeed, in times of high uncertainty, agents may be cautious in responding to any stimulus, which can make policy interventions less effective. As a result, investigating which are the effects of uncertainty on economic activity became a central issue among policymakers, who are interested in understanding how to respond to the consequences of heightened uncertainty on the one hand, and whether policy interventions can reduce uncertainty itself on the other hand.

This chapter empirically investigates the effects of global uncertainty shocks in open economies, by taking into account the role that different levels of country risk exposure might have in the transmission of the shock. We address the following questions: (i) which are the effects of a global uncertainty shock in an open economy and (ii) does countries' relative risk exposure play a role in the transmission the shock? To answer these questions, we perform a Structural Vector Autoregression (SVAR) analysis on a group of developed countries and take the U.S. as the benchmark to define our measure of relative riskiness.

More in detail, we estimate an Interacted VAR (I-VAR) model and examine the dynamic responses of output and exchange rate to a global uncertainty shock. The I-VAR model allows to account for time variation in country relative riskiness and for the possible presence of nonlinearities in the transmission mechanism of global uncertainty shocks, through the computation of state conditional impulse response functions, where the state of the economy is defined by the level of risk exposure. This cannot be done in a linear framework, like a linear SVAR, since in that case the computed impulse response functions only capture the average response of the endogenous variables to the shock, without accounting for the possible presence of different regimes. An Interacted VAR model is a standard VAR augmented with an interaction term, which includes the variable that we want to shock and a conditioning variable that identifies the two states of the economy that we think can be relevant for the transmission of the shock. This allows to get responses to the shock of interest conditionally on each of the two regimes we are interested in, and to account for the possible presence of nonlinear effects. Particularly, global uncertainty is the variable whose shocks we want to identify, whereas our conditioning variable is a measure of relative risk exposure.

As a measure of global uncertainty, we take the realized volatility of the MSCI World Index log returns, where the MSCI World Index is a stock market index that includes a collection of stocks of developed market countries. We employ interest rates to discriminate across countries' heterogeneous risk exposure. Taking the U.S. as the reference country, we consider the spread between each country's interbank rate and the Federal Funds rate (FFR) as our measure of relative riskiness. Following Gourio et al. (2013)'s two-country RBC model, we define a country as being in high risk regime when its interbank rate is lower than the FFR (negative spread), whereas we define the country in low risk regime when its interbank rate is higher than the FFR (positive spread). The spread reflects different levels of precautionary savings in the two countries. The country which is more exposed to aggregate risk experiences a higher level of precautionary savings, which implies a higher demand for safe assets and a lower (risk-free) rate. The country with lower exposure to risk has a lower level of precautionary savings, and a higher interest rate, since the demand for risk-free assets would be lower.

An important feature of the specification of our I-VAR is that both variables in the interaction term are endogenously modeled, which implies that interest rate spreads are likely to react to a global uncertainty shock. This means that the economy can endogenously switch from one regime to the other within each horizon. Therefore, following Pellegrino (2014) and Caggiano, Castelnuovo, and Pellegrino (2016), dynamic responses of the endogenous variables to the uncertainty shock are computed as Generalized Impulse Response Functions (GIRFs) à la Koop, Pesaran, and Potter (1996). Indeed, through GIRFs the nonlinearity of the system is fully taken into account, because the responses of the endogenous variables will depend on the size and the sign of the shock, as well as on the initial conditions of the system and the future shocks.

Our main results can be summarized as follows. First, concerning question (i) on the effects of global uncertainty shocks in open economies, the dynamic responses of our variables of interest show that output negatively responds to the shock and the exchange rate appreciates. The sign of the response of output is consistent with the main findings in the literature on uncertainty. Then, relative to question (ii) about the role of relative risk exposure in the transmission of the shock, we find that the level of countries' relative exposure to aggregate risk plays a relevant role in the transmission of a global uncertainty shock. Indeed, a global uncertainty shock generates a significant reduction in real activity when the economy is in high risk regime, whereas in low risk regime the response is generally not statistically different from zero. Moreover, the differences between the dynamic responses of output in the two regimes are statistically significant, meaning that the responses of output in high risk are estimated to be statistically larger than those in low risk. This results provide evidence for the presence of nonlinear effects in the transmission of global uncertainty shocks to economic activity. Further support to this evidence is provided by the results of an exercise in which we explore what happens when the two riskiness regimes become "extreme", i.e. when the distance in country relative risk exposure widens (meaning that interest rate spread increases in absolute value). Our main result is that, as the distance in countries' relative risk exposure increases, also the difference between estimated responses in the two regimes increases. These findings support the theoretical model proposed by Gourio et al. (2013), where an increase in aggregate risk produces a larger decline in economic activity in the country which is more exposed to aggregate risk. Concerning the exchange rate, we find that it appreciates on impact in response to a global uncertainty shock in both riskiness regimes, but we find little evidence in favor of the presence of nonlinearities in the transmission of the shock to the exchange rate, evidence which mainly comes from our exercise with "extreme" riskiness regimes.

We test the robustness of our results through a series of perturbations of the baseline model. In particular, we consider an uncertainty shock dummy built following Bloom (2009), which takes a value of 1 for each of the events that we define as global uncertainty shocks, and 0 otherwise. Moreover, we explore the role played by country-specific uncertainty and financial shocks in the transmission of global uncertainty shocks. Our main findings are supported by these further exercises.

This chapter contributes to the existing literature on uncertainty in several respects. We propose a multi-country analysis on the effects of global uncertainty shocks in open economies and investigate the role of countries' relative risk exposure in the transmission of the shock. As a measure of global uncertainty we propose the quarterly series of realized volatilities of the returns of the MSCI World Index.[1] Relative to Carrière-Swallow and Céspedes (2013), who also consider an open economy framework, we consider both the responses of economic activity and the exchange rate to the shock.[2] To examine how different levels of country

[1]Related contributions investigating the effects of global uncertainty on economic activity, as Carrière-Swallow and Céspedes (2013) and Cesa-Bianchi, Pesaran, and Rebucci (2014) propose different measures. Carrière-Swallow and Céspedes measure global uncertainty shocks as strong increases in the VIX index, whereas Cesa-Bianchi et al. construct a quarterly measure of global uncertainty by using daily returns across 109 asset prices worldwide.

[2]Benigno, Benigno, and Nisticò (2012) investigate the relationship between uncertainty and the exchange rate employing an open economy VAR and examine the response of the exchange rate to changes in the volatility of nominal and real shocks. The measures of uncertainty they use

risk exposure affect the transmission of a global uncertainty shock, we employ a nonlinear model, specifically an Interacted VAR model, which allows to account for the presence of two different riskiness regimes in the economy and to compute state-conditional responses to the global uncertainty shock.

The structure of the chapter is the following. Section 2 discusses the relation to the literature. Section 3 presents the empirical strategy and the data employed in the analysis. Section 4 describes the nonlinear model. Section 5 illustrates the results. Section 6 concludes.

1.2 Related literature

This chapter mainly relates to macroeconomic research which investigates the role of uncertainty in driving business cycle fluctuations. A non-exclusive list of recent works includes Bloom (2009); Bloom et al. (2014); Fernandez-Villaverde et al. (2011); Benigno et al. (2012). Bloom (2014) provides a survey of the main facts, issues and contributions related to uncertainty. A widely recognized result is that uncertainty shocks negatively affect economic activity by producing a fall in the levels of production and employment.

Theoretical contributions have emphasized two transmission channels for uncertainty to affect economic activity in closed economies. The first one relates to the idea of real options, for which high levels of uncertainty increase the option value of postponing investment decisions and hiring for firms, and durable consumption for households, particularly when the cost of reversing decisions is high. Then, a high level of uncertainty reduces the levels of investment, hiring and consumption, thus reducing economic activity (e.g., Bernanke, 1983; Bloom, 2009). The other channel examined in the literature focuses on risk aversion and risk premium. Arellano, Bai, and Kehoe (2012) and Christiano, Motto, and Rostagno (2014) among others emphasize how a higher level of uncertainty leads investors to ask for increasing risk premiums to be compensated for higher risk. Higher uncertainty also increases the probability of default. As a consequence, uncertainty raises borrowing costs,

are given by the time-varying volatilities of a monetary policy shock, an inflation-target shock and a productivity shock.

which can reduce growth. Ilut and Schneider (2011) explore the confidence effect of uncertainty in models where agents have pessimistic beliefs and act as if the worst outcomes will occur, showing a behaviour known as "ambiguity aversion". Increasing uncertainty expands the range of possible outcomes, and makes the worst outcome worse, which can induce agents to reduce hiring and investment. In a third mechanism that relates to risk aversion, a rise in uncertainty can induce consumers to increase the level of precautionary savings, thus reducing consumption and economic activity in the short-run (Bansal & Yaron, 2004; Fernandez-Villaverde et al., 2015; Leduc & Liu, 2015; Basu & Bundick, 2016).

Concerning open economies, recently Gourio et al. (2013) have proposed a two-country real business cycle model, to understand the effects of changes in aggregate risk on economic activity in small open economies, in the presence of heterogeneous country risk exposure. Aggregate risk, which Gourio et al. interpret as a global uncertainty shock, and heterogeneity in country risk exposure are the two key elements of their model.[3] Concerned with the effects of uncertainty shocks in open economies are also Fernandez-Villaverde et al. (2011), Benigno et al. (2012) and Carrière-Swallow and Céspedes (2013). Fernandez-Villaverde et al. focus on the role played by changes in the volatility of the real exchange rate in the dynamics of business cycle fluctuations of emerging economies. Benigno et al. analyze the response of the exchange rate to shocks to the volatilities of a monetary policy shock, a shock to the inflation target and a productivity shock, in an open economy VAR framework.[4] Carrière-Swallow and Céspedes estimate the response of investment and private consumption to a global uncertainty shock in

[3]The key mechanism of the model is the following. Following an increase in the probability of an economic disaster, investment falls because of a reduction in capital holdings by firms, due to increasing risk premiums. At the same time, output and employment reduce. Hence, an increase in disaster probability leads to a recession. The risk-free interest rate falls as the demand for safe assets rises (flight to quality effect) and equity prices drop. All these effects are stronger in the more risky country. Concerning the exchange rate, the currency of the most risky country appreciates in response to an increase in disaster probability.

[4]They find that the exchange rate appreciates in response to an increase in the volatility of the monetary and the inflation target shocks, and that it depreciates following an increase in the volatility of the productivity shock. They also develop a two-country open economy model in which the channel that links uncertainty and exchange rate is a hedging motive. The currency does not necessarily depreciates following an uncertainty shock. If the currency is relatively safer when the shock occurs, then heightened uncertainty may improve its hedging properties, leading to an appreciation.

40 countries in an open economy VAR. Global uncertainty shocks are measured as strong increases in the VIX index. Investigating the effects of global uncertainty shocks on economic activity is also the aim of Cesa-Bianchi et al. (2014), who estimate a Global VAR for 33 countries. A quarterly series for uncertainty is constructed using the realized volatilities of 109 asset prices worldwide.

Other empirical contributions on the effects of uncertainty shocks on economic activity employ country-specific measures of uncertainty, especially those capturing uncertainty in the U.S.. Moreover, most of them are single-country studies investigating the effects of country-specific uncertainty shocks, and in some cases exploring the presence of spillover effects in other countries (e.g., Colombo, 2013). From a methodological perspective, most contributions employ linear models for the analysis and particularly linear Structural VARs (e.g., Bloom, 2009; Alexopoulos & Cohen, 2009; Mumtaz & Theodoridis, 2015; Baker, Bloom, & Davis, 2016). Nevertheless, more recent works also take into account the possibility for the state of the economy to have a role in the transmission of uncertainty shocks, and investigate the issue through nonlinear models that allow for regime switches.

Among them, Enders and Jones (2013) employ a Smooth Transition autoregressive model to explore the presence of asymmetric effects of uncertainty shocks on a number of macroeconomic variables. Bijsterbosch and Guérin (2013) propose a two-step procedure in which they identify episodes of high uncertainty in the U.S., through a Markov switching approach, and then regress several macroeconomic and financial variables on this high uncertainty indicator. Caggiano, Castelnuovo, and Groshenny (2014) employ a Smooth Transition VAR to estimate the response of unemployment to uncertainty shocks during recessions. Caggiano, Castelnuovo, and Nodari (2015) employ the same methodology to explore the asymmetric effects of uncertainty shocks over the business cycle and to analyze the effectiveness of the systematic part of monetary policy in dealing with the real effects of uncertainty shocks. Alessandri and Mumtaz (2014) investigate the role of financial markets conditions in the transmission of uncertainty shocks. Ricco, Callegari, and Cimadomo (in press) analyze the effects of fiscal policy shocks in the presence of fiscal policy uncertainty. Caggiano, Castelnuovo, and Pellegrino (2016) employ an Interacted VAR to investigate whether the effects of uncertainty shocks on economic activity are greater when the economy is at the Zero Lower Bound (ZLB).

1.3 Empirical strategy

This chapter aims at answering two questions: (i) which are the effects of a global uncertainty shock in open economies and (ii) does countries' relative risk exposure play a role in the transmission the shock? To answer these questions, the empirical analysis is organized as follows. First, as a warm-up exercise, we explore the effects of global uncertainty in open economies, through the estimation of a linear VAR model for a group of eleven countries. To investigate whether countries' relative risk exposure does play a relevant role in the transmission of the shock, we employ a nonlinear specification and estimate an Interacted VAR model. Indeed, a nonlinear model such as an I-VAR allows to compute state-dependent impulse responses, i.e. responses of output and exchange rate conditional on the riskiness level of the economy. With respect to the sample of countries considered for the linear exercise, we perform the nonlinear analysis on a subsample of countries, where the selection criterion is given by the results of a linearity test. The nonlinear analysis will be limited to those countries for which the linearity test provides evidence in favour of the nonlinear specification, by rejecting the null hypothesis of a linear specification. Indeed, a nonlinear model would be misspecified if the true data generating process is linear.

1.3.1 Data

For our investigation we consider a group of eleven countries: Australia, Austria, Canada, Finland, France, Germany, Italy, Netherlands, Norway, Sweden and United Kingdom, which can all be considered as small open economies with respect to the U.S.. We employ quarterly data. The starting time for estimation changes across countries, depending on data availability,[5] whereas for all of them the estimation period ends in 2008Q2. The period starting in 2008Q3 and including the financial crisis and the subsequent Great Recession is excluded from the analysis. The reason for this choice is that, since the end of 2008, policy rate hit the zero lower bound in the U.S., as well as in most advanced economies thereafter, and as a consequence, interest rate spreads that capture countries' relative risk exposure in our analysis,

[5] Australia 1973Q1, Austria 1988Q1, Canada 1973Q1, Finland 1990Q1, France 1973Q1, Germany 1973Q1, Italy 1981Q1, Netherlands 1988Q1, Norway 1979Q1, Sweden 1973Q1, UK 1973Q1.

stayed almost constant and very close to zero during the subsequent period. This might significantly affect the results of our analysis.[6]

Six variables are included in the specification: (i) a measure of global uncertainty (VOL), which is obtained as the 90-day realized volatility of the MSCI World Index log returns, computed as the standard deviations of daily returns over calendar quarters; (ii) the MSCI World Index ($MSCI$), a stock market index that includes a collection of stocks of developed market countries; since we are in an open economy framework, (iii) the spot bilateral nominal exchange rate of country i with respect to U.S. dollar (USD) ($S_{\$/i}$);[7] (iv) a consumer price index (CPI_i) as a measure of prices and (v) gross domestic product (GDP_i) as a measure of economic activity; (vi) $SPREAD_i$, which is the difference between country i overnight interbank rate and the Federal Funds rate, and the variable that captures countries' relative riskiness with respect to the U.S.. Macroeconomic data are taken from the Federal Reserve Bank of St. Louis FRED database, whereas we refer to Bloomberg for financial data.[8]

The model is estimated via OLS for each of the countries in our sample. We consider the U.S. as the reference country when defining relative riskiness. For this reason the U.S. enter the specification through the exchange rate, which is measured as units of USD for one unit of foreign currency, and the interest rate spread, which is computed as the difference between each country's interbank rate and the FFR. All variables are taken in log-levels, with the exception of volatility

[6] The transmission of uncertainty shocks in the presence of the ZLB is explored in Caggiano, Castelnuovo, and Pellegrino (2016).

[7] The exchange rate is measured as units of USD for one unit of foreign currency, then an increase in $S_{\$/i}$ means an appreciation of the currency of country i and a USD depreciation.

[8] We use GDP Implicit Price Deflator, Index 2010=100, Quarterly, Seasonally Adjusted (all countries but Sweden); Consumer Price Index All Items, Index 2010=100, Quarterly, Not Seasonally Adjusted (Sweden); Gross Domestic Product by Expenditure in Constant Prices: Total Gross Domestic Product, Index 2010=1, Quarterly, Seasonally Adjusted; Gross Domestic Product by Expenditure in Constant Prices: Private Final Consumption Expenditure, Index 2010=1, Quarterly, Seasonally Adjusted; US Dollar to National Currency Spot Exchange Rate, US Dollar per National Currency Units, Quarterly, Not Seasonally Adjusted; Immediate Rates: Less than 24 Hours: London Clearing Banks Rate, Percent, Quarterly, Not Seasonally Adjusted (UK); Immediate Rates: Less than 24 Hours: Central Bank Rates, Percent, Quarterly, Not Seasonally Adjusted (Austria, Finland); Immediate Rates: Less than 24 Hours: Call Money/Interbank Rate, Percent, Quarterly, Not Seasonally Adjusted (France, Germany, Sweden); 3-Month or 90-Day Rates and Yields: Interbank Rates, Percent, Quarterly, Not Seasonally Adjusted; Effective Federal Funds Rate, Percent, Monthly, Not Seasonally Adjusted.

and interest rate spreads, which are in levels. Equation-specific constants are included in both the linear and nonlinear specifications and the number of lags is selected via the Akaike Information Criterion (AIC).[9]

To identify the global uncertainty shock from the vector of reduced form residuals we employ short-run restrictions (Cholesky decomposition), with the endogenous variables ordered as follows: (i) stock market index, (ii) volatility, (iii) exchange rate, (iv) prices, (v) output, (vi) interest rate spread. Following Bloom (2009) we order the stock market index before volatility, in order to control for the impact of stock market levels and to focus on a volatility shock which is orthogonal to market levels. Results obtained from an identification scheme with uncertainty ordered last will be illustrated in the section of robustness checks.

Measuring uncertainty. Concerning our proxy for global uncertainty, measures of implied volatility like the VIX index are usually preferred as proxies for uncertainty in the literature, because they are forward-looking variables and capture market expectations. Nevertheless, realized volatilities of stock market returns are considered as a good approximation and are largely used when measures of implied volatility are not available (e.g., Bloom, 2009), in that they generally show a high degree of correlation with measures of implied volatility. Also in our case correlation between the realized volatility of the MSCI index returns and the VIX is equal to 0.83. Moreover, in Gourio et al. (2013) a change in disaster probability is proxied by a change in equity market volatility, when they empirically test the key mechanism of their model. Indeed they find that there is a high degree of correlation between equity implied volatility and the risk of large drops in equity prices in the United States, which is consistent with their model. Hence Gourio et al. interpret shocks to equity realized volatility as shocks to disaster probability, thus linking their work to the literature on uncertainty. Figure 1.1 plots the quarterly time series of our measure of global uncertainty. The series displays large spikes at all major economic and political shocks in the recent history at a worldwide level, like the OPEC oil-price shocks in 1973 and 1978, the two Gulf wars in 1990 and 2003, the Asian crisis in 1997 and the 9/11 terrorist attack in 2001, when

[9]For some countries we also include a deterministic trend: Austria, Finland, Netherlands, Norway, Sweden for the linear VAR specification; Norway and Sweden for the I-VAR.

uncertainty appears to largely increase.[10]

1.3.2 A linear SVAR exercise

As a warm-up exercise to assess the responses of output and exchange rate to a global uncertainty shock, we estimate a linear SVAR model for each of the countries in our sample. A common SVAR representation is the following:

$$\mathbf{A}_0\mathbf{y}_t = \sum_{\ell=1}^{k} \mathbf{A}_\ell \mathbf{y}_{t-\ell} + \mathbf{u}_t$$

where $\mathbf{y}_t = [MSCI\ VOL\ S_{\$/i}\ CPI_i\ GDP_i\ SPREAD_i]'$ is the vector of endogenous variables, $\mathbf{A}_0$ is the matrix that captures the contemporaneous relations among the variables, $\mathbf{A}_\ell$ is the $q \times q$ matrix of autoregressive coefficients up to lag k and $\mathbf{u}_t$ is the vector of structural shocks.

Figures 1.3 and 1.4 plot the impulse responses of exchange rate and GDP to a one-standard deviation global uncertainty shock, along with 68% confidence bands, for each of the countries in our sample. Some regularities across countries can be noticed in the responses of both variables. Concerning the exchange rate, it responds to the shock by significantly appreciating on impact in all countries but Australia, Austria and Canada (fig. 1.3). The response of GDP is often not statistically different from zero on impact, but then turns significantly negative some quarters after the shock in the cases of Australia, Canada, Finland, France, Germany, Italy, Norway, Sweden and UK (fig. 1.4). Austria and Netherlands are the only two exceptions, and display a significant positive response. As a general conclusion for this linear part of the analysis, we have that in most countries the exchange rate appreciates on impact and output reduces in response to a global uncertainty shock. This last finding is in line with the main results in the literature on uncertainty.

[10] The spikes are identified following the procedure in Bloom (2009). We take the HP detrended ($\lambda = 129,600$) series of the 30-day realized volatility of the MSCI World Index log returns, computed as the standard deviations of daily returns over calendar months, and assign a value of one to the observations that correspond to a value of stock-market volatility more than 1.65 standard deviations above the HP detrended mean. Among the events selected by this procedure, we only keep those that we define as global shocks.

We now move to the core part of our empirical analysis, where we employ an Interacted VAR to evaluate whether the level of countries' risk exposure plays a relevant role in the transmission of a global uncertainty shock. Indeed, impulse responses computed from the linear model just allow to evaluate average responses of the endogenous variables to the shock, whereas we want to account for time variation in countries' relative riskiness and consider the possible presence of different states of the economy in our empirical specification.

1.4 Relative riskiness and Interacted VARs

1.4.1 Measuring countries' relative risk exposure

First, to investigate whether countries' relative exposure to risk does have a role in the transmission of global uncertainty shocks, a measure of relative riskiness is needed. Following Gourio et al. (2013), we employ interest rates to discriminate across countries' heterogeneous risk exposure in the empirical analysis that follows. Taking the U.S. as our reference country, we consider the spread between each country's interbank rate and the Federal Funds rate (FFR) as our measure of relative risk exposure. Indeed, movements in interest rate spreads are generally thought to deliver important signals about the evolution of economic activity, a view that is supported by a large literature on the predictive content of yield spreads. The idea is that fluctuations in spreads may reflect the quality of borrowers' balance sheets, on which their access to external finance depends, as well as shifts in the availability of funds provided by financial intermediaries. In both cases, movements in interest rate spreads may signal an increase in the cost of credit and/or a reduction in the supply of credit, which can cause a reduction in spending and production (see Gilchrist & Zakrajšek, 2012).

More in detail, for each country in our sample, when the interbank-FFR spread is positive, then the interbank rate is higher than the FFR and we define the country as less risky than the U.S., whereas when the spread is negative, the interbank rate is lower than the FFR and the country is defined as more risky than the U.S..

The way in which the two riskiness regimes are identified refers once again to one of the results in Gourio et al.'model. Indeed, as a result of model calibration, the high interest rate country has the lower exposure to disaster risk, whereas the low interest rate country is the more exposed to aggregate risk. Explanation for this result refers to different levels of precautionary savings in the two countries. A higher exposure to disaster risk would imply a higher level of precautionary savings, which means a higher demand for safe assets and hence a lower (risk-free) interest rate. On the other hand, a lower exposure to disaster risk would imply a lower level of precautionary savings and hence a higher interest rate, since the demand for risk-free assets would be lower. According to this view, interbank rate spreads that we use as a measure of relative riskiness would reflect the relative availability of risk-free assets in the two countries, which in turn depends on the level of precautionary savings, being the level of precautionary savings related to the perceived economic strength of the country, i.e. on the level of exposure to economic risk.[11]

Figure 1.2 shows the evolution over time of interest rate spreads for each of the countries in our sample. Time variation is an important dimension of this cross-country relationship, and it clearly emerges from the plots. Heterogeneity can be noticed across two dimensions. On the one hand, each country oscillates between low and high risk, displaying both positive and negative spreads over time (being zero the threshold that separates the two riskiness regimes according to our definition). On the other hand, the plots also show a high degree of variability in risk exposure across countries.

1.4.2 Interacted VARs

To evaluate the role of risk exposure in the transmission of global uncertainty shocks, we employ a nonlinear approach, and particularly consider an Interacted VAR model, following Pellegrino (2014) and Caggiano, Castelnuovo, and Pellegrino (2016). An I-VAR is a standard VAR augmented with an interaction term, which includes the variable that we want to shock and the conditioning variable that

[11] Rates on Treasury bills are generally used as a proxy for the risk-free rate. For the present analysis, we employ interbank rate spreads rather than sovereign spreads, because longer series are available. However, interbank and sovereign spreads display a high degree of correlation. For the same reason, we use the FFR, for which a longer series is available, rather than interbank rates for the U.S.. Also in this case, the degree of correlation between FFR and U.S. interbank rates is very high, almost equal to one.

identifies the two regimes we are interested in. This allows us to get responses to our shock of interest conditionally on the state of the economy which we think can be relevant for the transmission of the shock. In this framework, we can define two regimes for each country, a high risk regime and a low risk one relative to the U.S., depending on whether the interest rate spread is below or above zero, and compute state-dependent impulse response functions, in order to evaluate whether different levels of relative risk exposure do have an influence on the transmission of a global uncertainty shock.

Interacted VAR models have been recently introduced in macroeconomic studies. A panel I-VAR has been proposed by Towbin and Weber (2011) to analyze how the transmission of external shocks in open economies is influenced by the exchange rate regime, the level of foreign currency debt and by the import structure. Sá, Towbin, and Wieladek (2014) also use a panel I-VAR to explore how the mortgage-market characteristics influence the way in which shocks to capital inflows impact the housing market in a group of OECD countries. Lanau and Wieladek (2012) employ the same methodology to examine the relationship between financial regulation and the current account, whereas Nickel and Tudyka (2013) investigate the impact of fiscal policy at different levels of government debt. Aastveit, Natvik, and Sola (2013) employ an I-VAR to investigate the effectiveness of monetary policy shocks in low and high uncertainty regimes. A similar issue is analyzed in Pellegrino (2014), who adds an important novelty in that the variables entering the interaction term are fully endogenous in the model, whereas they were treated as exogenous in previous works. This requires to compute Generalized Impulse Response functions (GIRFs) à la Koop et al. (1996) to take the time-varying behaviour of the system into account. Caggiano, Castelnuovo, and Pellegrino (2016) employ the same methodology as Pellegrino (2014) to address the issue of the impact of uncertainty shocks at the ZLB. In this chapter we follow Pellegrino (2014) and Caggiano, Castelnuovo, and Pellegrino (2016) by making the interaction term with which we augment our VAR fully endogenous and then by computing GIRFs to recover state-dependent responses.

In this context, the use of an I-VAR model has several advantages with respect to alternative nonlinear specifications, such as Smooth-Transition VARs, Time-Varying-Parameters VARs, Nonlinear Local Projections and Threshold VARs.

STVARs are computationally more intensive than I-VARs and require calibrating the slope parameter in the transition function, which regulates the smoothness of the transition between regimes and affects the probability of being in one regime or the other. Such a calibration is not needed for estimating an I-VAR. Also TVP-VARs are computationally more demanding than I-VARs, and moreover require setting priors for estimation. Nonlinear Local Projections instead do not allow to endogenously model the conditioning variable and hence do not allow for endogenous switches from one regime to another, which is an essential feature in our specification, where both variables in the interaction term are endogenously modeled. T-VARs could offer an interesting alternative to I-VARs in this setting, since a T–VAR model is not computationally intensive and allows to model sudden regime changes like the ones we are considering. Moreover, in a T-VAR the threshold that defines the two states of the economy can be endogenously estimated. Nevertheless, a T-VAR does not allow for endogenous regime switches, whereas an I-VAR model does, and only allows for the computation of conditionally linear impulse response functions, rather than GIRFs.

Our I-VAR model has the following representation:

$$\mathbf{y}_t = \mu + \sum_{\ell=1}^{k} \mathbf{A}_\ell \mathbf{y_{t-\ell}} + \sum_{\ell=1}^{k} \mathbf{c}_\ell (VOL_{t-\ell} \times SPREAD_{t-\ell}) + \mathbf{u}_t$$

where $\mathbf{y}_t$ is the $q \times 1$ vector of endogenous variables, μ is the $q \times 1$ vector of intercepts, $\mathbf{A}_\ell$ is the $q \times q$ matrix of autoregressive coefficients up to lag k and $\mathbf{u}_t \sim \mathcal{N}(\mathbf{0}, \mathbf{\Sigma})$ is the $q \times 1$ vector of residuals, whose covariance matrix is $\mathbf{\Sigma}$. $(VOL_{t-\ell} \times SPREAD_{t-\ell})$ is the interaction term, which includes our measure of global uncertainty (VOL) and the difference between the interbank rate of each country and the FFR ($SPREAD$), as our measure of country's relative riskiness. Indeed, global uncertainty is the variable whose shocks we want to identify, whereas interest rate spread is the conditioning variable that defines the two states of low and high risk. $\mathbf{c}_\ell$ is the $q \times 1$ vector of coefficients. The same number of lags is imposed for the linear part and the interaction term.

Evidence in favour of nonlinear specification. Since a nonlinear model would be misspecified if the true data generating process is linear, we perform a linearity test to provide evidence in favour of the nonlinear specification. For this reason, the nonlinear part of the analysis will be performed only for those countries for which the test provides such an evidence. Since the linear VAR and the I-VAR are nested models, it is possible to use a likelihood ratio test for the null hypothesis of a linear specification against the alternative of an I-VAR model. We employ the following test statistic:

$$LR = T\left(ln\,|\,\tilde{\mathbf{\Sigma}}_{\mathbf{u}}^{\mathbf{r}}\,| - ln\,|\,\tilde{\mathbf{\Sigma}}_{\mathbf{u}}\,|\right)$$

where T is the sample size, $|\,\tilde{\mathbf{\Sigma}}_{\mathbf{u}}^{\mathbf{r}}\,|$ is the determinant of the estimated variance covariance matrix of residuals in the linear VAR (restricted model), and $|\,\tilde{\mathbf{\Sigma}}_{\mathbf{u}}\,|$ is the estimated variance covariance matrix of residuals in the I-VAR specification (unrestricted model). ln is the natural logarithm operator. The optimal number of lags is selected for the linear model through the AIC and is then imposed also to the nonlinear specification.

Under the null hypothesis of linearity, the test statistic has an asymptotic Chi-squared distribution, the number of degrees of freedom being the difference between the number of coefficients estimated under the alternative and the number of coefficients estimated under the null hypothesis, that is the number of restrictions between the two specifications.[12] Table 1.1 shows test results. The null hypothesis of a linear VAR model is rejected for six out of eleven countries: Australia, Germany, Netherlands and Norway (at 5% significance level), Canada (1% significance level) and Sweden (10% significance level). Therefore, the nonlinear part of the analysis will only consider these countries. The null hypothesis of a linear specification cannot be rejected for Austria, Finland, France, Italy and the United Kingdom.

Table 1.1: LR-test results

[12]Since the same number of lags is imposed for the linear part and the interaction term, and since the two models are estimated with the same number of lags, the number of restrictions is given by the product between the number of endogenous variables and the selected number of lags.

Country	LR	p-value
Australia	16.2197	0.0126
Austria	9.8241	0.1323
Canada	20.1593	0.0026
Finland	9.2098	0.1621
France	3.2595	0.7756
Germany	15.4709	0.0169
Italy	5.2204	0.5159
Netherlands	13.2060	0.0399
Norway	13.2547	0.0392
Sweden	11.8363	0.0657
UK	6.8959	0.3306

Notes: In red are the results which are not statistically significant.

1.4.3 Generalized Impulse Response Functions

Most I-VARs used in the literature employ interaction terms which include variables that are not endogenously modeled. This implies that the dynamic responses of endogenous variables to a shock in a given state are conditionally linear for a given value of the interaction variables. An important feature of the specification of our I-VAR is that both variables in the interaction term are endogenously modeled. This implies that interest rate spreads are likely to react to a global uncertainty shock, and that the economy can endogenously switch from one regime to the other within each horizon, as pointed out in Caggiano, Castelnuovo, and Pellegrino (2016).

Hence, following Pellegrino (2014) and Caggiano, Castelnuovo, and Pellegrino (2016), dynamic responses of the endogenous variables to a global uncertainty shock are computed as Generalized Impulse Response Functions (GIRFs) à la Koop et al. (1996), but working with orthogonalized shocks as in Kilian and Vigfusson (2011), so that we can talk of a global uncertainty shock. Through GIRFs we can fully take the nonlinearity of the system into account, since dynamic responses of endogenous variables will depend on the size and the sign of the shock as well as on the initial conditions of the system. Following Koop et al. (1996), the $GIRF_{\mathbf{y}}(h, \delta, \omega_{t-1})$ of the vector of endogenous variables $\mathbf{y}_t$, h periods ahead, for a given initial condition $\omega_{t-1} = \{\mathbf{y}_{t-1}, \ldots, \mathbf{y}_{t-k}\}$, k being the number of lags in the I-VAR, and a structural shock hitting at time t, δ, can be expressed as follows:

$$GIRF_{\mathbf{y}}(h, \delta, \omega_{t-1}) = E[\mathbf{y}_{t+h} \,|\, \delta, \omega_{t-1}] - E[\mathbf{y}_{t+h} \,|\, \omega_{t-1}]$$

where $E[\cdot]$ is the expectation operator and $h = 0, 1, \ldots, H$ indicates the horizons for which the GIRF is computed.[13]

1.5 Results

1.5.1 Nonlinear model: Baseline specification

Figures 1.5 and 1.7 plot the impulse responses of exchange rate and GDP to a one-standard deviation global uncertainty shock, computed from the estimation of the I-VAR model, along with 68% confidence bands, for high (red line) an low risk (blue line) regimes, for each of the countries in our sample. Figures 1.6 and 1.8 document the differences between the point estimates of the impulse responses computed in the two states, which are obtained by subtracting the response under low risk state from the response under high risk state. 68% confidence bands resulting from the empirical distribution of such differences are plotted.[14]

Concerning the exchange rate (fig. 1.5), it significantly appreciates on impact in response to the shock in both states of the economy, for all countries except Australia and Canada. For these two countries, responses are not statistically significant in neither of riskiness regime, except for low risk regime in Canada,

[13]Details on the algorithm used to compute state-conditional GIRFS are provided in Appendix C. I am grateful to Giovanni Caggiano, Efrem Castelnuovo and Giovanni Pellegrino for providing their Matlab code of the algorithm used to estimate the I-VAR model and compute GIRFs in this chapter.

[14]As explained in detail in Appendix C, GIRFs are obtained by simulating the path of endogenous variables by loading the VAR with a sequence of randomly extracted residuals, for each given initial condition. The empirical distribution of the differences between point estimates of the responses in the two states is given by the difference between the impulse responses in the two states computed for each draw of residuals.

where the exchange rate significantly appreciates some quarters after the shock. For all countries whose currencies display a significant response to the shock, response in low risk state seems to be larger than that in high risk state, but differences in the point estimates (fig. 1.6) show that this difference is only marginally statistically significant. Moreover, the two responses follow very similar patterns. Hence, we do not find significant evidence of nonlinearities driven by relative riskiness in the transmission of global uncertainty shocks to exchange rates.

For what concerns real activity (fig. 1.7), a global uncertainty shock generates a significant reduction in output when the country is in high risk state, in the cases of Germany, Norway and Sweden. The response of Australia is only marginally statistically different from zero. In low risk state, the responses of GDP are generally not statistically different from zero. Differences in the point estimates of responses in the two states confirm that the response in high risk state is significantly larger than that in low risk state, for all countries for which the response in high risk state is significantly negative (Germany, Norway and Sweden, fig. 1.8). Hence, state-conditional impulse responses of GDP obtained from the estimation of our nonlinear specification provide evidence in favour of the presence of nonlinearities in the transmission of global uncertainty shocks. Particularly, the level of relative risk exposure, as captured by short-term interest rate spreads, seems to play a significant role in the transmission of global uncertainty shocks to economic activity.

The results obtained for real activity also support the predictions of Gourio et al. (2013)'s model, about the effects of changes in aggregate risk on the economy in the presence of heterogeneous country risk exposure. Indeed, according to their model, the same increase in disaster probability has more negative effects on economic activity in the country which is more exposed to aggregate risk, by producing a larger reduction in investment and output. The estimated impulse response functions for some of the countries in our sample point in the same direction, since the response of output is estimated to be significantly more negative when the country is more exposed to risk. On the other hand, Gourio et al.'s model predicts that the currency of the more risky country appreciates in response to an increase in disaster probability, whereas our results do not display statistical difference between responses in the two regimes.[15] Hence, our findings do not provide supporting

[15]In Gourio et al.'s theoretical framework, the response of the exchange rate is driven by con-

evidence to these predictions, because currencies appreciate in response to a global uncertainty shock in both riskiness states, and the two responses are estimated to be statistically the same.

These results are confirmed by the patterns that emerge in figures 1.9 and 1.10, which report the dynamic responses of the exchange rate and output respectively, for each initial condition within each regime. Dynamic responses of both exchange rate and output display large variability both across and within regimes. However, a clear distinction between the two regimes can be noticed for the responses of output, whereas this distinction less clearly emerges when we look at the responses of the exchange rate.

1.5.2 “Very high” and ”very low” risk regimes

So far, we have explored the presence of nonlinear effects and the role of countries' relative risk exposure in the transmission of global uncertainty shocks in open economies. Our main finding is that a global uncertainty shock has larger negative effects on economic activity when the country is relatively more risky. In order to further investigate the issue, we ask which are the effects of a global uncertainty shock when the distance in relative risk exposure among countries widens, that is when the spread between short term interest rates increases in absolute value. This analysis is performed through the identification of two subsets of initial conditions, associated with different levels of the interest rate spread. We define as “very high”/“very low” risk regime initial conditions in which the value of the conditioning variable, namely interest rate spread, is below/above two standard deviations from the mean. Then, for each of these two subsets of initial conditions we recompute GIRFs.

Figures 1.11 and 1.12 show the GIRFs computed for the two extreme regimes and the differences in the point estimates of responses for both output and exchange rate, for each country in our sample.[16] Relative to our baseline results, the displayed

sumption. Indeed, the exchange rate reflects the relative value of current and future consumption in the two countries, and since the more risky country expects a larger decline in consumption growth than the less risky one, its marginal utility of consumption rises more and its currency appreciates.

[16] Differences in the point estimates are computed as $(GIRF_{very\,high\,risk} - GIRF_{very\,low\,risk})$.

impulse responses support our main findings for what concerns output, whereas they provide some evidence in favour of nonlinearities in the transmission of global uncertainty shocks to the exchange rate. Indeed, as the distance in the level of relative risk exposure increases, also the distance in estimated impulse responses widens, thus reinforcing the idea that relative riskiness plays a relevant role in the transmission of global uncertainty shocks.

Particularly, concerning the response of the exchange rate (fig. 1.11), it can be noticed that the distance between responses in the two "extreme" regimes is generally larger than the one observed in our baseline results. Further support is provided by the differences in point estimates, which are now larger than the ones displayed in the baseline case. Moreover, for Canada, Germany and Sweden responses in the two regimes display different patterns. For what concerns output (fig. 1.12), the response of economic activity becomes more negative and persistent as the level of riskiness increases in the cases of Germany, Norway and Sweden, consistently with our previous findings. This result is supported once again by the differences in point estimates, which in the case of Germany are estimated to be larger than in our baseline case. Some marginal evidence in the same direction also emerges for Australia, whereas we do not find any evidence in this sense for Canada.

To summarize the main results for this part of the analysis, it is worth noticing that estimated responses to a global uncertainty shock of both the exchange rate and output are sensitive to the level of relative riskiness. Indeed, responses are generally stronger as the regime becomes more "extreme", i.e. as countries become more distant in terms of their level of risk exposure. These findings provide supporting evidence to the main result of our I-VAR analysis, that cross-country differences in risk exposure are important in explaining the effects of a global uncertainty shock in open economies.

1.5.3 Consumption, external sector and financial flows

The results shown so far lead to the conclusion that following a global uncertainty shock economic activity reduces and the exchange rate appreciates. Moreover, countries' relative risk exposure seems to play a relevant role in the transmission of the shock, with significant nonlinearities arising especially in the effects on output. The channels through which a global uncertainty shock may affect the dynamics of exchange rate and economic activity are diverse. Here we examine three of them, which we think to be especially relevant: consumption, the external sector and financial flows.

First, in Gourio et al. (2013)'s theoretical model the response of the exchange rate is driven by consumption. Indeed, the exchange rate reflects the relative value of current and future consumption in the two countries, and because the more risky country expects a larger decline in consumption growth than the less risky one following a global uncertainty shock, then its marginal utility of consumption rises more and its currency appreciates. For this reason we estimate a specification of our model where we include consumption as an endogenous variable, ordered before output. Then, given that we examine an open economy framework, movements in the external sector may play a relevant role in the transmission of global uncertainty shocks. Hence, we estimate an alternative specification in which we include net exports, ordered before output in the vector of endogenous variables. Finally, international financial flows may be particularly helpful in explaining the dynamics of the exchange rate in response to the shock. For instance, heightened global uncertainty could in principle activate a flight to quality mechanism, with money leaving high risk countries and flowing towards less risky ones. This would affect foreign currency availability on currency markets and hence the exchange rate. Therefore, we propose a third alternative specification of our I-VAR, where a measure of financial flows is included, ordered after uncertainty and before the exchange rate.[17]

Plots illustrating our estimated responses are reported in Appendix A. Figures A.1-A.18 show GIRFs obtained from these three alternative estimations and differ-

[17] As a measure of consumption we use Gross Domestic Product by Expenditure in Constant Prices: Private Final Consumption Expenditure, Index 2010 = 1, Quarterly, Seasonally Adjusted. Net exports are computed as the difference between Gross Domestic Product by Expenditure in Constant Prices: Export of Goods and Services, Index 2010 = 1, Quarterly, Seasonally Adjusted and Gross Domestic Product by Expenditure in Constant Prices: Less: Imports of Goods and Services, Index 2010 = 1, Quarterly, Seasonally Adjusted. As a measure of financial flows we employ the Capital Accounts and Financial Accounts: Total Balance Including Change in Reserve Assets (US dollars, quarterly, not seasonally adjusted). The series of financial flows are only available since 1982Q1 for Sweden, 1990Q1 for Canada and 1994Q1 for Norway. All series are from Federal Reserve Bank of St. Louis (FRED) database.

ences in the point estimates, along with 68% confidence bands. First, we consider the specification that includes consumption (figures A.1-A.6). Our baseline results are confirmed for both output and the exchange rate. The response of output is significantly more negative when the country is in high risk, whereas the exchange rate responds to the shock in a very similar way in both regimes.[18] Concerning consumption (figures A.5-A.6), we find heterogenous responses across countries and across regimes. For Australia and Canada, the response of consumption is not statistically significant in either regime. For Germany, Netherlands and Sweden, consumption positively responds to the shock in low risk, whereas the response is not significant in high risk. Finally, consumption significantly negatively responds in both regimes in the case of Norway, and the response in high risk is marginally larger than that in low risk.

Figures A.7-A.12 refer to the specification including net exports. Once again, estimated responses are perfectly in line with our baseline results, for both output and exchange rate. The response of output is significantly more negative when the country is in high risk, whereas the exchange rate responds to the shock in a very similar way in both regimes.[19] Concerning the response of net exports (fig. A.11-A.12), as a general result we find that net exports negatively respond, which implies that either export decreases or both import and export decrease, and the response in low risk is larger than that in high risk, as confirmed by the differences in the point estimates for all countries but Norway.

Finally, figures A.13-A.18 refer to the specification including financial flows. Also in this case, the main findings coming from baseline estimation are still there. Concerning the response of financial flows (fig. A.17-A.18), it does not emerge a common pattern. For Australia and Sweden financial flows positively respond to the shock, and in the case of Australia the response in high risk is larger than that in low risk. In the case of Germany, financial flows fall on impact and then suddenly raise some quarters after the shock in low risk, whereas the response is

[18] Canada is the only country for which we find different patterns in the responses of the exchange rate in high and low risk. Indeed in low risk, the currency appreciate some quarters after the shock, whereas the response in high risk is not statistically different form zero. In our baseline estimation we find exactly the same result.

[19] Once again, Canada is the only country for which we find different patterns in the responses of the exchange rate in high and low risk, as in our baseline results.

not statistically significant in high risk. For the Netherlands, neither response is statistically different from zero.[20]

As a general result, these exercises aiming at exploring the channels through which a global uncertainty shock affects output and exchange rates confirm the main results coming from our baseline I-VAR estimation.

1.5.4 Robustness checks

Robustness of our results is tested through a series of perturbations of the baseline specification. We consider (i) uncertainty ordered last; (ii) an uncertainty shock dummy; (iii) the role of country-specific uncertainty; (iv) the role of financial shocks; (v) the role played by the size of the shock. Plots illustrating results are reported in Appendix B.

Uncertainty ordered last. Employing a recursive ordering VAR with the uncertainty measure ordered first, as we do, is a commonly used strategy to identify structural uncertainty shocks in the empirical literature on uncertainty (e.g., Bloom, 2009; Alexopoulos & Cohen, 2009; Mumtaz & Theodoridis, 2015).[21] Using this identification scheme implies that uncertainty shocks can immediately affect exchange rate, prices, output and interest rate spread, whereas stock market volatility does not immediately react to the other shocks in the model, except for the shock to stock market levels. Since we consider a measure of global uncertainty, whereas all other variables but stock market index are country-specific, this seems to be a reasonable assumption, in the sense that it is plausible to assume that a global measure does not immediately react to country-specific shocks, while the converse, with country-specific variables immediately responding to a global shock seems more reasonable.

Nevertheless, a shortcoming of Cholesky decomposition is that results might depend on the particular ordering of endogenous variables. For this reason, among

[20] For this part of the analysis including financial flows, results for Canada and Norway are not displayed, because the short available series for financial flows make our results unreliable.

[21] To be precise, uncertainty is ordered second after stock market index in our VAR, in order to identify a global uncertainty (volatility) shock which is orthogonal to shocks to stock market levels, following Bloom (2009).

robustness checks we also consider the case in which uncertainty is ordered last. This allows to remove the possible effects of other shocks from the estimated effects of the global uncertainty shock we are interested in. Figures B.1-B.4 show estimated responses and differences in the point estimates for both exchange rate and output. Results of our baseline estimation are confirmed: the negative response of output is larger when the country is more risky, whereas responses of the exchange rate are very similar in the two regimes.

Uncertainty shock dummy. To identify global uncertainty shocks, as an alternative to the volatility series included in baseline analysis, we build a global uncertainty shock indicator, following Bloom (2009) and applying a narrative approach. The indicator is a dummy variable that takes a value of 1 for each of the events that we define as global uncertainty shocks, and 0 otherwise. To select the events labeled as global uncertainty shocks, we follow Bloom and take the Hodrick-Prescott (HP) detrended ($\lambda = 129,600$) series of the 30-day realized volatility of the MSCI World Index log returns, computed as the standard deviations of daily returns over calendar months, and assign a value of one to observations that correspond to a value of stock-market volatility more than 1.65 standard deviations above the HP detrended mean. Among the events selected by this procedure, we only keep those that we define as global shocks and exclude those that are more country-specific in our view. Moreover, since the analysis is carried out with quarterly data, we build a quarterly indicator in which a value of 1 is assigned to each quarter for which there is at least one month taking a value of 1 in our monthly series. Chosen global uncertainty shock events are shown in table 1.2 (they are also highlighted in figure 1.1, where the volatility series is plotted). Selected events are major economic and political shocks in recent history at a global level. Results are reported in figures B.5-B.8. Estimates are less precise than those obtained from our baseline specification. Nevertheless, the exchange rate appreciates on impact in both regimes, and the negative response of output is larger in high risk than in low risk, in the cases of Germany and Sweden. These findings support our baseline results.

Table 1.2: Global uncertainty shocks

Quarter	Event
1973Q4	OPEC I, Arab-Israeli war
1982Q3	Monetary cycle turning point
1987Q4	Black Monday
1990Q3	Gulf war I
1997Q4	Asian crisis
1998Q3	Russian, LTCM default
2001Q1	Dotcom bubble
2001Q3	9/11
2002Q3	Worldcom, Enron
2003Q1	Gulf war II
2007Q3	Financial turmoils

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Country-specific uncertainty. As a further robustness check, we ask whether including a measure of country-specific uncertainty would affect the responses of output and exchange rate to a global uncertainty shock. Indeed, it can be the case that the effects that we find are due to heightened country-specific uncertainty rather than to a global shock. Hence, to control for idiosyncratic movements in uncertainty, we re-estimate our model by including a measure of country-specific uncertainty in the vector of endogenous variables. For each country in the sample, this measure is obtained as the realized volatility of log returns of a national stock market index at a quarterly frequency. Results are displayed in figures B.9-B.12. The main findings of our analysis are confirmed.

Financial shocks vs. uncertainty shocks. There is a recent strand of literature that focuses on financial markets frictions as a possible channel through which uncertainty shocks can affect macroeconomic variables (Arellano et al., 2012; Gilchrist, Sim, & Zakrajsek, 2014; Alessandri & Mumtaz, 2014; Caldara et al., 2016). Since measures of uncertainty are highly correlated with measures of financial distress, as pointed out by Stock and Watson (2012), it is difficult to disentangle between these two potential channels of economic fluctuations (Caldara et al., 2016).

Therefore, in order to isolate the effects of uncertainty shocks, it is important to control for financial shocks by including a measure of financial distress in the model. To this aim, we include as an endogenous variable in our specification the measure of credit spread recently proposed by Gilchrist and Zakrajšek (2012) as a proxy for financial distress, the "excess bond premium" (EBP). Figures B.13-B.16 illustrate dynamic responses of output and exchange rate and differences in the point estimates, and confirm our main results.

Size of the shock. In our baseline analysis, we compute GIRFs to a one standard deviation global uncertainty shock. In order to check whether our estimated responses are sensitive to the size of the global uncertainty shock, we re-compute GIRFs to shocks of a size up to five standard deviations. For the sake of illustration, figures B.17-B.20 show responses to a five standard deviations global uncertainty shock for both exchange rate and output. Our findings suggest that the size of the shock does not play a relevant role relative to the shape and magnitude of impulse responses.

1.6 Concluding remarks

What are the effects of a global uncertainty shock in an open economy? Does the level of country exposure to aggregate risk have a role in the transmission of the shock? To answer these questions, we estimate an Interacted VAR model for a group of countries relative to the U.S., to account for the possible presence of nonlinearities in the transmission of the shock. Indeed, this empirical framework allows to identify a high risk and a low risk regime and to account for time variation in country relative riskiness, through the computation of state-conditional impulse response functions. Global uncertainty is measured as the realized volatility of the MSCI World Index log returns. We employ the spread between each country's interbank rate and the Federal Funds rate as our measure of relative risk exposure and as the conditioning variable which separates the two regimes in the empirical analysis.

We examine the responses of output and the exchange rate. Concerning the response of output, our findings are in line with the main results in the literature on uncertainty, in that a global uncertainty shock significantly reduces real activity.

We also find that the exchange rate responds to the shock by appreciating on impact. Relative to the role of risk exposure in the transmission of the shock, evidence of nonlinear effects is found. Indeed, the response of economic activity to the shock is significantly negative in high risk regime and the reduction in output is estimated to be larger when the country is in high risk than when it is in low risk. This result also supports theoretical predictions of Gourio et al. (2013). For what concerns the exchange rate, it significantly appreciates on impact in response to the shock in both regimes, but we do not find evidence of a statistically significant difference between responses in the two riskiness states. Some evidence pointing to the presence of nonlinear effects in the transmission of global uncertainty shocks to the exchange rate is provided by the analysis of "extreme" riskiness regimes. Indeed, when the distance in countries' relative riskiness widens, responses of the exchange rate in the two regimes become more distant in both magnitude and shape. The same happens to the estimated responses of output, thus reinforcing our main findings.

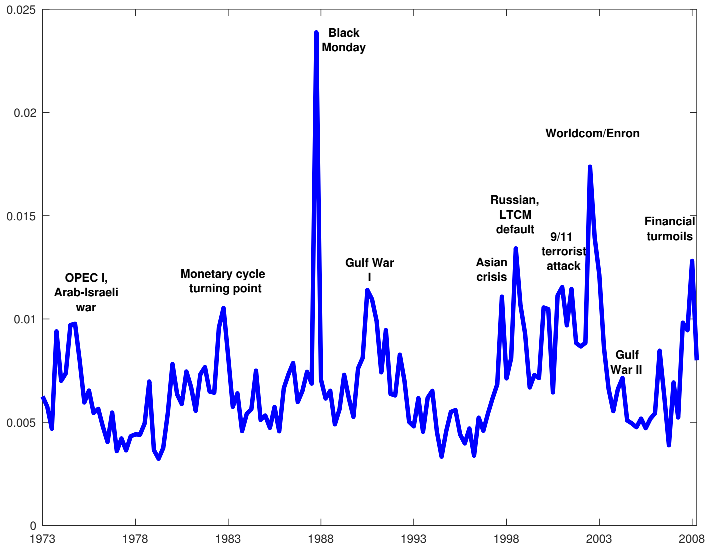


Figure 1.1: Plot of time series of MSCI World Index log returns realized volatility (1973:Q1-2008:Q2).

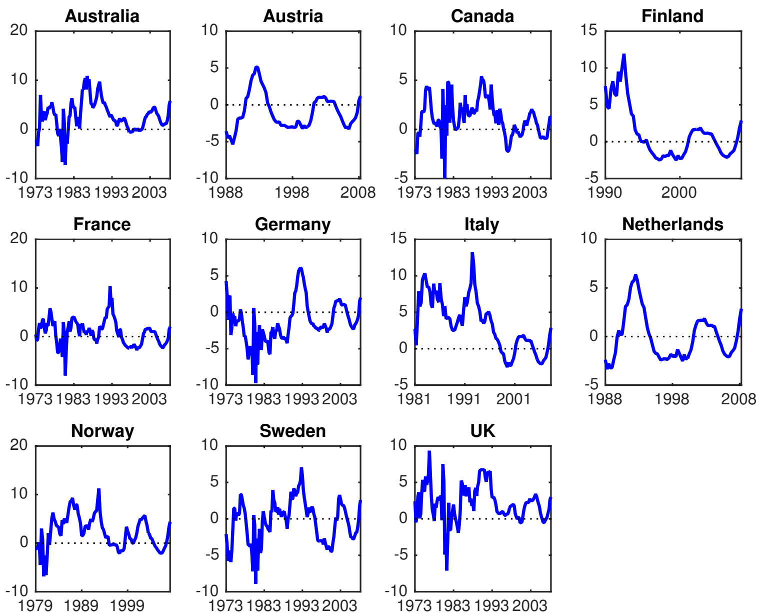


Figure 1.2: Time series of the spreads between each country's interbank rate and the Federal Funds rate.

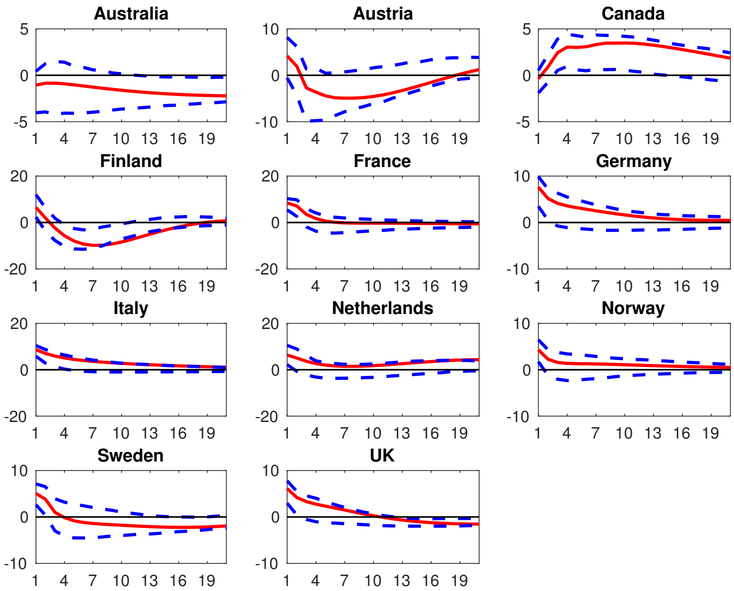


Figure 1.3: Linear VAR: Impulse responses of the exchange rate to a one standard deviation shock to global uncertainty (68% confidence bands).

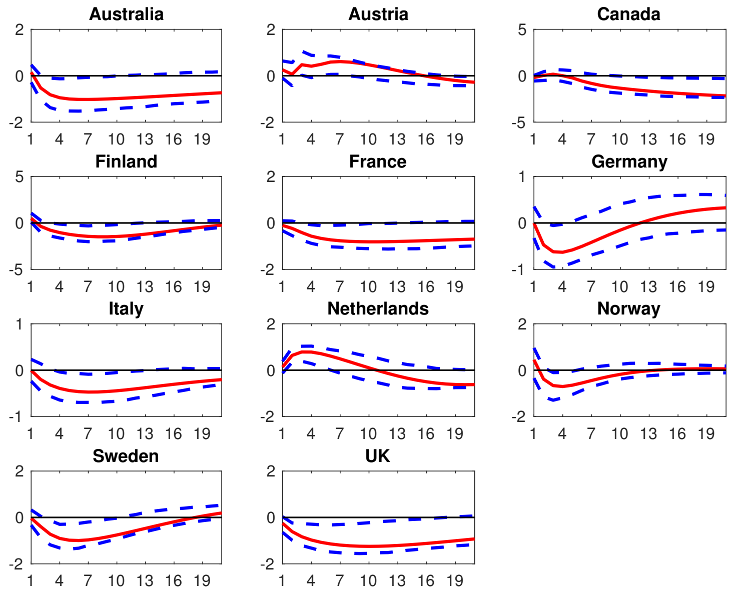


Figure 1.4: Linear VAR: Impulse responses of output to a one standard deviation shock to global uncertainty (68% confidence bands).

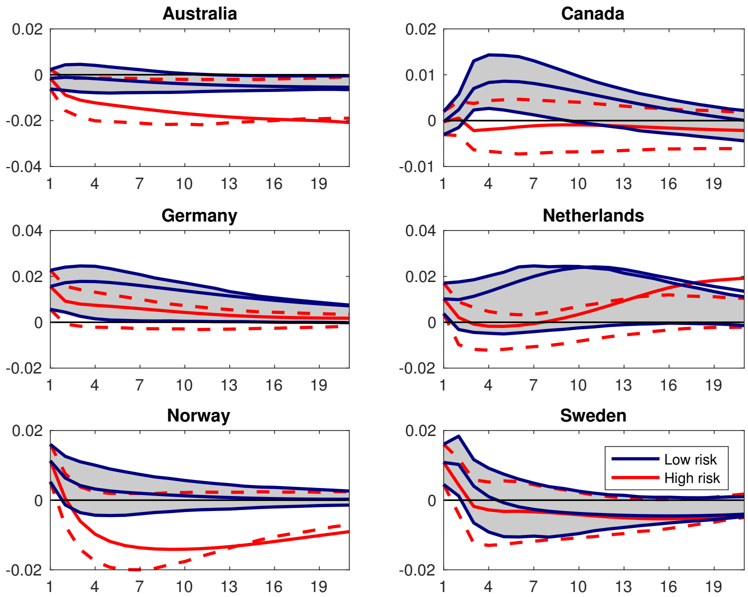


Figure 1.5: I-VAR: Impulse responses of the exchange rate to a one standard deviation shock to global uncertainty (68% confidence bands). Blue: low risk; red: high risk.

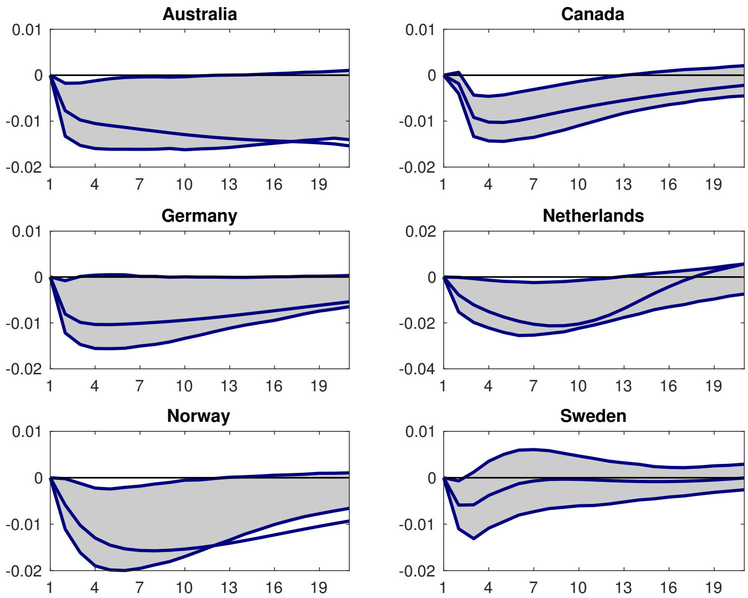


Figure 1.6: I-VAR: Differences in the point estimates of the impulse responses of the exchange rate in the two states (high risk - low risk). 68% confidence bands.

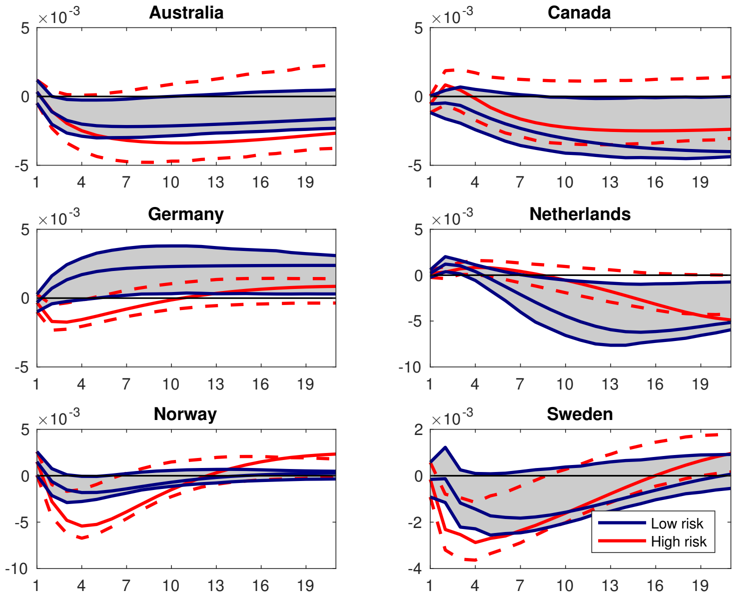


Figure 1.7: I-VAR: Impulse responses of output to a one standard deviation shock to global uncertainty (68% confidence bands). Blue: low risk; red: high risk.

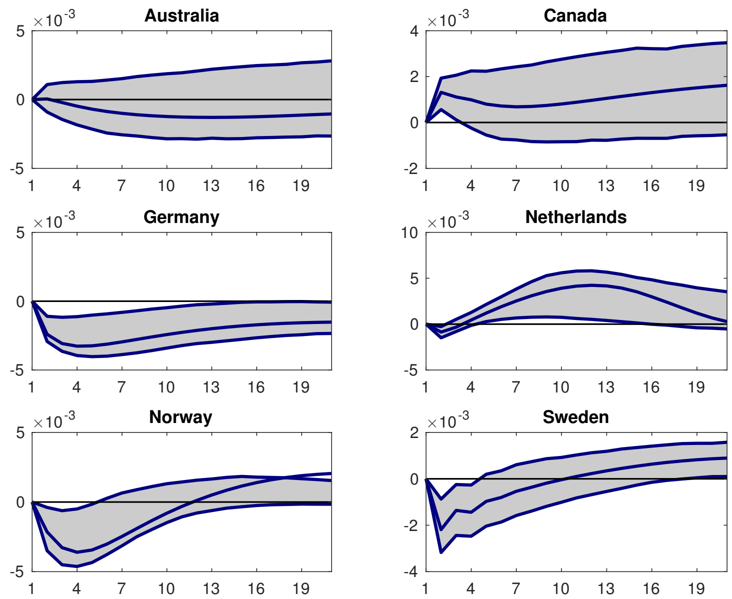


Figure 1.8: I-VAR: Differences in the point estimates of the impulse responses of output in the two states (high risk - low risk). 68% confidence bands.

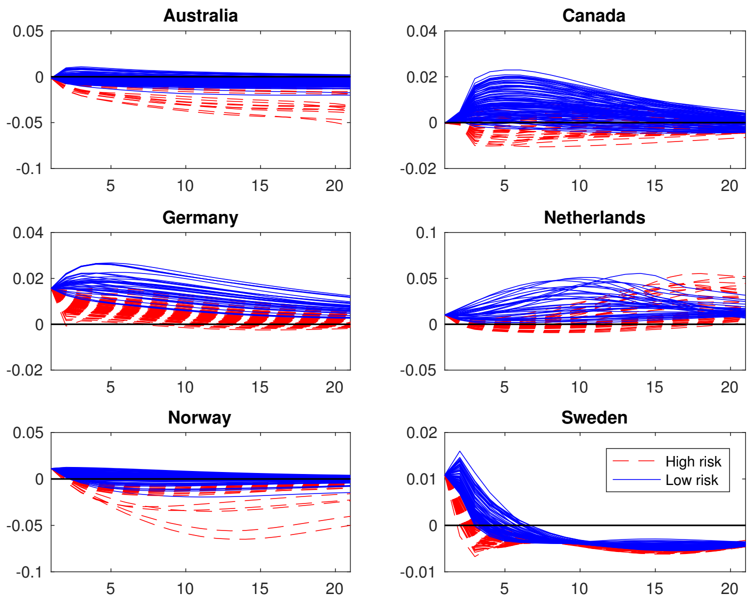


Figure 1.9: State-specific responses conditional on histories of the exchange rate. Blue: low risk; Red: high risk.

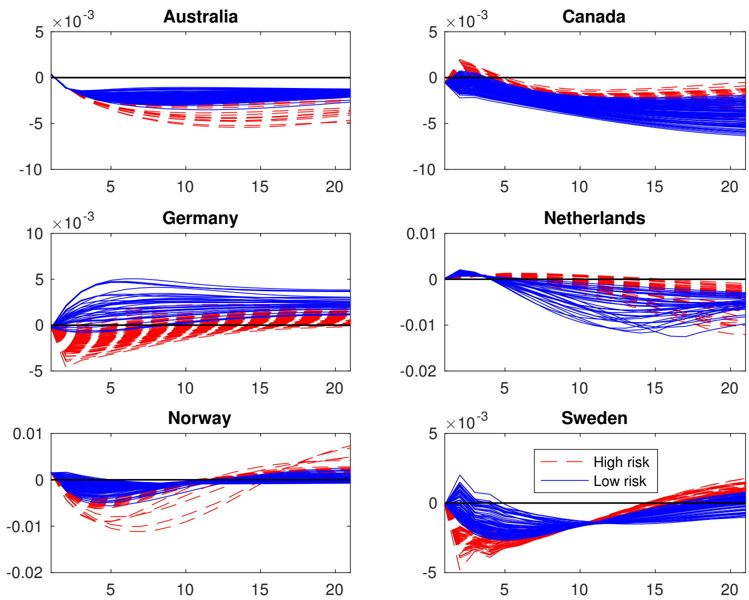


Figure 1.10: State-specific responses conditional on histories of output. Blue: low risk; Red: high risk.

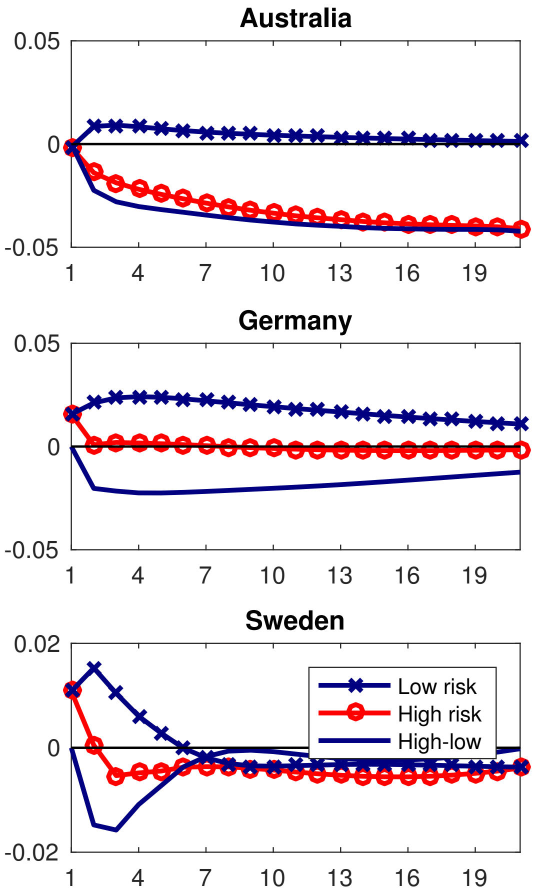


Figure 1.11: Impulse responses of exchange rate to a one standard deviation global uncertainty shock and differences in the point estimates. Very high risk: red line; very low risk: blue line.

Notes: For the Netherlands, there are no initial conditions in the "very high" risk regime subset, hence it is not possible to show the results for this part of the analysis.

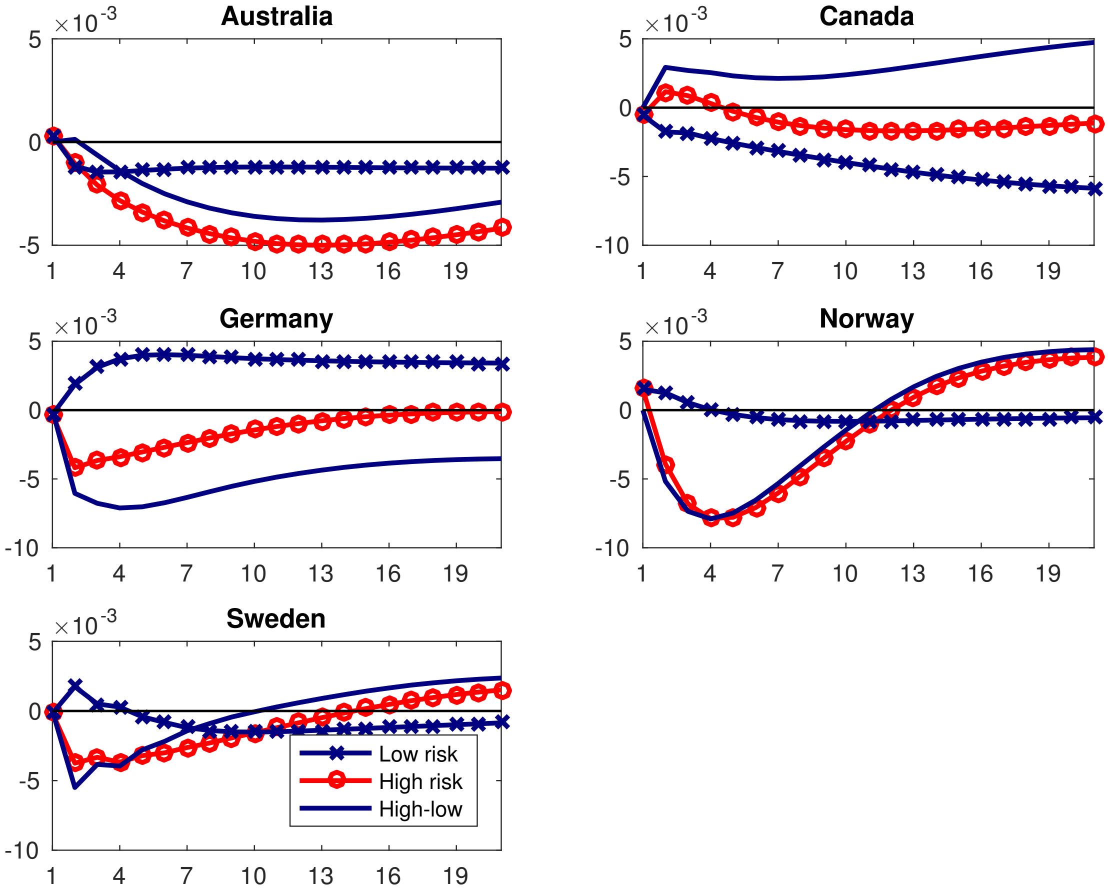


Figure 1.12: Impulse responses of output to a one standard deviation global uncertainty shock and differences in the point estimates. Very high risk: red line; very low risk: blue line.

Notes: For the Netherlands, there are no initial conditions in the "very high" risk regime subset, hence it is not possible to show the results for this part of the analysis.

Appendix A

Consumption, external sector and financial flows

This appendix includes the plots that illustrate results presented in subsection 1.5.3 of Chapter 1.

We explore three possible transmission channels of global uncertainty shocks:

- Consumption (figures A.1-A.6)
- The external sector (figures A.7-A.12)
- Financial flows (figures A.13-A.18)

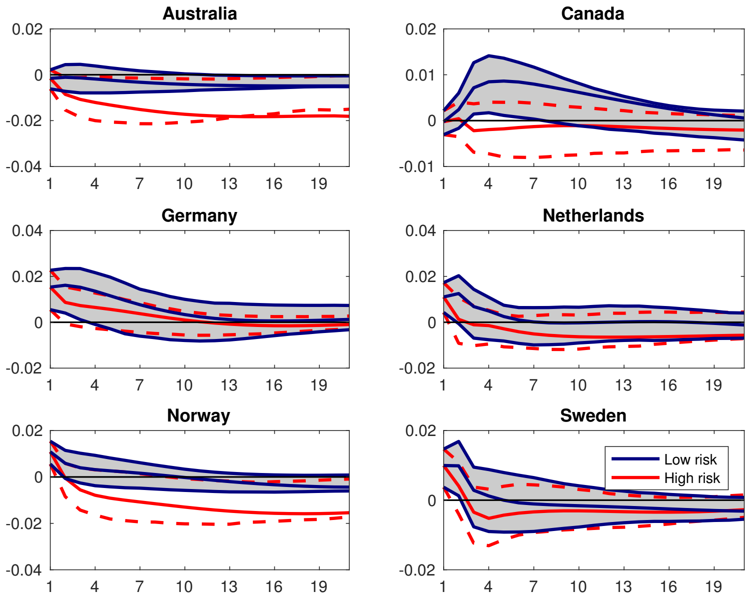


Figure A.1: Consumption. Impulse responses of the exchange rate to a one standard deviation shock to global uncertainty (68% confidence bands). Blue: low risk; red: high risk.

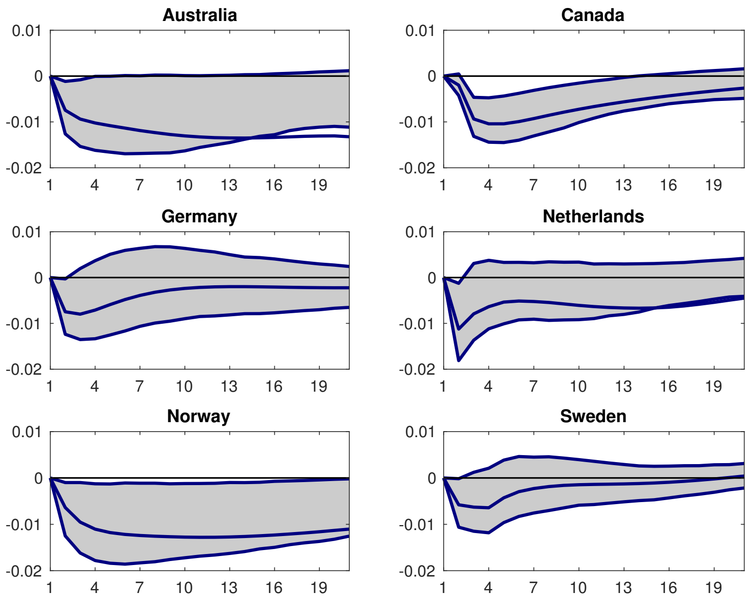


Figure A.2: Consumption. Differences in the point estimates of the impulse responses of the exchange rate in the two states (high risk - low risk). 68% confidence bands.

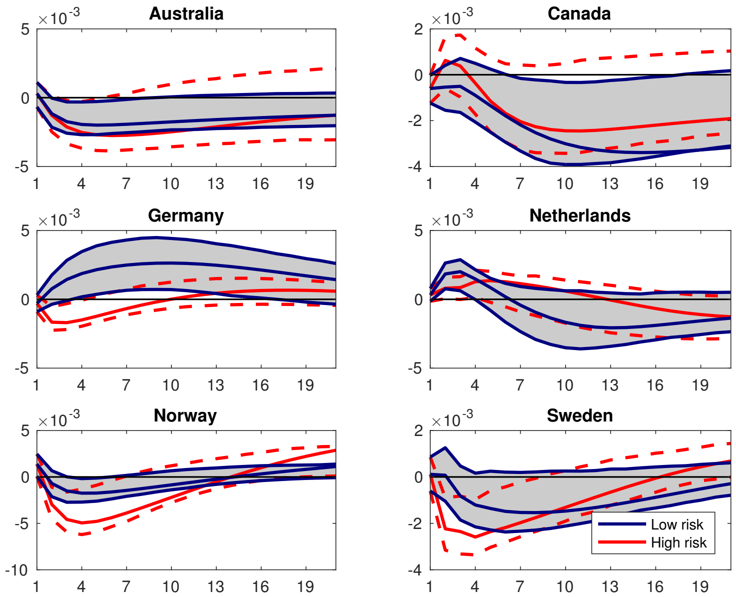


Figure A.3: Consumption. Impulse responses of output to a one standard deviation shock to global uncertainty (68% confidence bands). Blue: low risk; red: high risk.

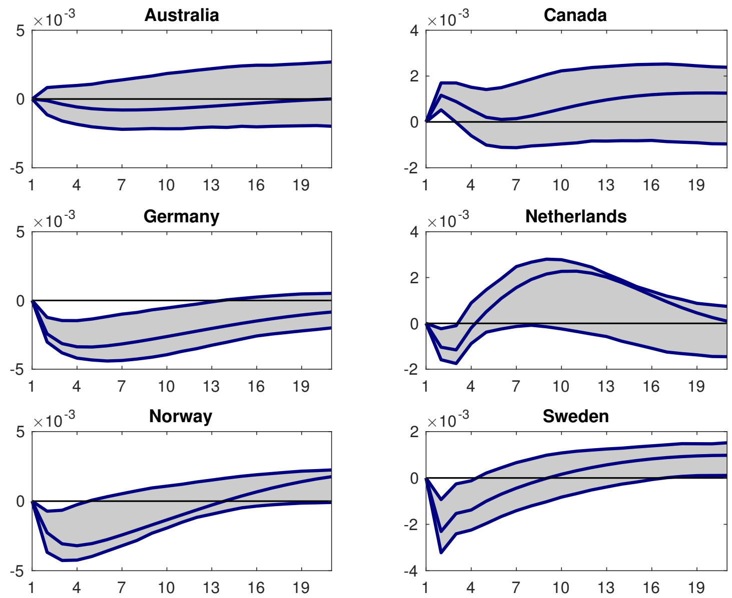


Figure A.4: Consumption. Differences in the point estimates of the impulse responses of output in the two states (high risk - low risk). 68% confidence bands.

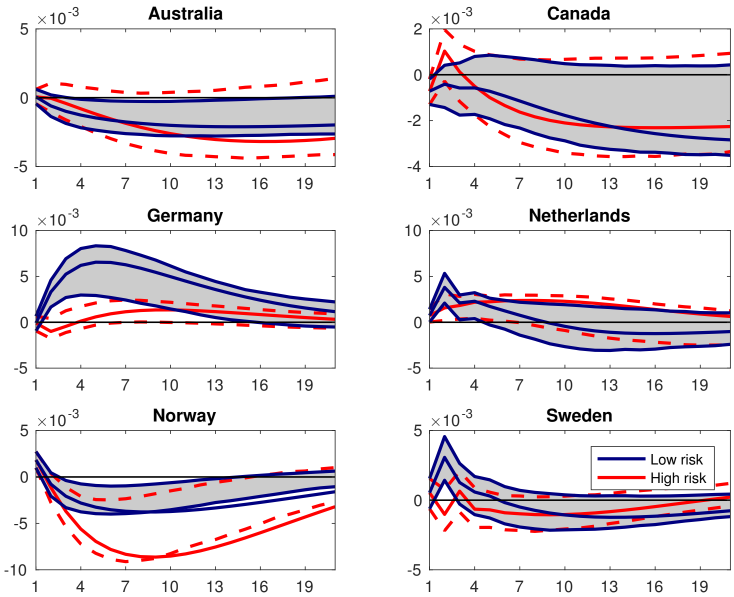


Figure A.5: Consumption. Impulse responses of consumption to a one standard deviation shock to global uncertainty (68% confidence bands). Blue: low risk; red: high risk.

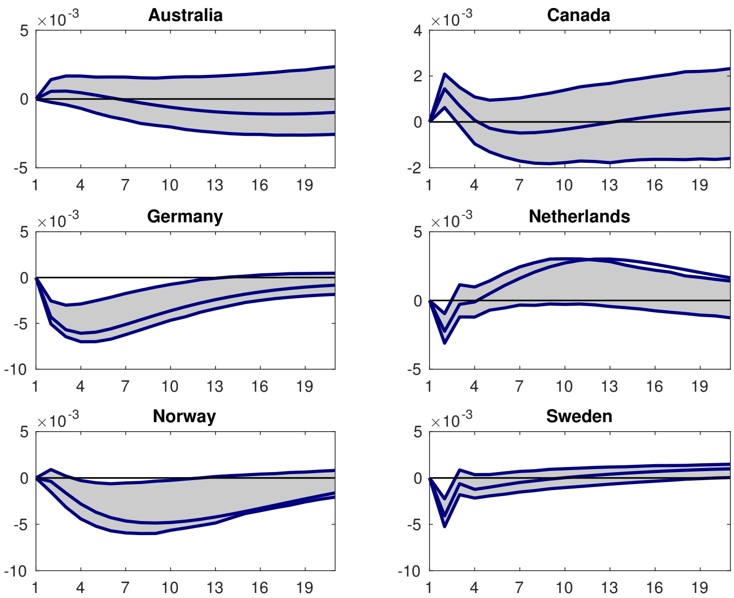


Figure A.6: Consumption. Differences in the point estimates of the impulse responses of consumption in the two states (high risk - low risk). 68% confidence bands.

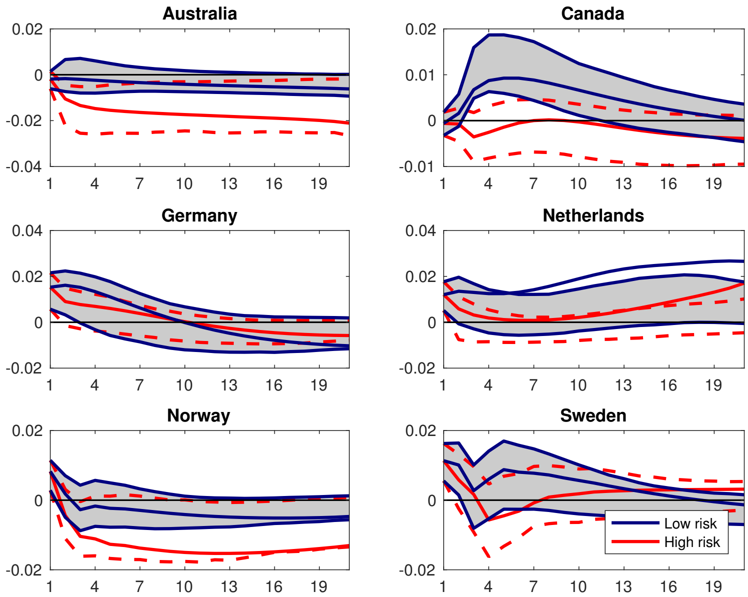


Figure A.7: Net exports. Impulse responses of the exchange rate to a one standard deviation shock to global uncertainty (68% confidence bands). Blue: low risk; red: high risk.

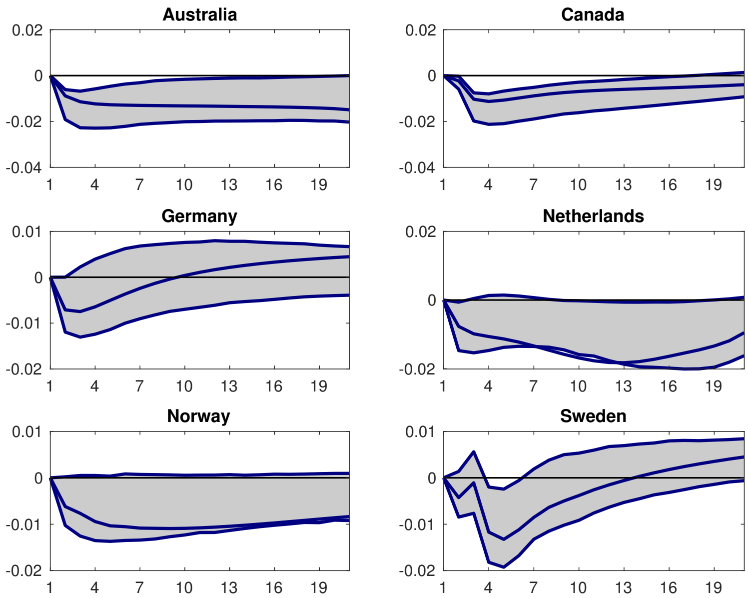


Figure A.8: Net exports. Differences in the point estimates of the impulse responses of the exchange rate in the two states (high risk - low risk). 68% confidence bands.

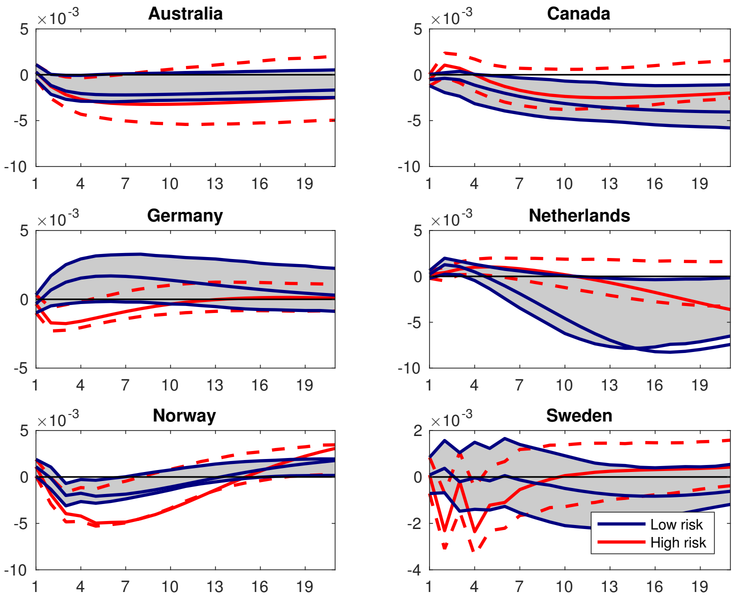


Figure A.9: Net exports. Impulse responses of output to a one standard deviation shock to global uncertainty (68% confidence bands). Blue: low risk; red: high risk.

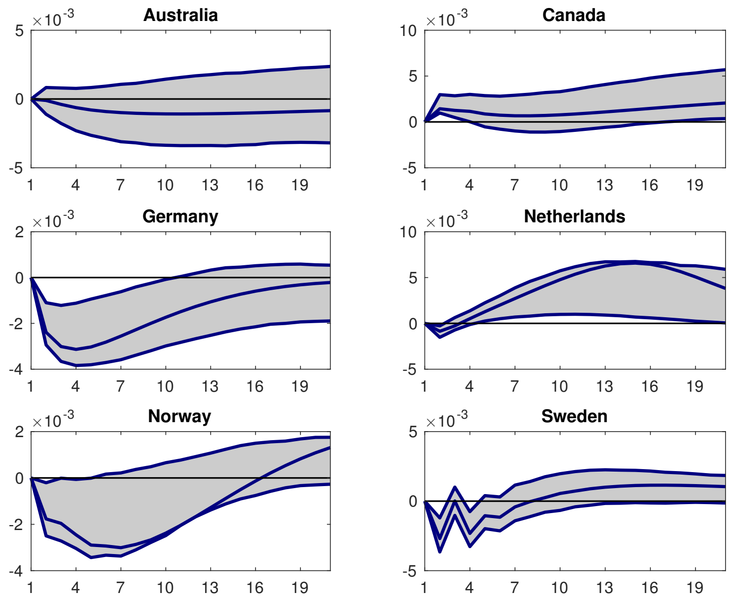


Figure A.10: Net exports. Differences in the point estimates of the impulse responses of output in the two states (high risk - low risk). 68% confidence bands.

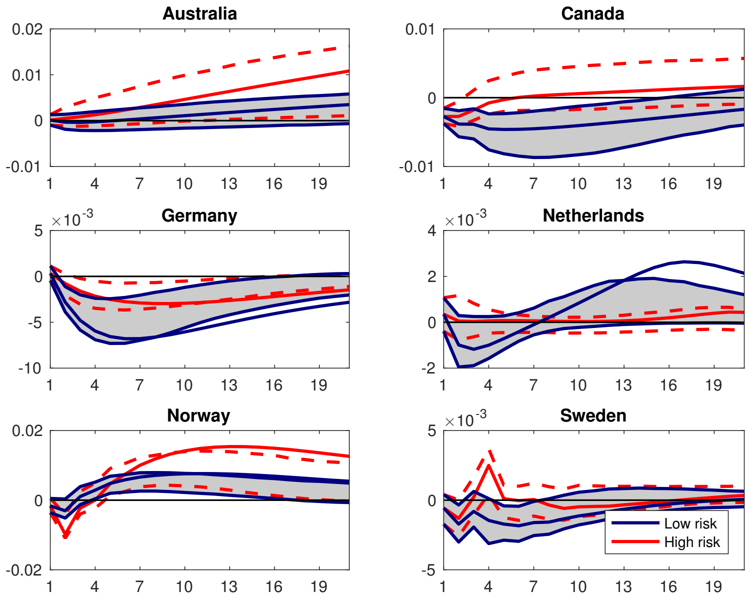


Figure A.11: Net exports. Impulse responses of net exports to a one standard deviation shock to global uncertainty (68% confidence bands). Blue: low risk; red: high risk.

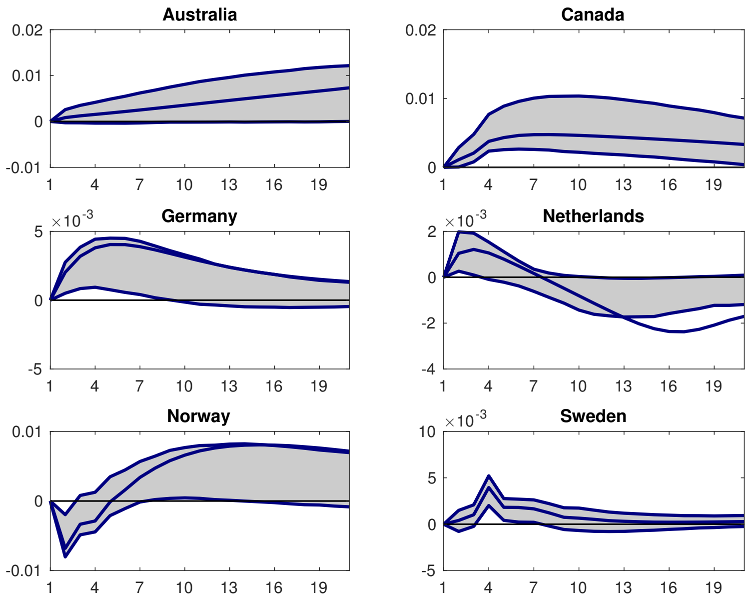


Figure A.12: Net exports. Differences in the point estimates of the impulse responses of net exports in the two states (high risk - low risk). 68% confidence bands.

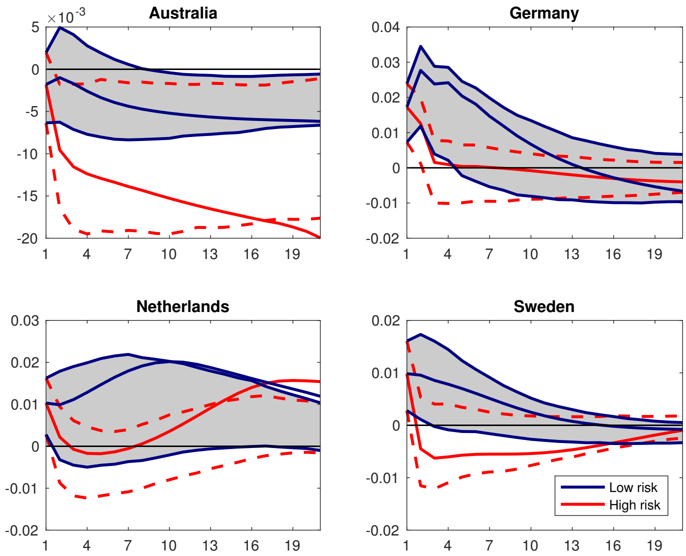


Figure A.13: Financial flows. Impulse responses of the exchange rate to a one standard deviation shock to global uncertainty (68% confidence bands). Blue: low risk; red: high risk.

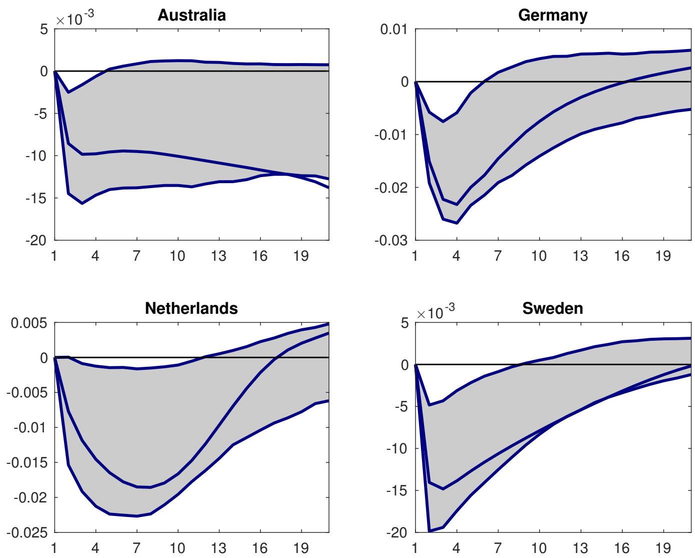


Figure A.14: Financial flows. Differences in the point estimates of the impulse responses of the exchange rate in the two states (high risk - low risk). 68% confidence bands.

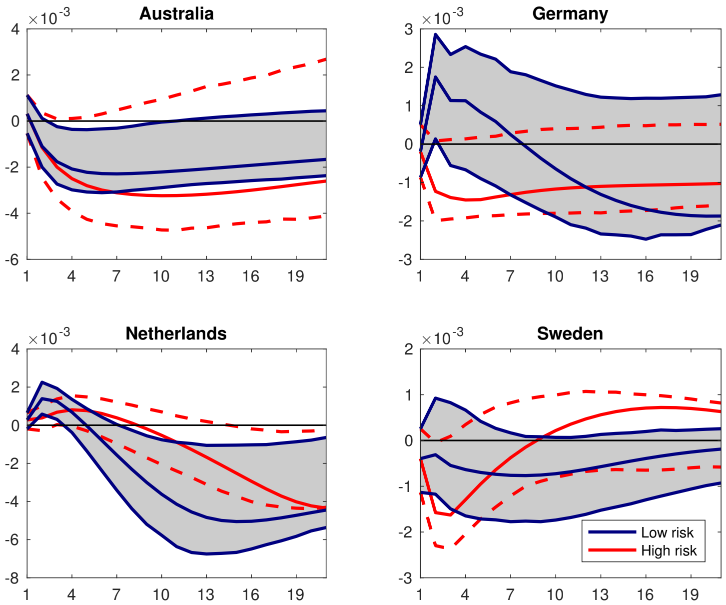


Figure A.15: Financial flows. Impulse responses of output to a one standard deviation shock to global uncertainty (68% confidence bands). Blue: low risk; red: high risk.

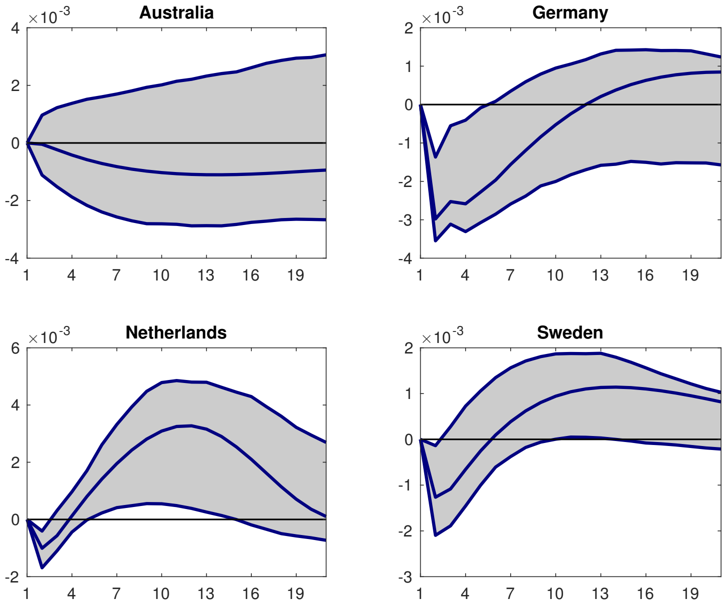


Figure A.16: Financial flows. Differences in the point estimates of the impulse responses of output in the two states (high risk - low risk). 68% confidence bands.

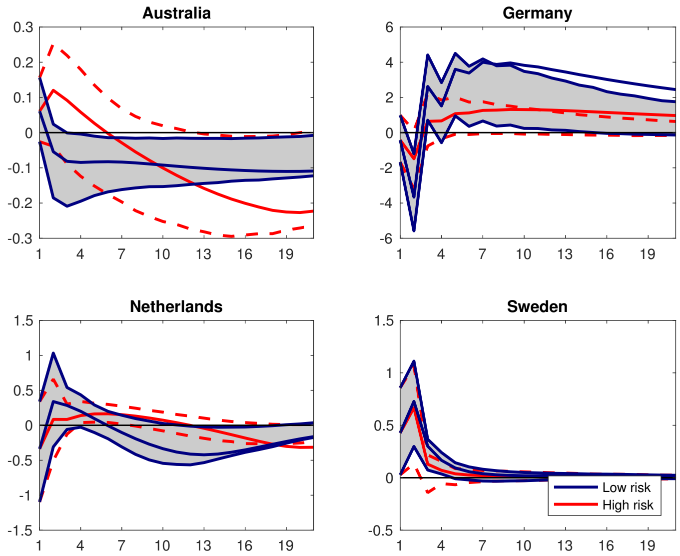


Figure A.17: Financial flows. Impulse responses of financial flows to a one standard deviation shock to global uncertainty (68% confidence bands). Blue: low risk; red: high risk.

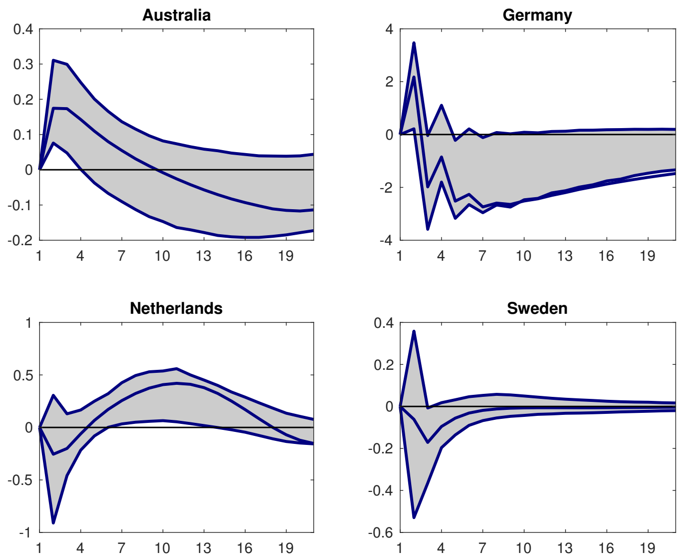


Figure A.18: Financial flows. Differences in the point estimates of the impulse responses of financial flows in the two states (high risk - low risk). 68% confidence bands.

Appendix B

Robustness checks

This appendix includes the plots that illustrate results presented in subsection 1.5.4 of Chapter 1.

We test the robustness of our results through a series of perturbations of the baseline model. We consider:

- Uncertainty ordered last (figures B.1-B.4)
- An uncertainty shock dummy (figures B.5-B.8)
- The role of country-specific uncertainty (figures B.9-B.12)
- The role of financial shocks (figures B.13-B.16)
- The size of the shock (figures B.17-B.20)

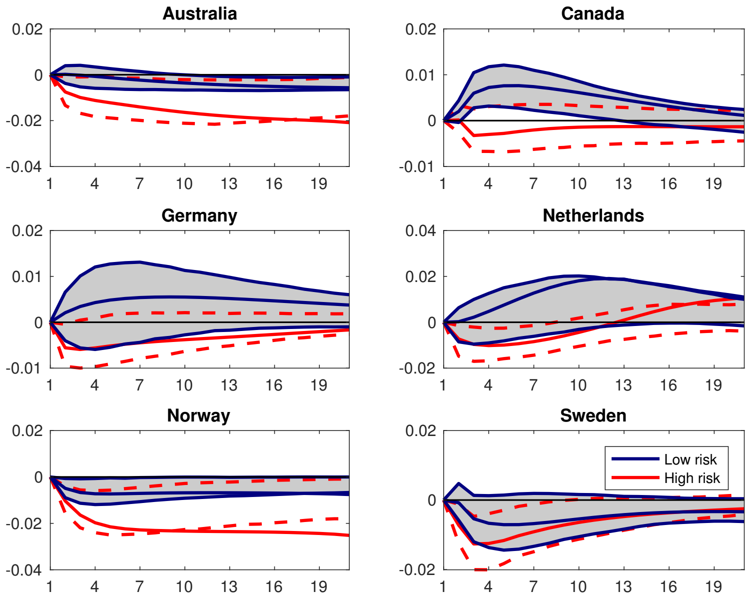


Figure B.1: Uncertainty last. Impulse responses of the exchange rate to a one standard deviation shock to global uncertainty (68% confidence bands). Blue: low risk; red: high risk.

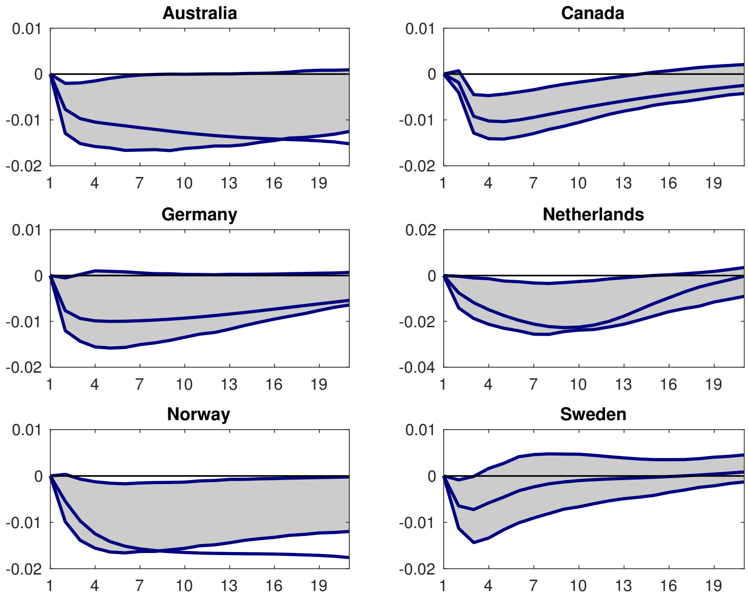


Figure B.2: Uncertainty last. Differences in the point estimates of the impulse responses of the exchange rate in the two states (high risk - low risk). 68% confidence bands.

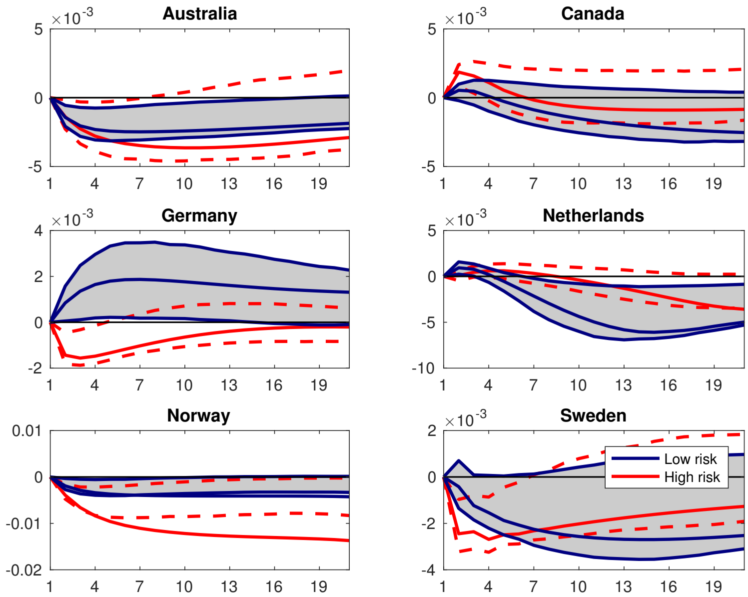


Figure B.3: Uncertainty last. Impulse responses of output to a one standard deviation shock to global uncertainty (68% confidence bands). Blue: low risk; red: high risk.

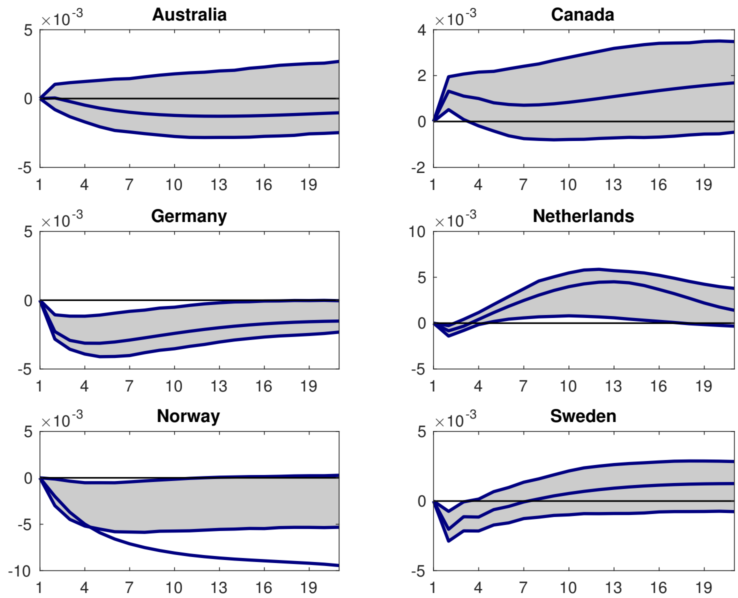


Figure B.4: Uncertainty last. Differences in the point estimates of the impulse responses of output in the two states (high risk - low risk). 68% confidence bands.

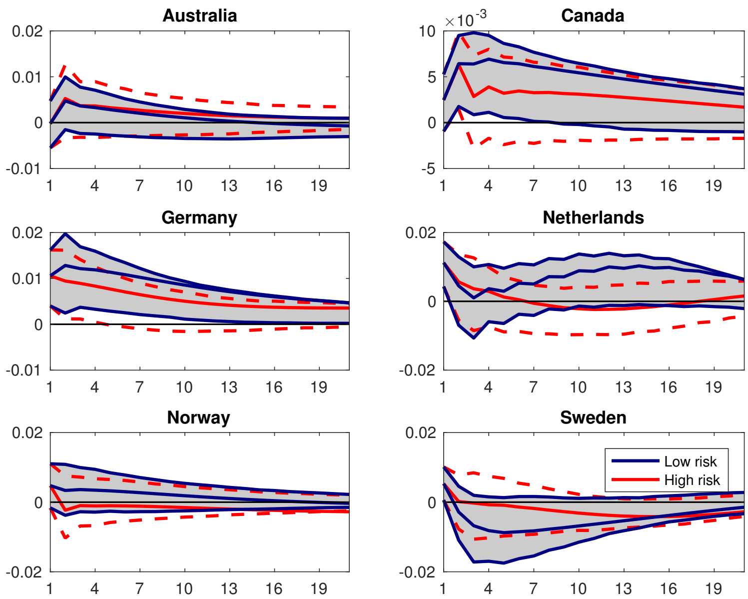


Figure B.5: Uncertainty dummy. Impulse responses of the exchange rate to a one standard deviation shock to global uncertainty (68% confidence bands). Blue: low risk; red: high risk.

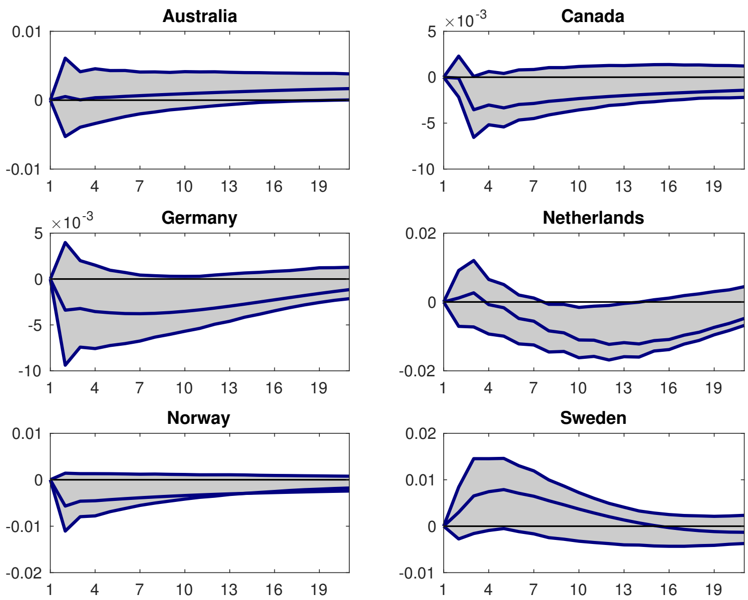


Figure B.6: Uncertainty dummy. Differences in the point estimates of the impulse responses of the exchange rate in the two states (high risk - low risk). 68% confidence bands.

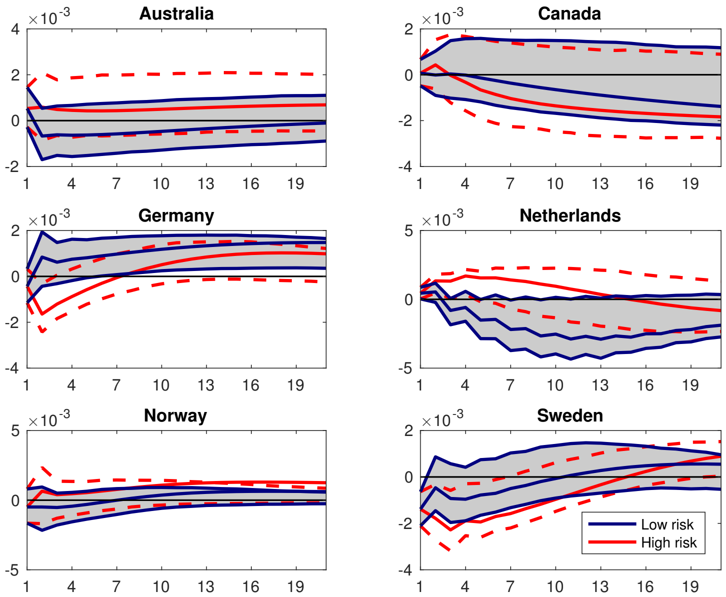


Figure B.7: Uncertainty dummy. Impulse responses of output to a one standard deviation shock to global uncertainty (68% confidence bands). Blue: low risk; red: high risk.

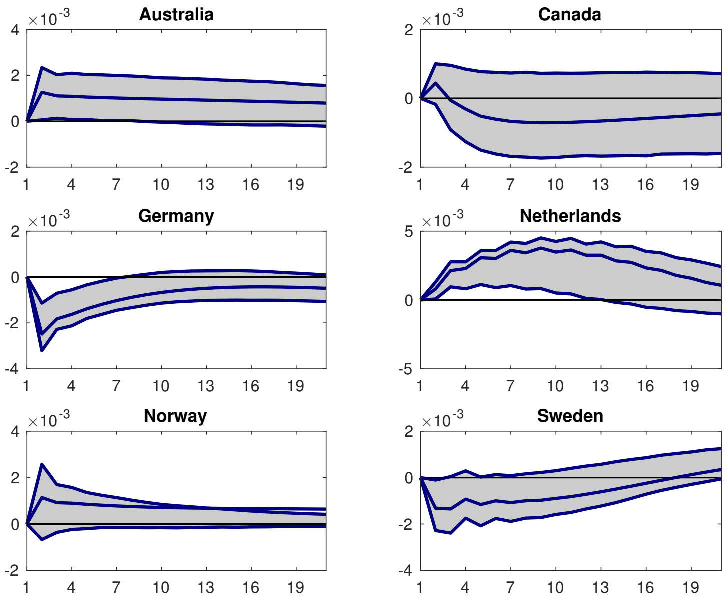


Figure B.8: Uncertainty dummy. Differences in the point estimates of the impulse responses of output in the two states (high risk - low risk). 68% confidence bands.

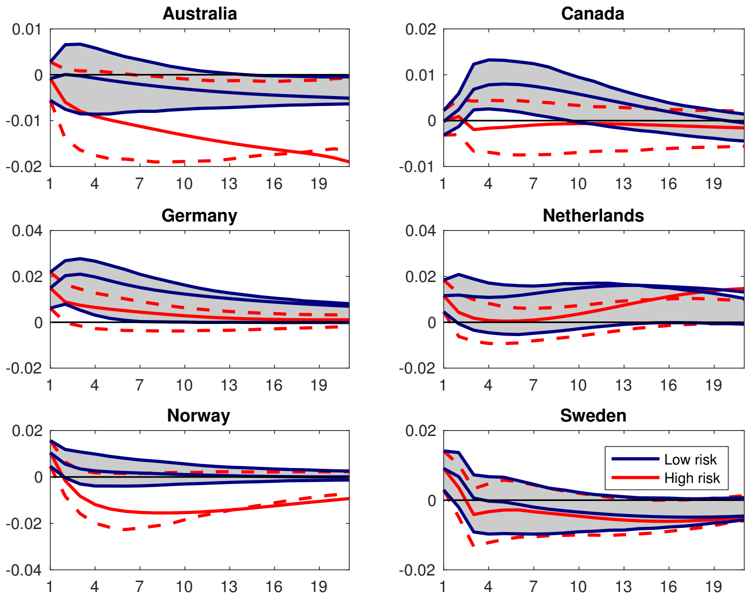


Figure B.9: Country-specific uncertainty. Impulse responses of the exchange rate to a one standard deviation shock to global uncertainty (68% confidence bands). Blue: low risk; red: high risk.

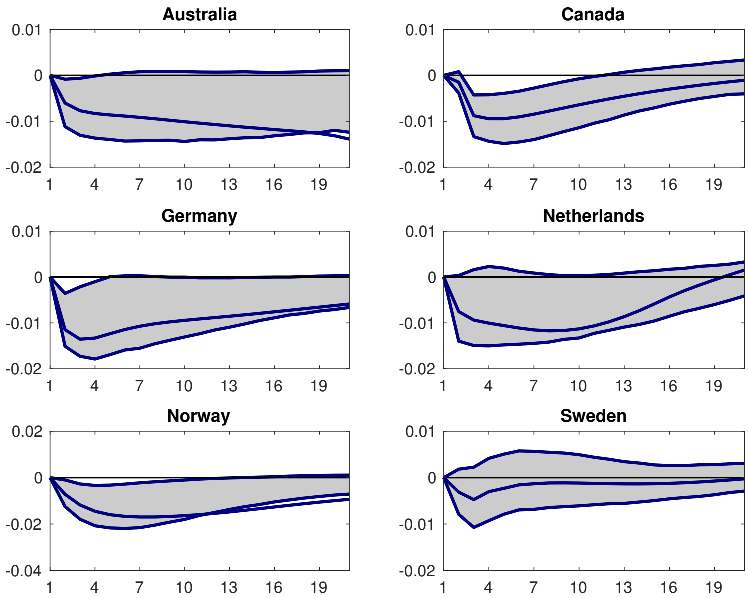


Figure B.10: Country-specific uncertainty. Differences in the point estimates of the impulse responses of the exchange rate in the two states (high risk - low risk). 68% confidence bands.

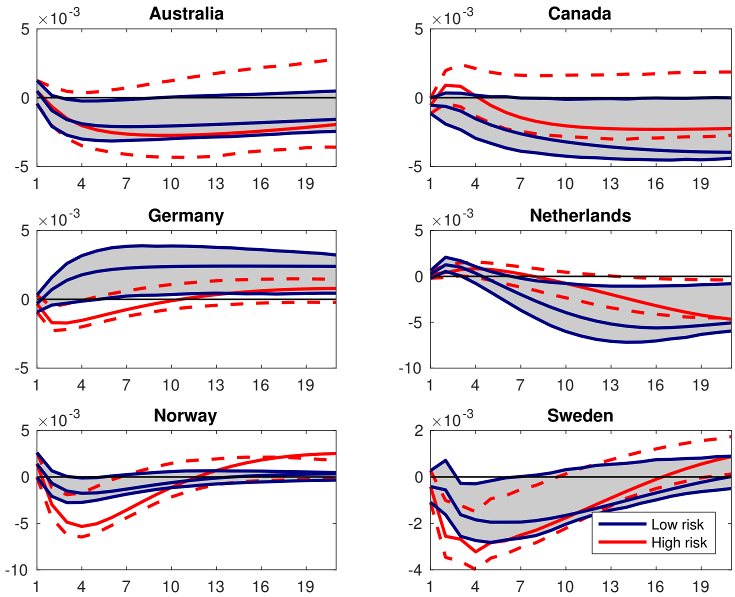


Figure B.11: Country-specific uncertainty. Impulse responses of output to a one standard deviation shock to global uncertainty (68% confidence bands). Blue: low risk; red: high risk.

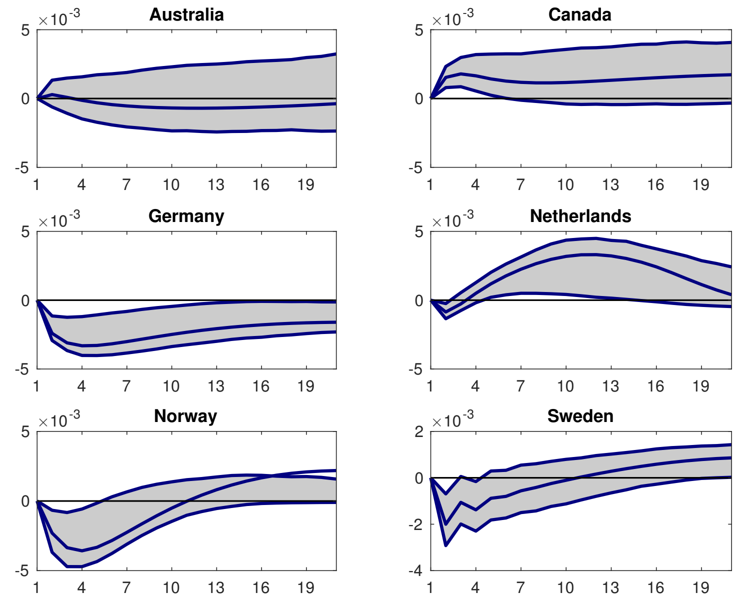


Figure B.12: Country-specific uncertainty. Differences in the point estimates of the impulse responses of output in the two states (high risk - low risk). 68% confidence bands.

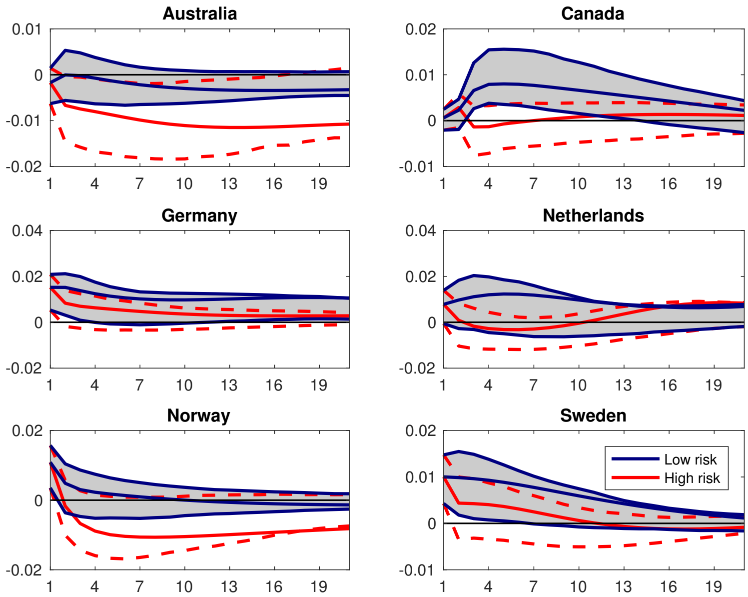


Figure B.13: EBP. Impulse responses of the exchange rate to a one standard deviation shock to global uncertainty (68% confidence bands). Blue: low risk; red: high risk.

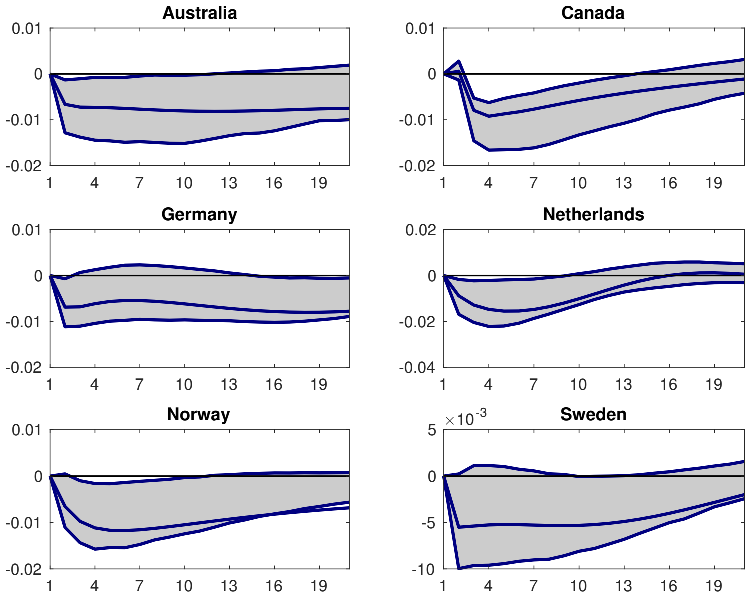


Figure B.14: EBP. Differences in the point estimates of the impulse responses of the exchange rate in the two states (high risk - low risk). 68% confidence bands.

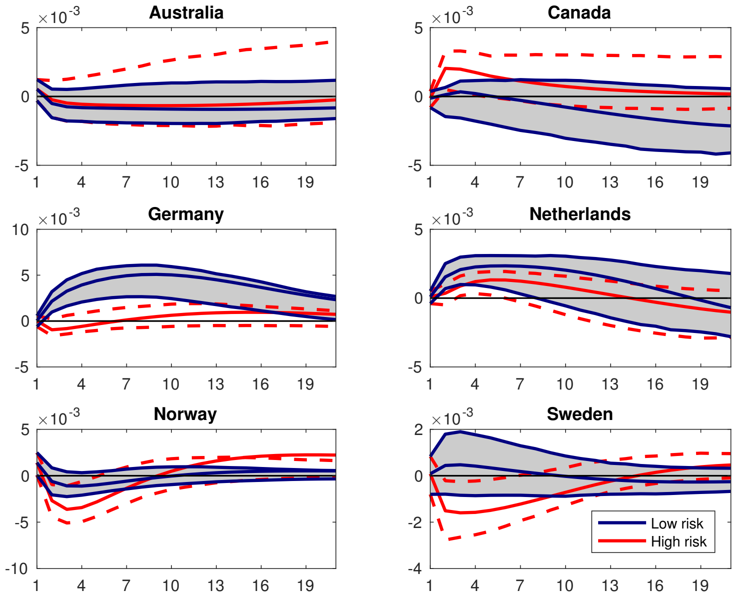


Figure B.15: EBP. Impulse responses of output to a one standard deviation shock to global uncertainty (68% confidence bands). Blue: low risk; red: high risk.

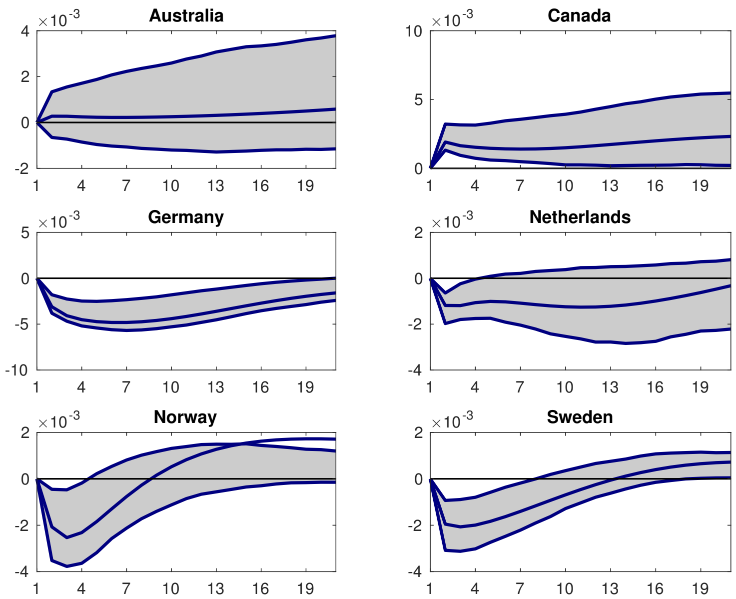


Figure B.16: EBP. Differences in the point estimates of the impulse responses of output in the two states (high risk - low risk). 68% confidence bands.

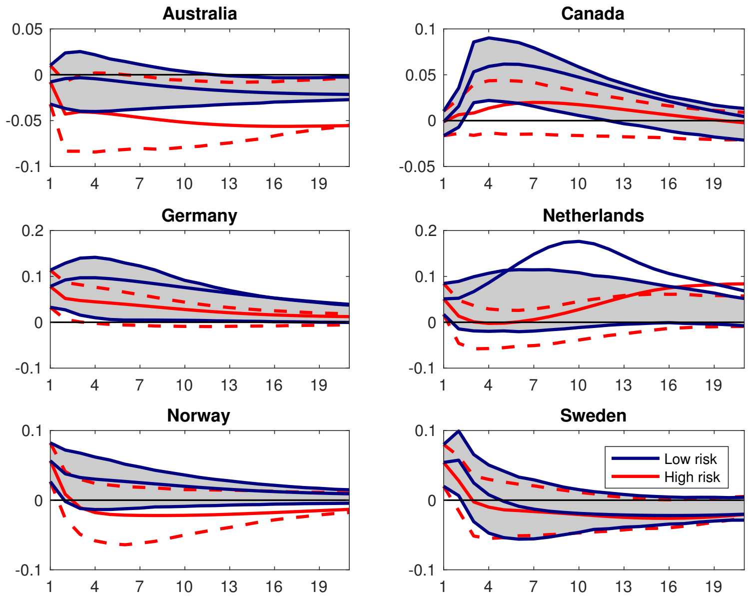


Figure B.17: Size of the shock. Impulse responses of the exchange rate to a one standard deviation shock to global uncertainty (68% confidence bands). Blue: low risk; red: high risk.

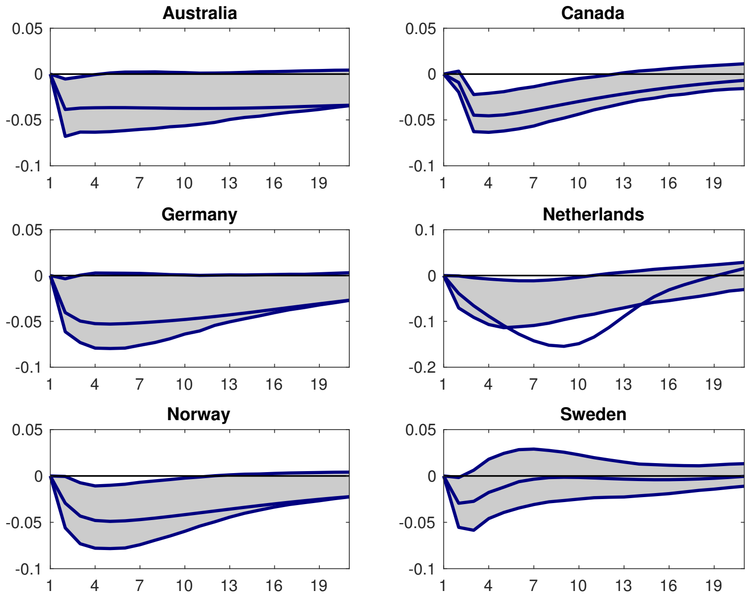


Figure B.18: Size of the shock. Differences in the point estimates of the impulse responses of the exchange rate in the two states (high risk - low risk). 68% confidence bands.

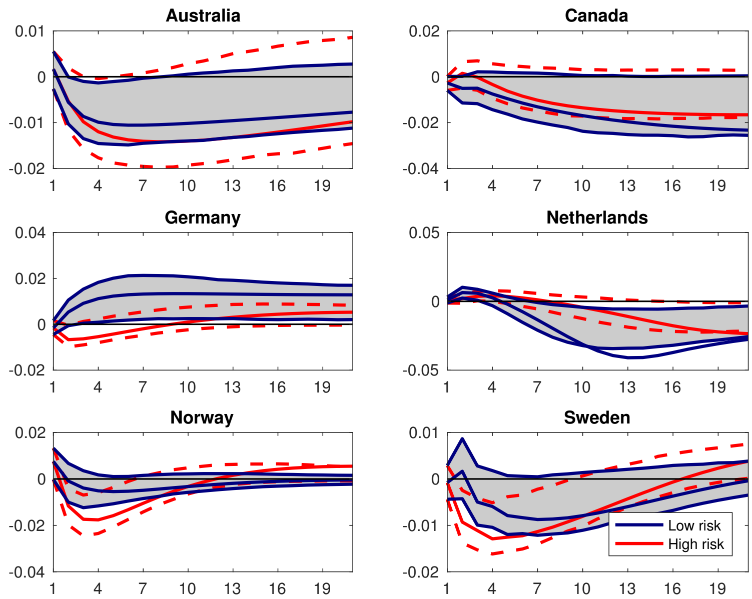


Figure B.19: Size of the shock. Impulse responses of output to a one standard deviation shock to global uncertainty (68% confidence bands). Blue: low risk; red: high risk.

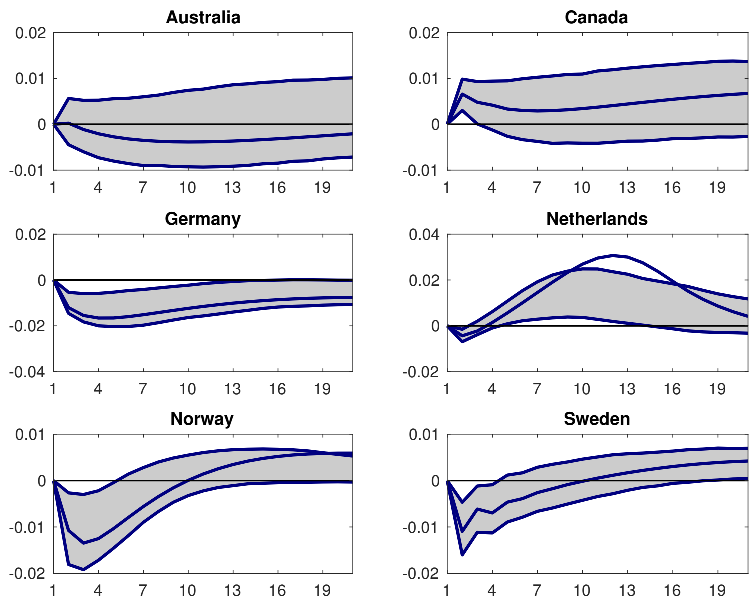


Figure B.20: Size of the shock. Differences in the point estimates of the impulse responses of output in the two states (high risk - low risk). 68% confidence bands.

Appendix C

Computation of GIRFs

To compute state-conditional Generalized Impulse Response Functions (GIRFs) we follow the algorithm proposed in Caggiano, Castelnuovo, and Pellegrino (2016), which in turn follows the steps in Koop et al. (1996) and simulates the effects of an orthogonal structural shock as in Kilian and Vigfusson (2011).

The idea is to compute the empirical counterpart of the theoretical $GIRF_{\mathbf{y}}(h, \delta, \omega_{t-1})$ of the vector of endogenous variables $\mathbf{y}_t$, h periods ahead, for a given initial condition $\omega_{t-1} = \{\mathbf{y}_{t-1}, \ldots, \mathbf{y}_{t-k}\}$, k being the number of lags in the I-VAR, and a structural shock δ hitting at time t. Following Koop et al. (1996), we express such GIRF as follows:

$$GIRF_{\mathbf{y}}(h, \delta, \omega_{t-1}) = E[\mathbf{y}_{t+h} \,|\, \delta, \omega_{t-1}] - E[\mathbf{y}_{t+h} \,|\, \omega_{t-1}]$$

where $E[\cdot]$ is the expectation operator and $h = 0, 1, \ldots, H$ indicates the horizons for which the GIRF is computed.

The procedure to compute it is the following:

1. Pick an initial condition ω_{t-1}.

2. Conditional on ω_{t-1} and the I-VAR structure of the model, simulate the path $[y_{t+h}|\omega_{t-1}]^r$, by loading the VAR with a sequence of randomly extracted (with repetition) residuals $\tilde{u}^r_{t+h} \sim d(0, \hat{\Sigma})$, where d is the empirical distribution of the residuals, $\hat{\Sigma}$ is the estimated variance-covariance matrix and r indicates the particular sequence of residuals extracted.

3. Conditional on ω_{t-1} and the structure of the model, simulate the path $[y_{t+h}|\delta, \omega_{t-1}]^r$, by loading the VAR with a perturbation of the randomly extracted residuals $\tilde{u}^r_{t+h} \sim d(0, \hat{\Sigma})$ obtained in Step 2.
   To obtain perturbed residuals, first recover the vector of orthogonalized shocks $\tilde{\epsilon}^r_t$. Take the Cholesky decomposition of $\hat{\Sigma} = \hat{C}\hat{C}'$, where $\hat{C}$ is a lower triangular matrix. The orthogonalized shocks are given by $\tilde{\epsilon}^r_t = \hat{C}^{-1}\tilde{u}^r_{t+h}$. Then, to obtain a series of perturbed orthogonalized shocks, add a quantity $\delta > 0$ to the element $\tilde{\epsilon}^r_{unc,t}$, which is the scalar stochastic element loading the uncertainty equation in the VAR. Finally, to move from perturbed orthogonalized shocks to the perturbed residuals that we use to simulate $[y_{t+h}|\delta, \omega_{t-1}]^r$, compute them as $\tilde{\tilde{u}}^r_t = \hat{C}\tilde{\tilde{\epsilon}}^r_{t+h}$.

4. At each horizon, compute the difference between the simulated paths $[y_{t+h}|\delta, \omega_{t-1}]^r - [y_{t+h}|\omega_{t-1}]^r$.

5. For each initial condition ω_{t-1}, repeat Steps 2-4 for $R = 500$ times. Then, store the average realization across repetitions for each horizon h. In this way, a consistent estimate of the GIRF for any given initial condition is obtained: $\widehat{GIRF}_{\mathbf{y}}(h, \delta, \omega_{t-1}) = \hat{E}[\mathbf{y}_{t+h} \,|\, \delta, \omega_{t-1}] - \hat{E}[\mathbf{y}_{t+h} \,|\, \omega_{t-1}]$.

6. To produce the point estimates of state-conditional GIRFs, average history-dependent GIRFs over a particular subset of initial conditions of interest. In our case, an initial history ω_{t-1} belongs to "high risk" regime if $SPREAD_{i,t-1} < 0$ and to "low risk" regime if $SPREAD_{i,t-1} \geq 0$.

7. Confidence bands are computed via a bootstrap procedure. To implement it, simulate $S = 1000$ samples of the same size as actual data. Then, for each simulated dataset estimate the I-VAR model and repeat Steps 1-6 to compute state-dependent GIRFs. Confidence bands are given by the 16th and the 84th percentiles of the resulting distribution of state-conditional GIRFs.

Chapter 2

Estimating Fiscal Multipliers at the ZLB: A TVP-VAR Approach

2.1 Introduction

As an effect of the Great Recession of 2008-2009, the issue of whether fiscal policy should be used to stimulate economic recovery received renewed attention in the policy debate (e.g Bils & Klenow, 2008; Hall & Woodward, 2008; Mankiw, 2008a, 2008b; Barro, 2009; Krugman, 2009; Feldstein, 2009). Several contributions were provided addressing the following issues: (i) how effective is fiscal policy in stimulating economic activity and (ii) which fiscal measures are the most effective and should be implemented in that situation. Part of this renewed attention to the effects of fiscal stimulus is certainly due to nominal short-term interest rates being at their zero lower bound, in the U.S. as well as in most advanced economies, meaning that central banks were deprived of their main policy tool to stabilize the economy. Relative to this debate, two main strands of literature emerged. The first one investigates whether the size of fiscal multipliers depends on the state of the economy, namely the economy being in expansion or recession, in the tradition of Auerbach and Gorodnichenko (2012). Other contributions focus on the interactions between monetary and fiscal policy, trying to assess whether monetary policy affects fiscal multipliers, and particularly considering the special case in which short-term interest rates hit the zero lower bound (ZLB). From a theoretical perspective, New Keynesian dynamic stochastic general equilibrium (DSGE) models predict that multipliers can be higher when the economy is at the ZLB than in normal times (see, among others, Woodford, 2010; Eggertsson, 2011; Christiano, Eichenbaum, & Rebelo, 2011). The general idea is that the size of the multiplier depends on the degree of monetary accommodation to fiscal stimulus. At the ZLB, being monetary policy constrained by short-term interest rates at their lower bound, it is plausible to expect that the central bank will not tighten policy in response to fiscal expansion. As a result, one could reasonably expect that real interest rates will decrease, to the extent that fiscal stimulus is associated with an increase in inflation expectations. However, alternative models have been proposed in which multipliers are not higher when the economy is at the ZLB (e.g., Mertens & Ravn, 2014; Kiley, 2014). With respect to other models, these works consider either different causes that drive the economy to a binding ZLB, such as a shift in expectations (Mertens & Ravn, 2014), or different assumptions regarding price dynamics (Kiley, 2014), and find that a deflationary equilibrium may exist, in which increasing government spending is less effective. On the empirical side, evidence on the effects of fiscal policy at the ZLB is also mixed. Some works (Almunia, Bénétrix, Eichengreen, O'Rourke, & Rua, 2010; Gordon & Krenn, 2010) estimate multipliers larger than unity during times of interest rates close to zero, whereas other contributions do not find evidence of spending multipliers larger than unity (Ramey, 2011; Carfts & Mills, 2013; Ramey & Zubairy, 2016). Moreover, the number of contributions is limited, and most of them focus on the interwar period, because in postwar data until 2008 interest rates are always positive (Almunia et al., 2010; Gordon & Krenn, 2010; Ramey, 2011; Carfts & Mills, 2013). Ramey and Zubairy (2016) are the first ones to propose a state dependent analysis of fiscal multipliers that considers the ZLB on interest rates as a state. Again, they find little and not robust evidence of higher multiplier at the ZLB.

Given that opposite predictions are provided by the theory and that limited empirical evidence is available, this chapter relates to this second strand of literature and aims at estimating time-varying fiscal multipliers. Special attention is devoted to the size of multipliers when the economy is at the ZLB. To address this issue we employ a structural time-varying parameter VAR with stochastic volatility (TVP-VAR) in the tradition of Primiceri (2005), which allows both shocks and the fiscal transmission mechanism to change over time. With respect to other regime-switching models, which allow to separate normal times versus ZLB regimes, and can thus be considered as alternative tools for this type of study, TVP-VARs allow for a richer analysis, in a more flexible setting, because they do not require a-priori imposition for regime identification. Indeed, several contributions in the literature have highlighted how both monetary and fiscal policy display substantial regime variability, especially the latter (e.g., Favero & Monacelli, 2003; Davig & Leeper, 2011). Moreover, the limited number of observations available for the ZLB period makes alternative regime-switching models such as threshold VARs less suitable for this kind of analysis, whereas a TVP-VAR allows to exploit all available information for the estimation.

Our work builds on the extant literature as follows. Blanchard and Perotti (2002) estimate a structural VAR with quarterly taxes, spending and GDP, where the expenditure variable is defined as government consumption plus government investment and taxes are defined as total tax revenues minus transfers. They employ institutional information to construct the automatic response of fiscal policy to economic activity. Auerbach and Gorodnichenko (2012) employ the same quarterly dataset in the baseline specification of their smooth-transition VAR and rely on the same identifying assumption that discretionary policy does not respond to output within a quarter. We build on these contributions by employing the same definition of government spending and revenues and by identifying a spending shock with government spending ordered first in our baseline specification, but differently with respect to their papers we also include a short term interest rate to account for the monetary policy stance, in line with Rossi and Zubairy (2011) and Mountford and Uhlig (2009). In a further exercise, Auerbach and Gorodnichenko (2012) control for expectations by using real-time professional forecasts of government spending to better identify unanticipated fiscal shocks. That of fiscal foresight is still an open issue for the identification of spending shocks in this work. The dimensionality of the estimation problem is the reason why we do not include additional variables to deal with it in our baseline specification. Nevertheless, addressing fiscal foresight is crucial for correctly identifying fiscal shocks and we will further explore the issue.

TVP-VARs have been quite largely used for analyzing monetary policy (e.g., Cogley & Sargent, 2001, 2005; Primiceri, 2005; Gambetti, Pappa, & Canova, 2008;

Canova & Gambetti, 2009). On the other hand, there are still few applications to fiscal policy issues: Kirchner, Cimadomo, and Hauptmeier (2010); Pereira and Lopes (2014); Hauzenberger (2012); Gerba and Hauzenberger (2013). Gerba and Hauzenberger (2013) is the closest study to ours. They apply a TVP-VAR to analyze the evolution over time of the degree of interaction between monetary and fiscal policy and their relative role in explaining fluctuations in U.S. economy. The main difference between their study and ours lies in our focus on the ZLB period. Indeed, Gerba and Hauzenberger examine the relative contributions of monetary and fiscal policy shocks to business cycle fluctuations in the U.S. over the period 1979-2012 and find a high degree of heterogeneity over time. On the other hand, we ask whether and how the monetary policy stance affects the transmission of fiscal policy shocks and pay particular attention to the size of fiscal multipliers at the ZLB. We ask whether being short-term nominal interest rates very close to zero represents an additional and relevant source of heterogeneity in the interactions between monetary and fiscal policy. To this aim we exploit all the available information on the ZLB period, by employing a dataset from 1954Q3 to 2015Q3. Moreover, we explicitly take unconventional monetary policy into account for the identification of monetary policy shocks in the last part of the sample. To this end, we include in our specification the shadow rate by Wu and Xia (2016). Indeed, the idea of the shadow rate is to estimate a short-term interest rate compatible with movements in the term structure of interest rates, that can be used as a powerful tool to describe the monetary policy stance and to capture information to assess the effects of unconventional monetary policy, when the effective rate is at the zero bound. In this sense, the shadow rate should be a better measure to describe monetary policy and to identify monetary policy shocks at the ZLB, than the effective policy rate is.

The distinction between active and passive monetary and fiscal policies proposed in Leeper (1991) and the estimated joint monetary-fiscal regimes in Davig and Leeper (2011) offer an interesting framework to interpret our results. Estimates obtained from our quarterly TVP-VAR show that government spending multipliers considerably vary over time, and are larger during periods in which monetary policy does not strongly react to inflation movements, like times of passive monetary policy regime and at the ZLB. These results are in line with New Keynesian models predictions of larger multipliers in the presence of accommodative monetary policy. Moreover, spending multipliers display an increasing trend over time. This result, jointly with the increasing variability of output accounted for by spending shocks over the investigated period suggested by our FEVDs, point to an increase over time in the relevance of fiscal policy in explaining output fluctuations.

The chapter is organized as follows. Section 2 discusses the relation to the literature. Section 3 presents the empirical strategy and the data employed in the analysis. Section 4 illustrates the identification strategy of spending shocks and discusses the issue of fiscal foresight. Section 5 presents and discusses the results. Section 6 concludes.

2.2 Related literature

This chapter relates to different strands of the literature. First, by aiming at evaluating the evolution of fiscal policy effectiveness over time, it naturally looks at the growing literature that provides evidence of state-dependent fiscal multipliers (see, among others, Tagkalakis, 2008; Auerbach & Gorodnichenko, 2012, 2013a, 2013b; Bachmann & Sims, 2012; Baum, Poplawski-Ribeiro, & Weber, 2012; Mittnik & Semmler, 2012; Owyang, Ramey, & Zubairy, 2013; Fazzari, Morley, & Panovska, 2015; Caggiano, Castelnuovo, Colombo, & Nodari, 2015). Indeed, as fiscal policy shocks may be more effective during periods of slacks, as pointed out by Parker (2011), this literature investigates whether the size of fiscal multipliers depends on the economy being in recession rather than in expansion. Among this large production, Ramey and Zubairy (2016) estimate a state-dependent model on historical U.S. data to investigate whether U.S. government spending multipliers depend (i) on the amount of slack in the economy, and (ii) on interest rates being near the zero lower bound. They do not find evidence of higher spending multipliers during high unemployment states and estimate multipliers below unity irrespective of the amount of slack. Concerning the zero lower bound, for the entire sample they do not find evidence of higher multipliers near the ZLB, whereas in the post-WWII sample they find evidence of multipliers as high as 1.5, even though these estimates are not statistically different from the normal state. Few other contributions estimate fiscal multipliers at the ZLB (Almunia et al., 2010; Gordon & Krenn, 2010; Ramey, 2011; Carfts & Mills, 2013), but none of them estimate a state-dependent model that considers the ZLB as a state. Rather they focus on specific episodes during the interwar period, being interest rates always positive in postwar data prior to 2008. Moreover, they provide mixed evidence relative to the size of spending multipliers at the ZLB.[1]

This chapter also relates to the literature investigating the interactions between monetary and fiscal policy (see, among others, Rossi & Zubairy, 2011; Canova & Pappa, 2011; Corsetti, Meier, & Müller, 2012; Gerba & Hauzenberger, 2013). Indeed, Rossi and Zubairy (2011) stress that jointly considering monetary and fiscal policy in empirical analyses is crucial for understanding the relative importance of fiscal and monetary policy shocks in explaining fluctuations in macroeconomic variables. In the same way, Mountford and Uhlig (2009) claim the importance of also identifying a monetary policy shock to correctly identify fiscal policy surprises. On the theoretical side, there are also several contributions highlighting the need to incorporate a fiscal sector in the analysis of optimal policies (see, among others, Chadha & Nolan, 2007; Galí & Monacelli, 2008; Davig & Leeper, 2011). Among them, some works investigate the effectiveness of government spending at the ZLB, pointing out that monetary policy behaviour matters for the effects of changes in government spending on economic activity. No consensus emerge on the size of fiscal multipliers. Plausible theories are proposed, which predict both higher and lower multipliers when interest rates are close to zero relative to normal times. New Keynesian models suggest that spending multipliers would be substantially higher when the economy is at the ZLB (see, among others Hall, 2009; Woodford, 2010; Eggertsson, 2011; Christiano et al., 2011; Leeper, Traum, & Walker, 2011; Cogan, Cwik, Taylor, & Wieland, 2010; Coenen et al., 2012; Erceg & Lindé, 2010). Indeed, in a framework with sticky prices or wages, monetary policy affects real

[1] Ramey (2011) investigates the size of U.S. spending multiplier over the period 1931-51 and finds no evidence of a higher multiplier. Carfts and Mills (2013) estimate the spending multiplier for UK over the period 1922-1938. The estimated multiplier is below unity. Almunia et al. (2010) estimate a panel VAR for 27 countries over the period 1925-39 and look at the response of economic activity to innovations in defense purchases, taken to capture exogenous changes in government spending. They estimate a multiplier larger than two. Gordon and Krenn (2010) examine the effects of innovations in government purchases on U.S. real GDP during the military buildup between 1940Q2 and1941Q4 and estimate a multiplier larger than unity.

activity and the effects of changes in government spending also depend on the response of monetary policy, i.e. the increase in output following an increase in government spending will depend on the degree of monetary accommodation to inflation pressure generated by fiscal stimulus. When interest rates approach their lower bound, it is especially reasonable to suppose that the central bank would not tighten policy in response to an increase in government spending. Being monetary policy constrained, this is a case in which it is plausible to assume not merely that the real interest rate would not rise following fiscal stimulus, but even that it would decrease, to the extent that fiscal stimulus is associated with higher inflation expectations, given that nominal interest rates would not rise. This mechanism would amplify the effects of fiscal stimulus, which would be especially strong in these circumstances.[2] Nevertheless, some other models predict lower multipliers at the ZLB (e.g. Mertens & Ravn, 2014; Braun, Körber, & Waki, 2013; Kiley, 2014; Aruoba, Cuba-Borda, & Schorfheide, 2014). The common mechanism that leads to multipliers lower than one in these models is that an increase in government purchases has deflationary effects, which in turn lead to higher real interest rates and crowding out of private consumption, which limit the expansionary effects of higher government spending. In Mertens and Ravn (2014), such a deflationary equilibrium arises in the case of an expectations-driven liquidity trap, e.g. a state of low confidence in which households expect a persistent drop in income, whereas Kiley (2014) considers a sticky-information model, a framework in which nominal prices slowly respond to shocks because of slow updating of information.

[2]It has been pointed out that what matters in the interaction between monetary and fiscal policy, it is not the zero lower bound per se, rather the fact that nominal interest rate stay constant following an increase in government spending, namely accommodative monetary policy, which amplifies the effects of government spending on economic activity. This result will provide some interesting insights in the analysis that follows. Moreover, Cogan et al. (2010) and Coenen et al. (2012) claim that government spending has larger effects when accommodative monetary policy lasts for a prolonged period. However, they also underline that the stimulus effects reduce if the increase in government purchases is perceived to be permanent.

2.3 Empirical strategy

2.3.1 The model

We estimate a structural TVP-VAR model with stochastic volatility in the tradition of Primiceri (2005). The model has the following representation:

$$y_t = C_t + B_{1,t}y_{t-1} + \cdots + B_{p,t}y_{t-p} + u_t$$

where $y_t = (g_t \; \tau_t \; x_t \; i_t)'$ is the vector of endogenous variables, with g_t federal spending, τ_t federal revenues, x_t a measure of output and i_t the interest rate. C_t is the $n \times 1$ vector of time varying intercepts, $B_{i,t}$ $(i = 1, \ldots, p)$ is the $n \times n$ matrix of time-varying autoregressive coefficients and u_t is the $n \times 1$ vector of residuals, with time varying variance-covariance matrix Ω_t. p is the number of lags and it is fixed to be $p = 2$, as it is usually assumed in the TVP-VAR literature.

Following the specification proposed by Primiceri (2005), consider the following decomposition of Ω_t

$$A_t \Omega_t A_t' = \Sigma_t \Sigma_t'$$

where A_t is the lower triangular matrix of covariances with ones on the main diagonal and Σ_t is the diagonal matrix of standard deviations. It follows that

$$u_t = A_t^{-1} \Sigma_t \varepsilon_t$$

where ε_t is the vector of structural shocks, with identity variance-covariance matrix I_n. Let α_t be the vector of non-zero and non-one elements of the matrix A_t and σ_t be the vector of the diagonal elements of Σ_t. Let $\beta_t = \text{vec}\,(B_t : C_t)$. The low of motion of the time-varying parameters is specified as follows

$$\beta_t = \beta_{t-1} + \nu_t$$

$$\alpha_t = \alpha_{t-1} + \zeta_t$$

$$\log \sigma_t = \log \sigma_{t-1} + \eta_t$$

The elements of vector β_t and the free elements of matrix A_t are modeled as random walks, whereas standard deviations σ_t are assumed to evolve as geometric random walks, thus falling in the class of models known as stochastic volatility. In principle, it is possible to consider more general autoregressive processes to model the dynamics of time varying parameters. Nevertheless, the random walk assumption allows to reduce the number of parameters to be estimated.

All the innovations in the model are assumed to be jointly normally distributed with zero means and variance-covariance matrix defined as follows

$$V = Var\left(\begin{bmatrix} \varepsilon_t \\ \nu_t \\ \zeta_t \\ \eta_t \end{bmatrix}\right) = \begin{bmatrix} I_n & 0 & 0 & 0 \\ 0 & Q & 0 & 0 \\ 0 & 0 & S & 0 \\ 0 & 0 & 0 & W \end{bmatrix}$$

with I_n n-dimensional identity matrix and Q, S and W positive definite matrices. S is assumed to be block diagonal, with blocks corresponding to parameters belonging to separate equations. This implies that the coefficients of the contemporaneous relations among variables are assumed to evolve independently in each equation.[3] The choice of this particular structure for V has two main advantages. The first one is related to the high number of parameters to be estimated. Having non-zero blocks out of the main diagonal in matrix V would mean to further increase the already high dimensionality of the model. The second advantage is related to the interpretation of innovations. Indeed, a general correlation structure among different innovations would prevent their structural interpretation. Both assumptions on the dynamics of the model's time-varying parameters and the structure of V are standard in the TVP-VAR literature.

Priors and estimation. We employ Bayesian methods to simulate the posterior distributions of parameters of interest, i.e. time-varying coefficients B^T, variances Σ^T and covariances A^T and hyperparameters of the variance-covariance matrix V. The Markov chain Monte Carlo (MCMC) algorithm by Del Negro and Primiceri (2015) is applied, which builds on the methods presented in Carter and Kohn (1994) and in Kim, Shephard, and Chib (1998). A Gibbs sampling algorithm is used to

[3] Primiceri (2005) states that this assumption is not crucial, but simplifies inference and increases the efficiency of the algorithm. He also considers the case of S unrestricted.

generate a sample from the joint posterior of (B^T, A^T, Σ^T, V), which exploits the blocking structure of the unknowns and estimates the joint posterior distribution of all parameters by drawing the parameters in each block from a conditional distribution. The algorithm works as follows:

1. Draw Σ^T from $p(\Sigma^t|y^T, B^T, A^T, V)$;
2. Draw B^T from $p(B^t|y^T, \Sigma^T, A^T, V)$;
3. Draw A^T from $p(A^t|y^T, \Sigma^T, B^T, V)$;
4. Draw V from $p(V|y^T, \Sigma^T, A^T, B^T)$.

It has been proven that, as the number of iterations increases, the conditional distributions generated by the Gibbs sampler converge to the joint and marginal distributions of the parameters.

Prior distributions are very similar to the ones in Primiceri (2005). The initial states for the coefficients, for the covariances, for the log-volatilities and for the hyperparameters are assumed to be independent of each other. The priors of the hyperparameters, Q, W and the blocks of S, are assumed to be distributed as independent inverse-Wishart, whereas the priors for the initial states of the time-varying coefficients, covariances and log-volatilities are assumed to be normally distributed. These assumptions, together with the assumed low of motion of the time-varying parameters, imply normal priors on the entire sequences of the B's, α's and $\log \sigma$'s, conditional on Q, W and S. We use the first twenty years of the sample (from 1954:Q3 to 1974:Q2) to calibrate our prior distributions, through the OLS point estimates of a time-invariant VAR model. As a results, the priors are defined as follows:

$$B_0 \sim N(\hat{B}_{OLS}, 4 \cdot V(\hat{B}_{OLS}))$$

$$A_0 \sim N(\hat{A}_{OLS}, 4 \cdot V(\hat{A}_{OLS}))$$

$$\log \sigma_0 \sim N(\log \hat{\sigma}_{OLS}, I_n)$$

$$Q \sim IW(k_Q^2 \cdot 80 \cdot V(\hat{B}_{OLS}), 80)$$

$$W \sim IW(k_W^2 \cdot 5 \cdot I_n, 5)$$

$$S_i \sim IW(k_S^2 \cdot (i+1) \cdot V(\hat{A}_{i,OLS}), i+1)$$

where S_i $(i = 1, \ldots, 3)$ are the four blocks of S and $\hat{A}_{i,OLS}$ denotes the corresponding block of $\hat{A}_{OLS}$. 80 is the size of the initial subsample. $k_Q = 0.01$, $k_S = 0.1$ and $k_W = 0.01$.

2.3.2 Data

Four endogenous variables are included in the specification: (i) federal spending, (ii) net taxes, (iii) output, and (iv) short-term interest rate. We take quarterly data for the U.S., spanning the period from 1954Q3 to 2015Q3. Except for the short-term interest rate, all variables are taken from the National Income and Product Accounts (NIPA) from the Bureau of Economic Analysis (BEA). Fiscal variables are defined as in Blanchard and Perotti (2002). Federal spending is defined as total purchases of goods and services (consumption and investment), whereas net taxes are defined as total tax revenues minus transfers and interest payments.[4] As a measure of output we take the gross domestic product.[5] All real variables (government spending, net taxes and output) are in logs of real per capital values. Inflation is computed as the annualized quarterly change of the GDP deflator.[6]

The short-term interest rate in our specification is the shadow rate by Wu and Xia (2016), whose series is built by joining the Federal Funds rate (FFR) series until 2008Q4, and the estimated shadow rate from 2009Q1 on. Wu and Xia (2016) employ a shadow rate term structure model to describe the behaviour of interest rates and monetary policy at the ZLB and employ the estimated shadow rate as a tool for measuring the effects of monetary policy at the ZLB. Figure 2.1 plots the shadow rate and the effective FFR. It is worth noticing that while the effective policy rate is stuck at the ZLB since 2009, the shadow rate turns negative and displays meaningful variation. In this sense the shadow rate is a potential tool to describe the monetary policy stance and the effects of monetary policy at the ZLB.

[4] Federal spending is given by federal consumption expenditures and gross investment (table 1.1.5, line 22); net taxes are given by the difference between current receipts (table 3.1, line 1) and the sum of current transfer payments (line 22), interest payments (line 27) and subsidies (line 30).

[5] Table 1.1.5, line 1.

[6] Table 1.1.4, line 1.

2.4 Identifying a government spending shock

Several identifications strategies have been proposed in the literature to recover fiscal policy shocks. Blanchard and Perotti (2002), Rossi and Zubairy (2011), and Mountford and Uhlig (2009) among others, employ structural vector autoregressions (SVARs), either using Cholesky decomposition (Blanchard & Perotti, 2002; Rossi & Zubairy, 2011) or sign restrictions (Mountford & Uhlig, 2009) to identify structural shocks. Ramey and Shapiro (1998), Eichenbaum and Fisher (2005), Romer and Romer (2010), Mertens and Ravn (2011) and Ramey (2011) identify exogenous changes in taxation and public spending by including a narrative variable that captures major events, e.g. military buildups, in their VARs. To explain the lack of consensus on the size of fiscal multipliers, Caldara and Kamps (2012) focus on the role of identification strategies and perform a comprehensive analysis showing how different identification schemes imply putting different priors on output elasticities of fiscal variables, which measure the endogenous response of tax and spending policies to economic activity. Then they examine how this choice affects estimated fiscal multipliers.

In this chapter we start focusing on the identification of a government spending shock, which seems to be a less controversial issue in the literature than that of the identification of tax shocks. To identify a government spending shock we build on the classical paper by Blanchard and Perotti (2002) and employ Cholesky decomposition with government spending ordered first. Public spending ordered first in the vector of endogenous variables means that shocks in tax revenues and output have no contemporaneous effect on government spending. The main assumption on which this identification rests is that discretionary policy does not respond to output within a quarter, because of decision and implementation lags. Concerning the automatic effects of economic activity on spending, which are captured by the elasticities to output of government purchases, it is commonly assumed in the literature that the value of this elasticity is zero (Caldara & Kamps, 2012). Existing evidence generally supports this assumption of a-cyclical government spending.

Given these identifying assumptions, we recover structural responses to a government spending shock in the following way. Iterating on the TVP-VAR(p)

defined above, we obtain the corresponding moving average (MA) representation, which is the following

$$y_t = \mu_t + \sum_{h=0}^{\infty} \Theta_{h,t} u_{t-h}$$

with $\Theta_{0,h} = I_n$, $\mu_t = \sum_{h=0}^{\infty} \Theta_{h,t} C_t$ and $\Theta_{h,t} = J \tilde{B}_t^h J'$, where $\tilde{B}_t$ is the corresponding TVP-VAR(1) companion form of the TVP-VAR(p) and J is a selector matrix:

$$\tilde{B}_t = \begin{bmatrix} & B_t & \\ I_{k(p-1)} & : & 0_{k(p-1)\times k} \end{bmatrix} \quad \text{and} \quad J = \left(I_k \ : \ 0_{k\times k(p-1)} \right)$$

The parameters $\Theta_{h,t}$ for $h = 1, \ldots, H$ represent the reduced-form impulse response functions. To obtain structural impulse responses, we recover the structural government spending shock from the relation

$$u_t = A_t^{-1} \Sigma_t \varepsilon_t$$

where u_t is the vector of innovations (reduce-form residuals), ϵ_t is the vector of structural shocks and $A_t^{-1}\Sigma_t$ is the Cholesky decomposition of the reduced form variance-covariance matrix Ω_t, coming from the triangular decomposition stated above. Then, structural relations are imposed on the reduced-form impulse response functions to obtain

$$\Phi_t = (\Theta'_{0,t}, \ldots, \Theta'_{H,t})' A_t^{-1} \Sigma_t$$

where Φ_t are our structural impulse response functions.

2.4.1 Fiscal foresight

An important issue that has received a great deal of attention in the literature (e.g., Yang, 2005; Mertens & Ravn, 2011; Fisher & Peters, 2010; Ramey, 2011; Leeper, Walker, & Yang, 2013; Forni & Gambetti, 2014) and that needs to be taken into account for the identification of fiscal policy shocks is that of "fiscal foresight". By this expression we mean the fact that fiscal shocks estimated in VARs are not truly unpredictable, but contain some anticipated components. The reason why it is the case is that, as Blanchard and Perotti (2002) already pointed out, two types of lags can be identified in the conduct of fiscal policy, decision and implementation lags, which imply that it takes some time for policymakers to react to a shock, decide the measures to be taken, approve and implement them. As a result, policy change may be anticipated by the private sector and affect macroeconomic variables before we actually observe a change in fiscal variables. This implies that fiscal shocks estimated in VARs are predictable, that is they are non-fundamental (Giannone & Reichlin, 2006; Forni & Gambetti, 2010).

A way to deal with this issue is to include variables that help predict changes in fiscal variables in the VAR, i.e. variables that embed information on future shocks anticipated by agents, and to order them first in the vector of endogenous variables. This would allow to identify truly unanticipated government spending shocks. Auerbach and Gorodnichenko (2012) control for expectations by including real time professional forecasts for government spending as the first variable in the vector of endogenous variables of their VAR. Alternative approaches are in the literature. Ramey (2011) and Fisher and Peters (2010), among others, employ a narrative approach and create series of news about government spending by extracting information from periodicals or other sources, such us surprises in the returns of US military contractors. Caggiano, Castelnuovo, Colombo, and Nodari (2015) construct a measure of anticipated fiscal spending shock, given by the sum of revisions of expectations about future government spending collected by the Survey of Professional Forecasters (SPF). In a recent work, Ben Zeev and Pappa (in press) identify a defense spending news shock as a shock that is orthogonal to current defense spending and that best explains future movements in defense spending over a five year horizon, and use it to evaluate the macroeconomic effects of anticipated defense spending shocks.

Nevertheless, Perotti (2011) compares results provided by the two approaches, the SVAR à la Blanchard and Perotti (2002) and the "expectations-augmented" VAR (EVAR) à la Ramey (2011), and finds that the responses of GDP to a government spending shock obtained through the two approaches are almost the same. Moreover, he shows that the growth of federal spending predicted by professional forecasters and used in SPF EVARs to identify unanticipated government spending shocks, has very little explanatory power for actual federal spending growth. For these reasons, Perotti claims, SVARs and SPF EVARs give almost identical impulse responses. These results are in line with evidence provided by Chahrour, Schmitt-Grohé, and Uribe (2012).

This latter evidence supports our choice to start our analysis by estimating a structural TVP-VAR that does not include a news variable, and where a government spending shock is identified by means of Cholesky decomposition with federal spending ordered first. The reason for this choice primarily relates to the dimensionality of our estimation problem. Adding one variable to our vector of endogenous variables hugely increases the number of parameters to be estimated and affects the precision of the obtained estimates. Nevertheless, since addressing fiscal foresight is crucial for correctly identifying a government spending shock, we will further explore the issue.

2.5 Results

2.5.1 Impulse responses and spending multipliers

Figures 2.3-2.7 illustrate our estimation results. Figures 2.3-2.4 show the median impulse response functions to a unitary government spending shock at each point in time for all endogenous variables. In general terms, they display variability over time both in terms of magnitude and persistence, even though the sign of responses are consistent across regimes. This is especially true for the responses of taxes and output. Net taxes and the interest rate negatively respond to the shock, whereas the response of output is always positive, at least on impact.

Focusing on the response of output, which is of main interest in this work, we compute cumulative output spending multipliers as the integral of the response of output, divided by the integral of the response of government expenditure. The result is then rescaled by the ratio of output over government spending at time t,

$\frac{Y_t}{G_t}$ to convert it in dollar terms.[7] Hence we compute

$$\frac{\sum_{h=1}^{H} \frac{\partial \log Y_{t+h}}{\partial \log G_t}}{\sum_{h=1}^{H} \frac{\partial \log G_{t+h}}{\partial \log G_t}} \cdot \frac{Y_t}{G_t}$$

for each horizon H, where $\partial \log Y_{t+h}/\partial \log G_t$ and $\partial \log G_{t+h}/\partial \log G_t$ are estimated responses of output and government expenditure to a spending shock. Figures 2.5 and 2.6 show estimated cumulative multipliers. Figure 2.5 plots cumulative output spending multipliers at each point in time and at every horizon, whereas figure 2.6 displays the time series of computed cumulative multipliers at selected horizons, namely on impact, and from one to four years after the shock. Cumulative multipliers are always positive, at least on impact and display variability over time. They display very similar time patterns at all selected horizons and are generally larger on impact than at longer horizons. This implies that an increase in government purchases is more effective in the short term than in the medium term. A possible explanation for this result refers to higher levels of public debt produced by increased spending and/or to the fact that agents expect higher taxes in the future to finance current government purchases, which could both reduce effectiveness of increased government spending by crowding out private consumption and investment. An interesting result, that deserves further investigation, is that estimated cumulative multipliers show lower levels at the beginning of the analyzed period and display an increasing trend until 2003, going from a minimum of 0.41 in 1980 to a maximum of 2.71 in the third quarter of 2003. Thereafter, multipliers decrease reaching a minimum of 0.84 at the end of 2008, and then start rising again,

[7] Ramey and Zubairy (2016) point out that converting elasticities to multipliers by using $\frac{Y}{G}$ as conversion factor can lead to upward biased estimates of the multipliers, if $\frac{Y}{G}$ varies over time to a great extent. As they point out, this issue can be more relevant for long samples, where $\frac{Y}{G}$ considerably changes from the beginning to the end of the sample. In shorter, post-war samples as the one we use for this analysis, the ratio of output over government spending displays lower variability, meaning that the bias that it potentially introduces in the computation of multipliers should be smaller. Specifically, our Y over G ratio varies between a minimum around 10 at the beginning of the sample and a maximum around 16 in the early 2000s (see figure 2.2). In our computation we employ $\frac{Y_t}{G_t}$ as a conversion factor, where t refers to the time of the shock, and as a further check for the relevance of the factor we also compute multipliers by employing averages over the entire sample and over different subsamples. Our results do not significantly change when different factors are used, neither in terms of magnitude nor in terms of time pattern.

towards a maximum of 3 in the second quarter of 2015.[8] Table 2.1 presents some summary statistics relative to our estimated spending multipliers.

Table 2.1: Cumulative spending multipliers: summary statistics

Horizon	Min	Max	Mean
1	0,41 (1980Q2)	3,04 (2015Q2)	1.58
4	-0,11 (1979Q3)	3,08 (2015Q2)	1,32
8	-0,50 (1979Q3)	2.90 (2015Q2)	1.07
12	-0,75 (1979Q3)	2,71 (2015Q2)	0,90
16	-0,90 (1980Q2)	2,59 (2015Q2)	0,79
20	-1,07 (1980Q2)	2,47 (2015Q2)	0,71

Notes: Minimum, maximum and average multipliers are computed over the sample 1975Q1-2015Q3 for each horizon. In parenthesis is the point in time to which multipliers refer.

Concerning spending multipliers estimated for the second half of the sample, those relative to the late 1990s and the 2000s, we find evidence of higher multipliers with respect to most findings in the literature. Indeed, as Ramey (2016) point out, most estimates of government spending multipliers in aggregate data are between 0.6 and 1.5. Our findings for the first part of the sample are more in line with these results. Larger values of spending multipliers, in line with the ones that we find for the last part of our investigated period, are among the results presented by Auerbach and Gorodnichenko (2012) and Caggiano, Castelnuovo, Colombo, and Nodari (2015), both relative to recessions. Auerbach and Gorodnichenko (2012) using quarterly data from 1947 to 2008, estimate multipliers up to 3.6 in recessions, whereas Caggiano, Castelnuovo, Colombo, and Nodari (2015) find multipliers up to 3.15 in recessions over the sample 1981Q3-2013Q3.

2.5.2 Interpreting spending multipliers

We now ask how to interpret results on spending multipliers presented so far. To this aim, we focus on the interactions between monetary and fiscal policy, and

[8] All these numbers refer to impact multipliers.

particularly refer to the interesting framework offered by Leeper (1991). More in detail, we start from the distinction between active and passive monetary and fiscal policies proposed in Leeper (1991) and to the estimated joint monetary-fiscal regimes in Davig and Leeper (2011). Leeper (1991) identifies an active and a passive stance for both monetary and fiscal policies, depending on their responsiveness to government debt shocks. An active authority pays no attention to the state of government debt and freely chooses its decision rule, whereas a passive authority is constrained by consumer optimization and by the active authority's actions, and sets its decision rule so to generate sufficient tax revenues to balance the budget. Hence, four alternative joint monetary-fiscal regimes may realize: (i) active monetary/passive fiscal (AM/PF), where monetary policy is unconstrained and actively pursue price stability by reacting to inflation pressures, and fiscal policy passively adjusts taxes to balance the budget; (ii) passive monetary/active fiscal (PM/AF), in which the money stock responds to deficit shocks and fluctuations in government debt generate current or future money creation (accommodating monetary policy); (iii) passive monetary/passive fiscal (PM/PF), where both monetary and fiscal authorities act under the constraint of balancing the budget; (iv) active monetary/active fiscal (AM/AF), which may generate an unsustainable growth of debt to GDP ratio, because both authorities set their policy rules in an unconstrained way.

Davig and Leeper (2011) propose a theoretical framework in which they investigate whether and how monetary/fiscal policy interactions affect the effects of changes in government spending on the economy. In a New Keynesian framework as the one they consider, the general mechanism through which a change in government spending affects the economy, regardless of the monetary-fiscal regime, is the following: (i) higher government spending raises demand, which in turn increases the demand for labour by firms; (ii) higher demand for labour increases real wages and real marginal costs; (iii) firms will eventually raise their prices. The policy regime plays a role in the responses of real rates, consumption and inflation. More in detail, on the one side final macroeconomic outcome of a government spending shock depends on movements in the real interest rate, which in turn depend on how monetary policy reacts to higher expected inflation. An active monetary authority would raise the nominal interest rate, which raises the real rate and reduces consumption. On the other hand, passive monetary policy would not react to inflation pressures and the real rate would fall, thus increasing consumption. On the other side, also the expected path of future taxes affects agents' decision, and hence consumption. Under passive fiscal policy, households expect higher taxes to finance increased government spending and reduce consumption, whereas under active fiscal policy higher taxes are not expected to fully finance higher government purchases, which in turn does not negatively affect consumption path.

To account for possible changes in policy regime, Davig and Leeper (2011) estimate regime-switching monetary and fiscal rules and obtain an estimate of the timing of joint monetary-fiscal regimes. Following their estimated joint policy regime path, as well as the two fiscal regimes identified by Favero and Monacelli (2003),[9] we identify four monetary-fiscal regimes in the time span 1975-2015, which is the sample period for which our model is estimated, and check whether monetary/fiscal policy interactions can explain the time pattern that we observe for our spending multipliers. Identified periods are the following:

1. 1975-1979, characterized by both passive monetary and passive fiscal policies (PM/PF).

2. 1980-1986, characterized by active monetary and active fiscal policies (AM/AF). Fiscal policy in the U.S. is described as unsustainable in this period, because government debt was growing rapidly as a share of GDP (Favero & Monacelli, 2003). For monetary policy, it is generally acknowledged that a sharply-reacting-to-inflation regime was in place since 1979-1980 and continued thereafter.

3. 1987-2000, in which monetary policy remained active, whereas fiscal policy turned passive by entering a fiscal discipline regime (AM/PF).

4. 2001-2008, mostly characterized by passive monetary policy and active fiscal policy (PM/AF).

[9] Favero and Monacelli (2003) identify two fiscal policy regimes in the U.S. between 1974 and 2000: (i) 1974Q1-1986Q2, characterized by a large increase in government debt to GDP ratio and destabilizing systematic response of primary deficit to debt to GDP ratio; (ii) 1987-2000, in which primary deficit starts moving in accordance with a debt stabilization motive.

5. 2009-2015, characterized by both monetary and fiscal policy strongly responding to the recession of 2008-2009 and by the policy rate hitting the ZLB since December 2008.

According to this classification, we compute average output spending multipliers for each of the identified policy regimes. Table 2.2 shows the results. Consistently with the main findings presented in the previous section, multipliers display variability and are increasing over time. In the first part of the sample, between 1975 and 1986, they display values below one, whereas multipliers are much higher, above 1.5, between 1987 and 2015. In detail, they display the highest values in the very last part of the sample, those corresponding to the last two regimes, PM/AF and ZLB respectively, when multipliers are estimated above 2 on impact. Interestingly, the regimes for which we estimate the largest effects of a government spending shock on output are those characterized by passive monetary policy regime and by interest rates at their lower bound respectively, a result which is in line with predictions of New Keynesian models, like the one in Davig and Leeper (2011). In those models, changes in government spending produce larger effects on economic activity when monetary policy accommodates higher inflation expectations and responds to increases in inflation less than one-for-one. This allows the real interest rate to decline and stimulates consumption, thus amplifying the effects of increased government purchases.

Table 2.2: Average cumulative spending multipliers

Horizon	**1975-79**	**1980-86**	**1987-2000**	**2001-08**	**2009-15**
1	0,80	0,86	1,63	2,06	2,23
4	0,38	0,55	1,34	1,85	2,18
8	0,07	0,28	1,08	1,60	2.00
12	-0,14	0,11	0,91	1,42	1,85
16	-0,27	-0,01	0,80	1,31	1,75
20	-0,38	-0,08	0,72	1,24	1,68

2.5.3 Variance decomposition

We compute forecast error variance decomposition, i.e. the percentage of variance of GDP explained by the spending shock at selected horizons as

$$\frac{\sum_{j=0}^{h} \Phi_{xg,t}^{2}}{\sum_{j=0}^{h} \sum_{k=1}^{M} \Phi_{ik,t}^{2}}$$

where the numerator is the variance of GDP (x_t) generated by the government spending shock ($\varepsilon_{g,t}$) and the denominator is the total variance of GDP, both at horizon h. $\Phi_{ik,t}$ indicates the structural impulse response function of variable i to shock k at time t. Figure 2.7 shows the time series of the percentage of forecast error variance of GDP accounted for by the government spending shock, at various horizons.

In general terms, government spending shocks account for a small share of output variability. The variance of GDP accounted for by a spending shock after 4 quarters oscillates between a minimum close to zero in the first part of the sample and a maximum above 2% at the end of the sample, corresponding to the ZLB period. The percentage of variance of GDP generated by the shock decreases across horizons, but displays the same pattern for all of them. Particularly, it displays large variability over time and an increasing trend clearly emerges from the plots. Also, uncertainty around the share of GDP variability accounted for by public expenditure is increasing over time and reaches its largest spike in the last part of the investigated period. Drops can be noticed in general around recessions. Particularly meaningful are the one around the monetary cycle turning point in the early 1980s and that during the recent recession of 2008-2009, times in which changes in output are to a large extent accounted for by other shocks, e.g. a monetary policy shock in the early 1980s.

The larger share of variance of GDP accounted for by government spending shocks over time is in line with the increasing trend in the size of fiscal multipliers illustrated in the previous section, and points to increased relevance of fiscal policy in explaining output fluctuations over the investigated period. Again, it is worth noticing that spending shocks account for a larger share of output variability in times characterized by either passive monetary policy regime or at ZLB.

2.5.4 How does the Great Recession matter?

So far, we have investigated the size of government spending multipliers and the role of fiscal policy in accounting for output variability over time. Our main results suggest larger multipliers when monetary policy does not actively react to inflation pressures and increasing relevance of fiscal policy for output fluctuations over the investigated period. We now ask to what extent our results are driven by the dynamics of variables in the last part of the sample, namely by how much our findings are attributable to the Great Recession. Further, we ask whether using the shadow rate to account for unconventional monetary policy measures implemented in recent years affects the results.

To this aim, we re-estimate our model with two alternative specifications. In the first one we consider a reduced sample, from 1954Q3 to 2008Q3, to exclude the Great Recession and the ZLB periods. Results on multipliers are shown in figures 2.8-2.9 and summarized in table 2.3.[10] Then, we estimate a TVP-VAR that includes the effective Federal Funds rate (FFR) rather than the shadow rate of Wu and Xia (2016). Figures 2.10-2.11 display results and table 2.4 summarizes estimated multipliers for selected periods.

Both specifications confirm our main findings on the size of spending multipliers in the U.S.. Estimated multipliers display variability over the investigated period and are increasing over time, supporting our view of increased relevance of fiscal policy measures in accounting for output fluctuations. Moreover, multipliers are still estimated to be higher in times of passive monetary policy stance and at the ZLB (for the specification including the effective FFR), thus supporting our reading of baseline results based on the interaction between monetary and fiscal policy. As table 2.3 shows, multipliers obtained from the reduced-sample estimation are higher and more persistent than those computed from our baseline results, whereas those obtained from the specification with the FFR are very close to our baseline ones on impact, even though somewhat more persistent. This last result suggests

[10] Estimating our TVP-VAR by excluding the last part of the sample does not necessarily imply that results for the previous part of the sample would stay the same as in baseline estimation. Indeed, the Gibbs sampling algorithm exploits all available information, namely the entire sample, to estimate time-varying parameters, meaning that data relative to the Great Recession are also relevant for estimating the coefficients relative to previous periods.

that not accounting for unconventional monetary policy might lead to attribute to fiscal shocks movements in output that are indeed attributable to monetary policy shocks. Nevertheless, this does not affect our main conclusion that fiscal multipliers are higher in times of low responsive or constrained monetary policy.

Table 2.3: 1954Q3-2008Q3 sample: Average cumulative spending multipliers

Horizon	**1975-79**	**1980-86**	**1987-2000**	**2001-08**
1	0,95	1,22	2,17	2,92
4	0,86	1,25	2,49	3,54
8	0,74	1,18	2,50	3,62
12	0,67	1,14	2,47	3,61
16	0,64	1,13	2,45	3,60
20	0,66	1,14	2,46	3,60

Table 2.4: FFR: Average cumulative spending multipliers

Horizon	**1975-79**	**1980-86**	**1987-2000**	**2001-08**	**2009-15**
1	0,74	0,89	1,61	2,03	2,37
4	0,38	0,64	1,39	1,92	2,38
8	0,11	0,42	1,20	1,74	2,29
12	-0,05	0,27	1,06	1,60	2,18
16	-0,18	0,15	0,95	1,47	2,09
20	-0,26	0,06	0,87	1,37	2,03

2.6 Concluding Remarks

We model a set of standard U.S. macro-fiscal variables over the period 1954Q3-2015Q3 by using a TVP-VAR with stochastic volatility to assess the evolution of U.S. fiscal policy effectiveness over time. We ask whether and how the monetary policy stance affects transmission of fiscal policy shocks and devote special attention to the size of spending multipliers when the economy is at the zero lower bound. To account for unconventional monetary policy in the last part of the sample, we use the shadow rate by Wu and Xia (2016), which captures relevant information about the monetary policy stance from movements in the term structure of interest rates when the effective policy rate is stuck at its lower bound. Our main findings point to a significant variation of government spending multipliers over time. Particularly, we estimate larger multipliers when monetary policy is passive or constrained by the zero bound, namely when monetary policy does not strongly react to inflation pressures. This result is in line with the predictions of New Keynesian models, which suggest that spending multipliers are larger when monetary policy accommodates increases in government purchases. According to these models, increased government spending raises inflation expectations, which in turn lower the real interest rate if the nominal interest rate does not move. Lower real interest rates stimulate consumption and this amplifies the effects of increased government spending on output.

Another interesting finding in this chapter is that the relevance of fiscal policy in explaining output fluctuations displays an increasing trend over time. This result is suggested by both the increasing trend in spending multipliers, as well as by the increasing trend in the share of output variability accounted for by fiscal shocks.

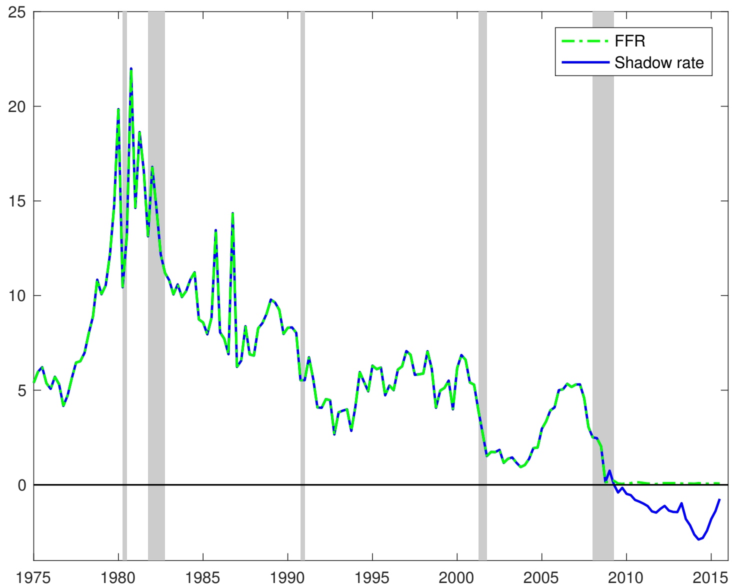


Figure 2.1: Time series of the FFR and the shadow rate of Wu & Xia (2016) over the period 1975Q1-2015Q3.

Notes: Grey bands indicate NBER recession dates.

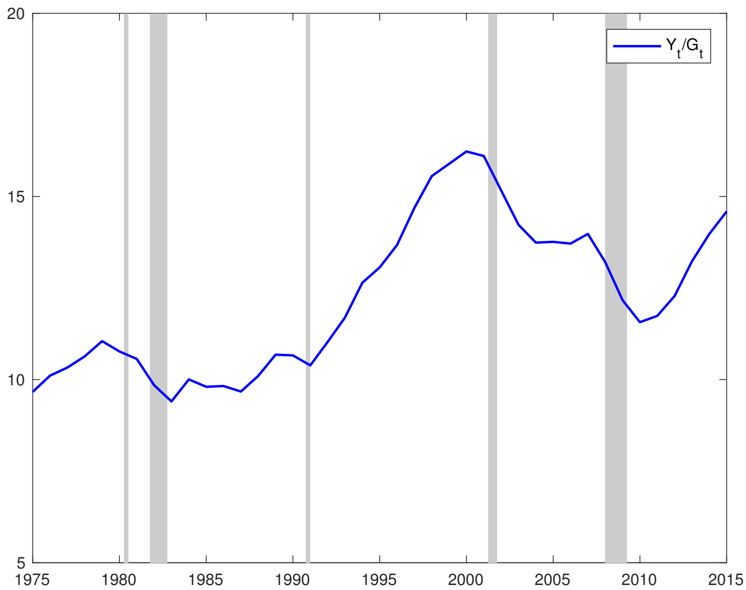
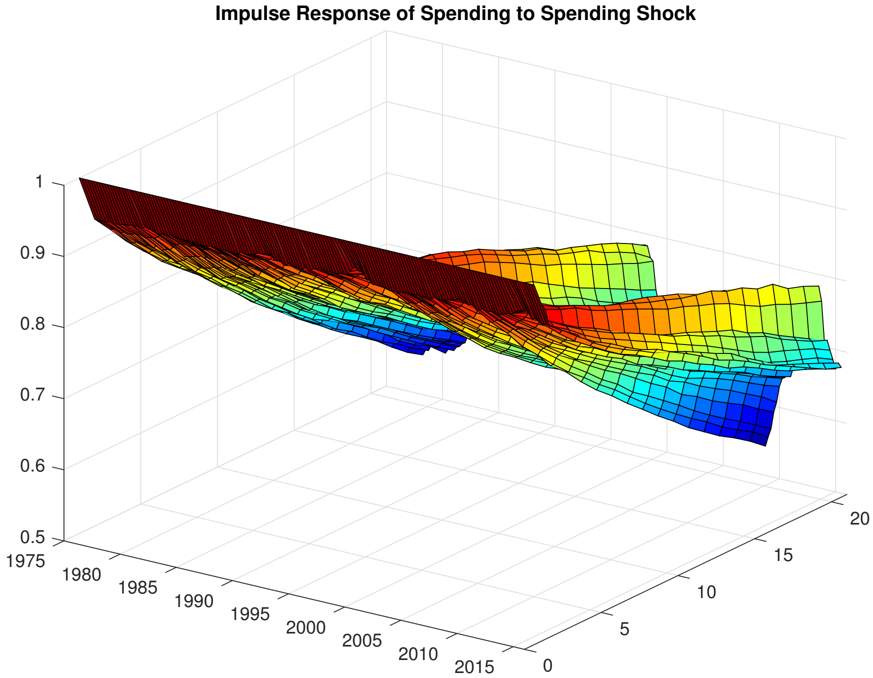
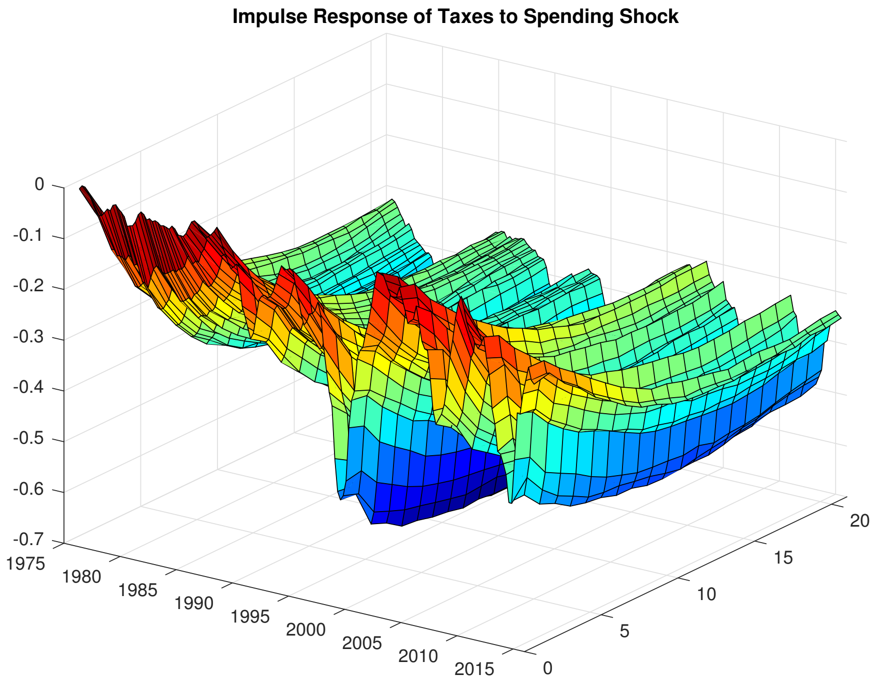


Figure 2.2: Time series of the GDP to federal spending ratio Y_t/G_t.

Notes: Grey bands indicate NBER recession dates.

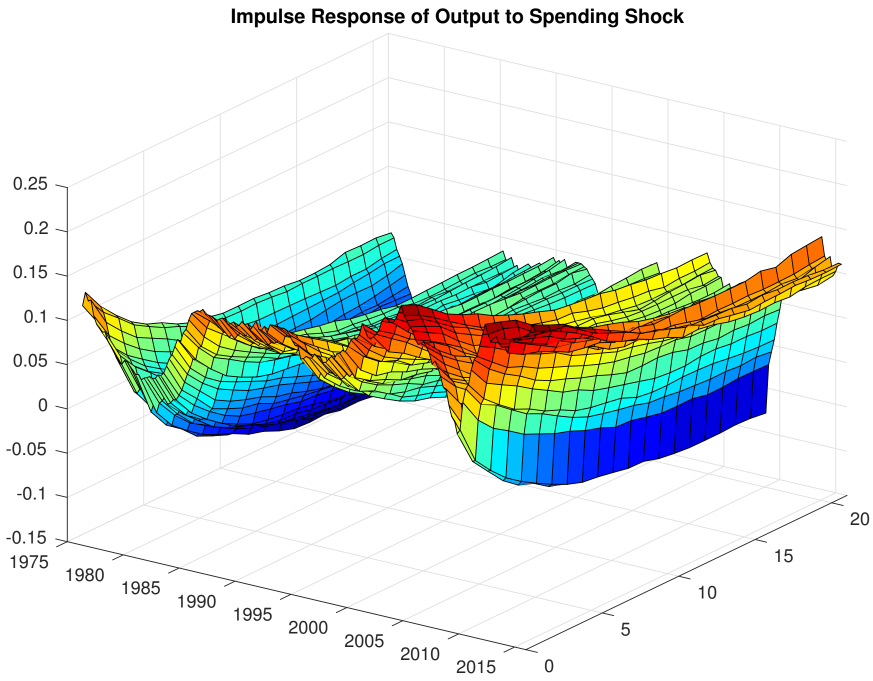


(a)

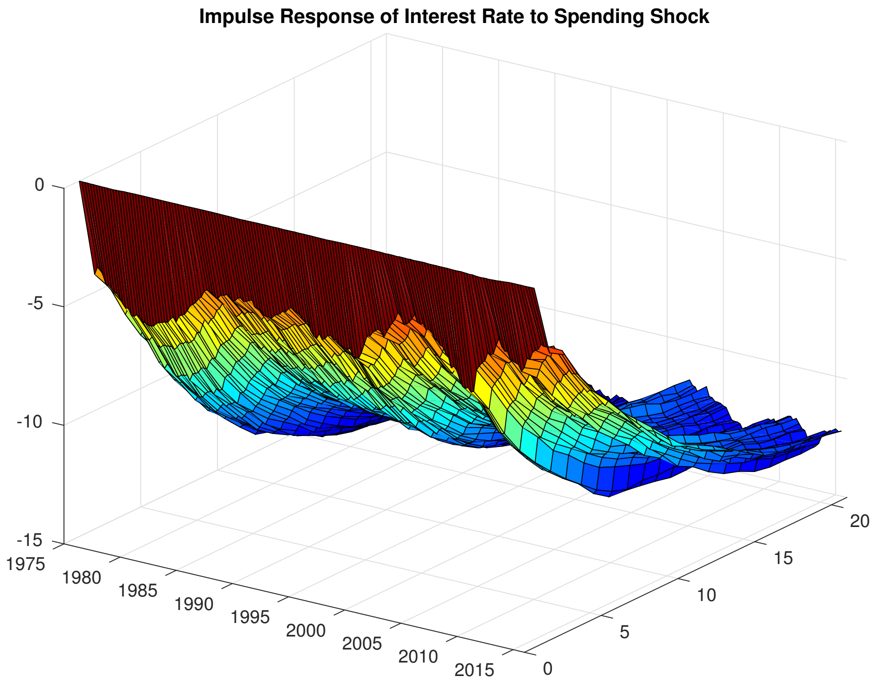


(b)

Figure 2.3: Median impulse response functions to a unitary government spending shock.



(a)



(b)

Figure 2.4: Median impulse response functions to a unitary government spending shock.

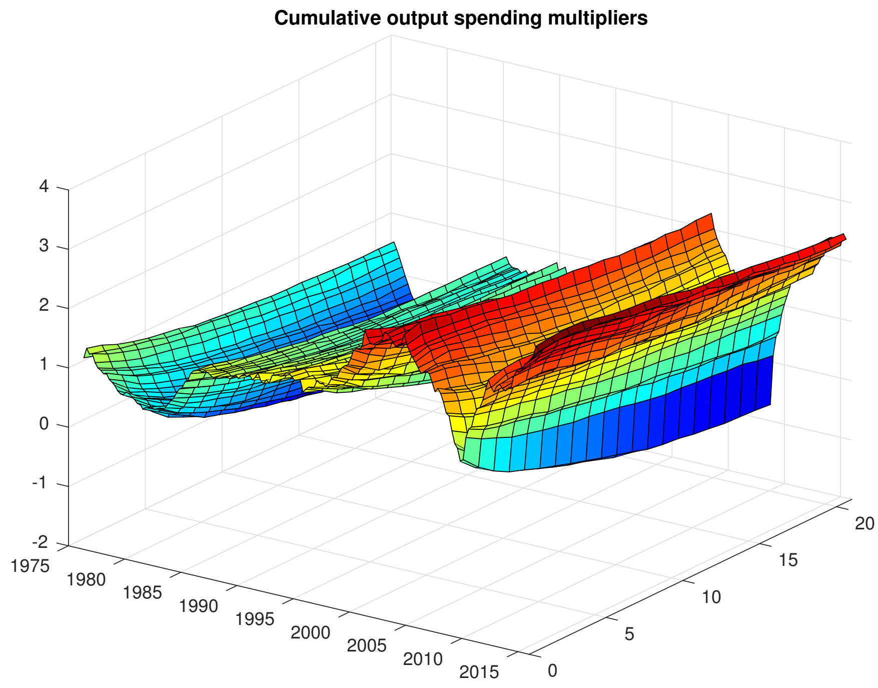


Figure 2.5: Median cumulative output spending multiplier.

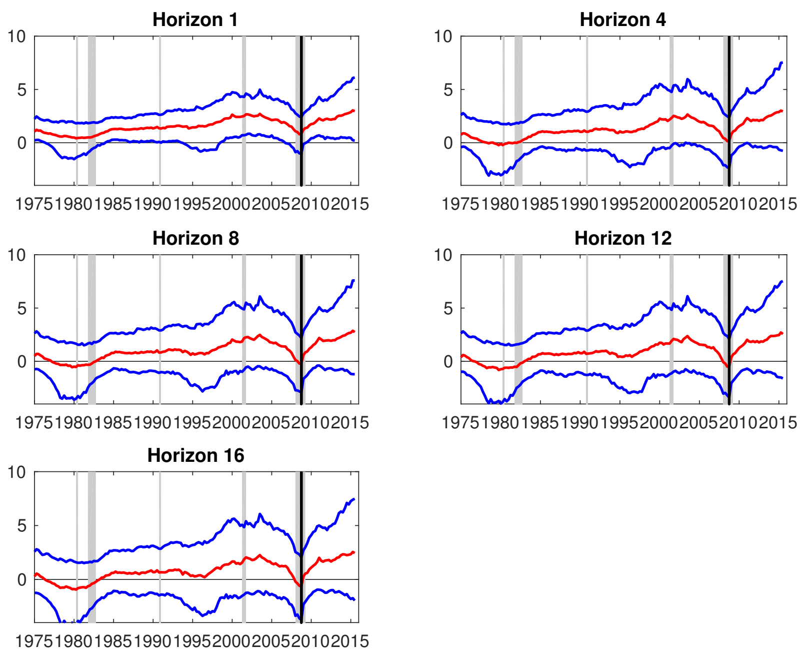


Figure 2.6: Median, 16th and 84th percentiles cumulative spending multipliers of output at selected horizons.

Notes: Grey bands indicate NBER recession dates.

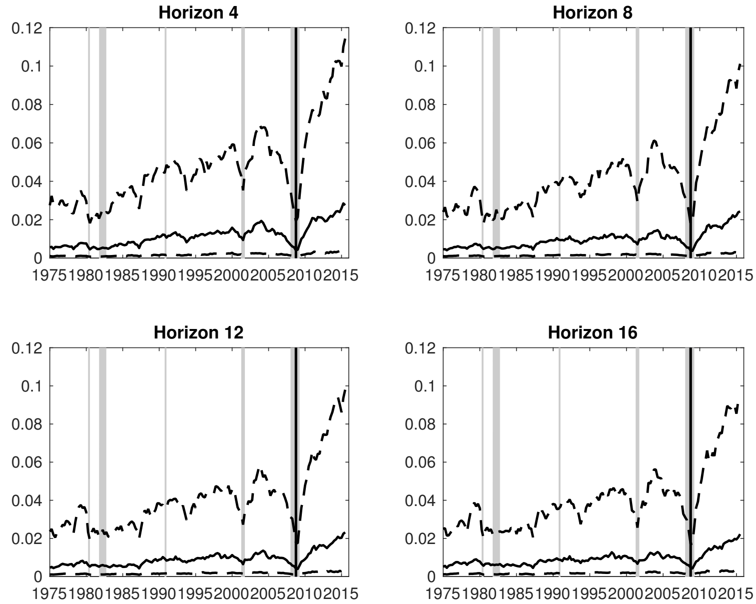


Figure 2.7: Percentage of forecast error variance of output accounted for by a spending shock at selected horizons.

Notes: Grey bands indicate NBER recession dates.

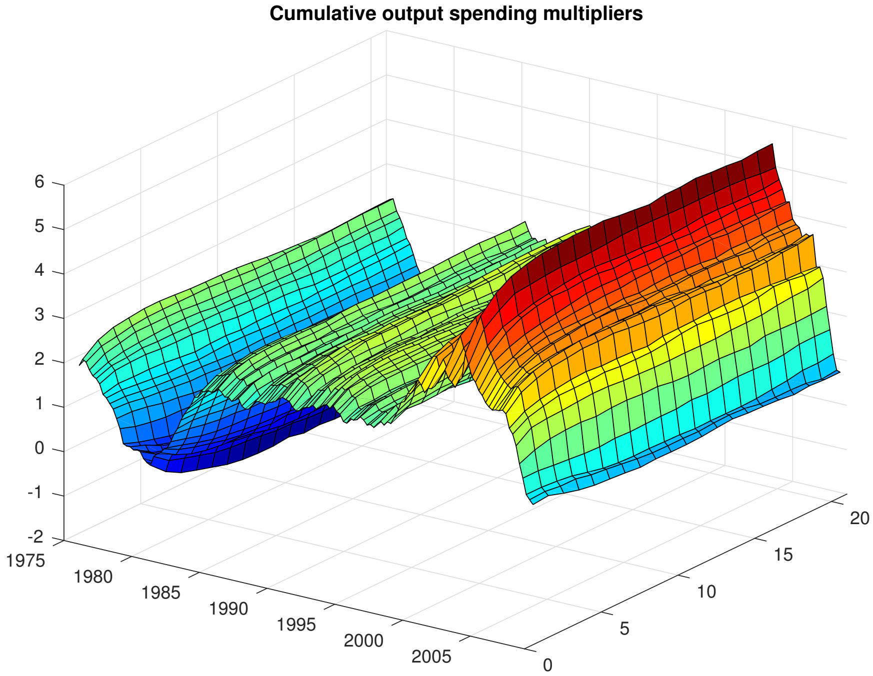


Figure 2.8: 2008Q3 sample: Median cumulative output spending multiplier.

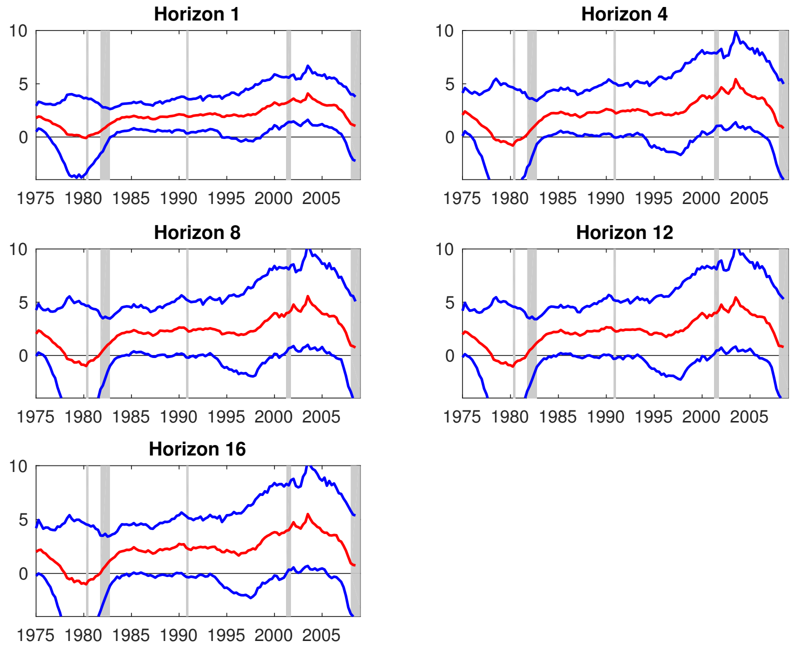


Figure 2.9: 2008Q3 sample: Median, 16th and 84th percentiles cumulative spending multipliers of output at selected horizons.

Notes: Grey bands indicate NBER recession dates.

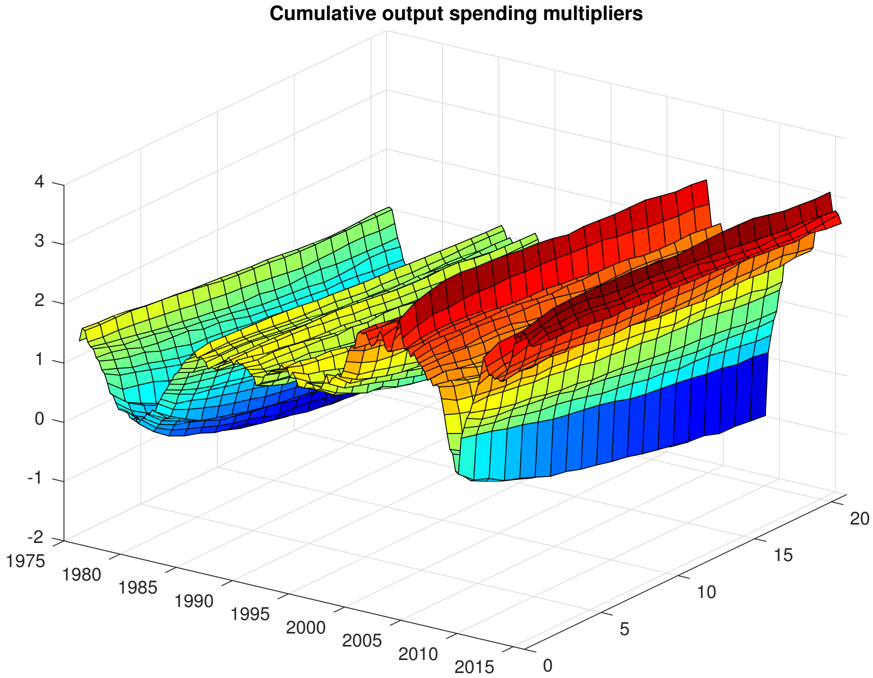


Figure 2.10: FFR: Median cumulative output spending multiplier.

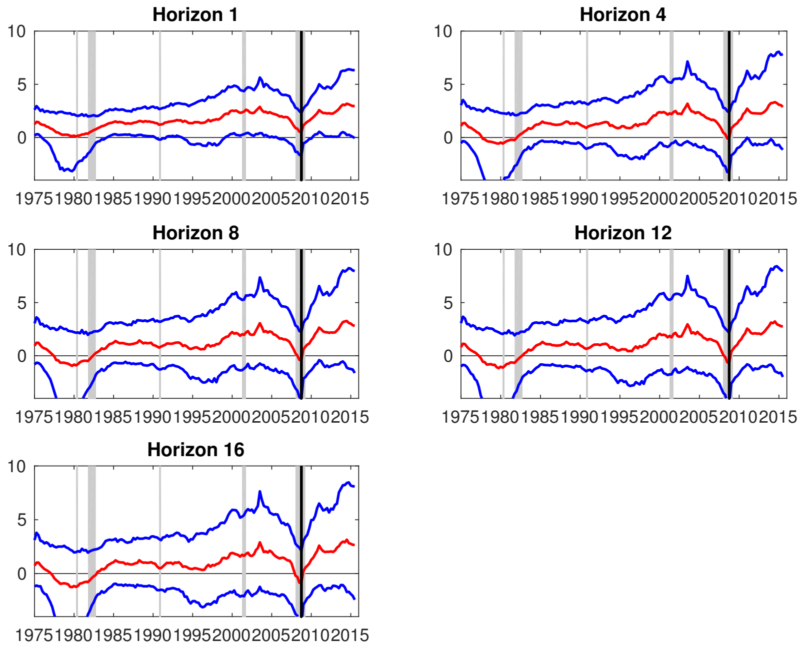


Figure 2.11: FFR: Median, 16th and 84th percentiles cumulative spending multipliers of output at selected horizons.

Notes: Grey bands indicate NBER recession dates.

Chapter 3

Time-Dependent Finance-Uncertainty Multipliers[1]

3.1 Introduction

Since Bloom (2009)'s contribution, a strand of the recent empirical macroeconomic literature has been concerned with the role played by uncertainty shocks as a driver of the business cycle. Bloom (2014) surveys this literature and concludes that second-moment shocks are potentially a relevant force behind real activity's fluctuations. Another strand of the literature has recently revamped the attention on financial frictions, both in terms of first-moment shocks as drivers of the business cycle (Gilchrist, Yankov, & Zakrajšek, 2009; Gilchrist & Zakrajšek, 2012; Caldara et al., 2016) and as an element amplifying the impact of non-financial shocks (Bernanke, Gertler, & Gilchrist, 1999; Canzoneri, Collard, Dellas, & Diba, 2016; Alfaro et al., 2016).

This chapter estimates time-dependent finance-uncertainty multipliers. An uncertainty multiplier captures the response of a measure of real activity (industrial production, employment, unemployment) to an uncertainty shock. We aim at understanding to what extent financial conditions affect this multiplier. To do so, we jointly model measures of uncertainty and indicators of financial spreads to

[1]This chapter is based on a joint work with Giovanni Caggiano, Efrem Castelnuovo and Tim Robinson.

isolate exogenous variations in uncertainty and assess their real impact conditional on financial markets' stance. We work with the measure of financial uncertainty estimated with a data-rich approach by Ludvigson et al. (2016). Building on a previous contribution by Jurado, Ludvigson, and Ng (2015), Ludvigson et al. (2016) show that measures of macroeconomic uncertainty estimated with models considering uncertainty around future realizations of a large number of indicators are likely to approximate exogenous variations in uncertainty when financial variables are taken into account. Our multivariate framework also embeds the microfounded measure of financial spread recently proposed by Gilchrist and Zakrajšek (2012), which can be related to the supply side of the credit market. Following Gilchrist and Zakrajšek (2012), we decompose this spread in two orthogonal components, an exogenous component - known as the "excess bond premium" (EBP) - and an endogenous one. It is well known that the separate identification of uncertainty and financial shocks is challenging (Stock & Watson, 2012). Hence, we take the EBP into account to control for financial shocks and sharpen the identification of financial uncertainty shocks. Differently, the endogenous component of the financial spread is modeled to allow for amplification effects via financial frictions to take place. We then use counterfactual simulations conducted by shutting down the endogenous component of the financial spread to quantify to what extent this amplification effects affect the finance-uncertainty multiplier. Our analysis is conducted by estimating a time-varying parameter-vector autoregressive (TVP-VAR) model à la Primiceri (2005) and Del Negro and Primiceri (2015). This enables us to allow for (without any a-priori imposition) uncertainty shocks to exert time-dependent effects in a sample featuring well-documented fluctuations in uncertainty (Bloom, 2014; Jurado et al., 2015) and dramatic variations in credit conditions (Gilchrist & Zakrajšek, 2012). Estimates obtained with a parsimonious monthly VAR modeling measures of uncertainty, financial stress, credit spread and real activity show that uncertainty shocks have indeed substantial time varying effects.

Our work builds on the extant literature as follows. Furlanetto, Ravazzolo, and Sarferaz (2014) and Caldara et al. (2016) identify financial and uncertainty shocks and study their relative importance with respect to other macroeconomic shocks. We build on these contributions by jointly considering, as they do, measures of uncertainty and financial stress. Differently with respect to these papers, we use the latest estimate of financial uncertainty proposed by Ludvigson et al. (2016), which is likely to sharpen the identification of financial uncertainty shocks and, jointly, financial shocks. Importantly, we employ a TVP-VAR, which is a framework naturally handling instabilities in the finance-uncertainty relationship as well as the time-dependent effects of uncertainty shocks. Recent contributions in the literature have already tackled the issue of unstable effects of uncertainty shocks over time. Caggiano et al. (2014), Caggiano, Castelnuovo, and Nodari (2015), and Caggiano, Castelnuovo, and Figueres (2016) find that uncertainty shocks are more powerful when an economy is already experiencing a downturn; Beetsma and Giuliodori (2012) and Mumtaz and Theodoridis (2016) show that the effects of uncertainty shocks are time-dependent; and Caggiano, Castelnuovo, and Pellegrino (2016) show that the real effects of second-moment shocks are particularly forceful in presence of the zero lower bound. Our contribution adds to this literature by focusing on the interactions between second- and first-moment financial shocks and unveiling the time-dependence of the finance-uncertainty multiplier for a number of real activity indicators.

The chapter is organized as follows. Section 2 discusses the relation to the literature. Section 3 presents the empirical strategy and the data employed in the analysis. Section 4 presents our preliminary results. Section 5 concludes.

3.2 Related Literature

The effects of uncertainty shocks on macroeconomics outcomes have traditionally been investigated in the context of irreversible investment (Bernanke, 1983; Bloom, 2009; Bloom et al., 2014), in which heightened uncertainty increases the option value of postponing investment decisions, especially when the cost of reversing decisions is high, thus reducing economic activity.

Strongly motivated by the investigation of the sources of the Great Recession of 2008-2009 (Stock & Watson, 2012), recently another strand of the literature has emerged, focusing on frictions in financial markets as an additional channel through which uncertainty can affect economic activity (see, among others, Arellano et al., 2012; Christiano et al., 2014; Gilchrist et al., 2014). The highlighted mechanism is the following: because of the existence of agency or moral hazard problems in financial contracts, a higher level of economic uncertainty rises the risk premium asked by investors to be compensated for higher risk, and increases the probability of default. As a result, increased uncertainty leads to an increase the cost of capital for firms and reduces investment.

Gilchrist et al. (2014) show that an uncertainty shock produces a widening of credit spreads, which leads firms to reduce capital expenditures and to deleverage. They also show that this channel is absent in an economy without financial frictions, where the response of investment to heightened uncertainty is reduced. As well, Chen (2016) shows that time-varying risk premiums amplify the impact of uncertainty shocks. Alfaro et al. (2016) show theoretically and empirically that higher uncertainty leads firms to reduce investment and hiring and to increase cash holdings with precautionary motives, these effects being larger in periods of higher financial frictions and for the most financially constrained firms.

On the empirical side, Alessandri and Mumtaz (2014) and Lhuissier and Tripier (2016) employ nonlinear VAR models on U.S. data and show that the effects of uncertainty shocks on macroeconomic variables depend on financial markets conditions. Alessandri and Mumtaz (2014) estimate a VAR model where structural shocks have time-varying, stochastic volatilities and allow for regime shifts corresponding to periods of financial markets distress, where the regime is determined by the level of the Chicago Fed's Financial Condition Index relative to a threshold. Uncertainty is captured by the average volatility of the economy's structural shocks. They find that an uncertainty shock has recessionary effects in both good and bad credit regimes, but the effects on output are larger in periods of financial distress. To assess the role of financial markets conditions in the transmission of uncertainty shocks, Lhuissier and Tripier (2016) estimate a Markov-switching VAR that allows both variances of structural disturbances and equation coefficients to vary over time. They use the VIX as a proxy for uncertainty and the BAA-AAA credit spread to capture financial markets regimes. As well, they find that increased uncertainty has larger negative effect on output in periods of financial distress than in tranquil times.

3.3 The TVP-VAR Model

We estimate a structural TVP-VAR model with stochastic volatility in the tradition of Primiceri (2005), employing monthly data for the U.S. over the sample period 1973M1 - 2015M3. The model has the following representation:

$$y_t = C_t + B_{1,t}y_{t-1} + \cdots + B_{p,t}y_{t-p} + u_t$$

where y_t is the vector of endogenous variables, C_t is the $n \times 1$ vector of time varying intercepts, $B_{i,t}$ $(i = 1, \ldots, p)$ is the $n \times n$ matrix of time varying autoregressive coefficients and u_t is the $n \times 1$ vector of residuals, with time varying variance-covariance matrix Ω_t. p is the number of lags and it is fixed to be $p = 6$.

Following the specification in Primiceri (2005), consider the following decomposition of Ω_t

$$A_t \Omega_t A_t' = \Sigma_t \Sigma_t'$$

where A_t is the lower triangular matrix of covariances with ones on the main diagonal and Σ_t is the diagonal matrix of standard deviations. It follows that

$$u_t = A_t^{-1} \Sigma_t \varepsilon_t$$

where ε_t is the vector of structural shocks, with identity variance-covariance matrix I_n. Let α_t be the vector of non-zero and non-one elements of the matrix A_t and σ_t be the vector of the diagonal elements of Σ_t. Let $\beta_t = \text{vec}\,(B_t : C_t)$. The low of motion of the time varying parameters is specified as follows

$$\beta_t = \beta_{t-1} + \nu_t$$

$$\alpha_t = \alpha_{t-1} + \zeta_t$$

$$\log \sigma_t = \log \sigma_{t-1} + \eta_t$$

The elements of vector β_t and the free elements of matrix A_t are modeled as random walks, whereas standard deviations σ_t are assumed to evolve as geometric random walks, thus falling in the class of models known as stochastic volatility. In principle, it is possible to consider more general autoregressive processes to model the dynamics of time varying parameters. Nevertheless, the random walk assumption allows to reduce the number of parameters to be estimated.

All the innovations in the model are assumed to be jointly normally distributed with zero means and variance-covariance matrix defined as follows

$$V = Var\left(\begin{bmatrix} \varepsilon_t \\ \nu_t \\ \zeta_t \\ \eta_t \end{bmatrix}\right) = \begin{bmatrix} I_n & 0 & 0 & 0 \\ 0 & Q & 0 & 0 \\ 0 & 0 & S & 0 \\ 0 & 0 & 0 & W \end{bmatrix}$$

with I_n n-dimensional identity matrix and Q, S and W positive definite matrices. S is assumed to be block diagonal, with blocks corresponding to parameters belonging to separate equations. This implies that the coefficients of the contemporaneous relations among variables are assumed to evolve independently in each equation.[2] The choice of this particular structure for V has two main advantages. The first one is related to the high number of parameters to be estimated. Having non-zero blocks out of the main diagonal in matrix V would mean to further increase the already high dimensionality of the model. The second advantage is related to the interpretation of innovations. Indeed, a general correlation structure among different innovations would prevent their structural interpretation. Both assumptions on the dynamics of the model's time varying parameters and the structure of V are standard in the TVP-VAR literature.

Priors and estimation. We employ Bayesian methods to simulate the posterior distributions of the parameters of interest, i.e. the time varying coefficients B^T, variances Σ^T and covariances A^T and the hyperparameters of the variance-covariance matrix V. The Markov chain Monte Carlo (MCMC) algorithm in Del Negro and Primiceri (2015) is applied, which builds on the methods presented in Carter and Kohn (1994) and in Kim et al. (1998). A Gibbs sampling algorithm is used to generate a sample from the joint posterior of (B^T, A^T, Σ^T, V), which exploits the blocking structure of the unknowns and estimates the joint posterior distribution of all parameters by drawing the parameters in each block from a conditional

[2] Primiceri (2005) states that this assumption is not crucial, but simplifies inference and increases the efficiency of the algorithm. He also considers the case of S unrestricted.

distribution. The algorithm works as follows:

1. Draw Σ^T from $p(\Sigma^t|y^T, B^T, A^T, V)$;
2. Draw B^T from $p(B^t|y^T, \Sigma^T, A^T, V)$;
3. Draw A^T from $p(A^t|y^T, \Sigma^T, B^T, V)$;
4. Draw V from $p(V|y^T, \Sigma^T, A^T, B^T)$.

It has been proven that, as the number of iterations increases, the conditional distributions generated by the Gibbs sampler converge to the joint and marginal distributions of the parameters.

The prior distributions are defined as follows. The initial states for the coefficients, for the covariances, for the log-volatilities and the hyperparameters are assumed to be independent of each other. The priors of the hyperparameters, Q, W and the blocks of S, are assumed to be distributed as independent inverse-Wishart, whereas the priors for the initial states of the time varying coefficients, covariances and log-volatilities are assumed to be normally distributed. These assumptions, together with the assumed low of motion of the time varying parameters, imply normal priors on the entire sequences of the B's, α's and $\log \sigma$'s, conditional on Q, W and S. To calibrate the prior distributions, we use a Minnesota-type prior for the time-varying autoregressive coefficients B's and uninformative priors for the other parameters in the model. As a results, the priors are defined as follows:

$$B_0 \sim N(B_{MIN}, 4 \cdot V_{MIN})$$

$$A_0 \sim N(0, 4 \cdot I_n)$$

$$\log \sigma_0 \sim N(0, I_n)$$

$$Q \sim IW(k_Q^2 \cdot 24 \cdot V_{MIN}, 24)$$

$$W \sim IW(k_W^2 \cdot 5 \cdot I_n, 5)$$

$$S_i \sim IW(k_S^2 \cdot (i+1) \cdot I_n, i+1)$$

where S_i $(i = 1, \ldots, n-1)$ are the blocks of S. $k_Q = 0.01$, $k_S = 0.1$ and $k_W = 0.01$.

Identifying uncertainty shocks. Our uncertainty shock is identified by employing the Cholesky decomposition of the variance-covariance matrix of reduced-form residuals Ω_t. Iterating on the TVP-VAR(p) defined above, we obtain the corresponding moving average (MA) representation, which is the following

$$y_t = \mu_t + \sum_{h=0}^{\infty} \Theta_{h,t} u_{t-h}$$

with $\Theta_{0,h} = I_n$, $\mu_t = \sum_{h=0}^{\infty} \Theta_{h,t} C_t$ and $\Theta_{h,t} = J\tilde{B}_t^h J'$, where $\tilde{B}_t$ is the corresponding TVP-VAR(1) companion form of the TVP-VAR(p) and J is a selector matrix:

$$\tilde{B}_t = \begin{bmatrix} & B_t & \\ I_{k(p-1)} & \vdots & 0_{k(p-1)\times k} \end{bmatrix} \quad \text{and} \quad J = \left(I_k \; \vdots \; 0_{k\times k(p-1)}\right)$$

The parameters $\Theta_{h,t}$ for $h = 1, \ldots, H$ represent the reduced-form impulse response functions. To obtain structural impulse responses, we recover the structural uncertainty shock from the relation

$$u_t = A_t^{-1} \Sigma_t \varepsilon_t$$

where u_t is the vector of innovations (reduce-form residuals), ϵ_t is the vector of structural shocks and $A_t^{-1}\Sigma_t$ is the Cholesky decomposition of the reduced form variance-covariance matrix Ω_t, coming from the triangular decomposition stated above. Then, the structural relations are imposed on the reduced-form impulse response functions to obtain

$$\Phi_t = (\Theta'_{0,t}, \ldots, \Theta'_{H,t})' A_t^{-1} \Sigma_t$$

where Φ_t are our structural impulse response functions.[3]

[3]An identification strategy based on Cholesky decomposition imposes assumptions on the time in which shocks affect variables that can be difficult to motivate, such as credit shocks not contemporaneously affecting uncertainty. Prieto, Eickmeier, and Marcellino (in press) explore alternative identification strategies, such as different ordering of the variables and sign restrictions, in order to show that their results are not affected by alternative strategies used to identify the shocks. The identification of uncertainty and financial shocks is crucial for our analysis, and deserves further and careful exploration.

3.4 Results

We estimate a parsimonious VAR specification modeling measures of uncertainty, financial stress, credit spread and real activity. Four endogenous variables are included in the specification: (i) the measure of financial uncertainty by Ludvigson et al. (2016); (ii) the EBP; (iii) the endogenous component of the financial spread; (iv) the log-difference of manufacturing industrial production index. Estimates obtained with this parsimonious monthly VAR show that uncertainty shocks have substantial time varying effects. First, we find that uncertainty shocks, identified recursively by Cholesky-decomposing the variance-covariance matrix of residuals, have always recessionary effects, although with time-varying persistence. These results are shown in Figure 3.1, where the average response of industrial production to a one standard deviation uncertainty shock for different sub-periods has beed plotted. As the figure shows, the response of industrial production is always negative, but it displays a quick rebound only in the decade 1986 - 1995, a period characterized, on average, by a low degree of financial stress. To dig deeper on the drivers of such heterogenous responses, we condition the responses on the initial level of financial stress, as measured by the EBP. Results, displayed in Figure 3.2, show that the recessionary effects of uncertainty are amplified when the economy is in a period of financial distress. In particular, Figure 3.2 plots the impulse response of industrial production to an uncertainty shock, along with 68% credible sets, when the level of the EBP was at its highest and lowest observed levels. The response is much more persistent in the high financial stress state, while in the low financial stress state there is a negative effect followed by a quick rebound to the pre-shock level. Our preliminary results lend support to recent contributions by, among others, Alessandri and Mumtaz (2014) and Caldara et al. (2016).

3.5 Concluding Remarks

In this chapter, we present some preliminary results from the estimation of a parsimonious monthly TVP-VAR modeling measures of uncertainty, financial stress, credit spread and real activity, with the aim of evaluating to what extent financial conditions affect the response of real activity to an uncertainty shock.

Our estimates show that uncertainty shocks have substantial time-varying effects. In particular, an uncertainty shock always has recessionary effects, but these recessionary effects are amplified when the economy is in a period of financial distress. These preliminary results lend support to recent evidence provided by Alessandri and Mumtaz (2014) and Caldara et al. (2016), among others.

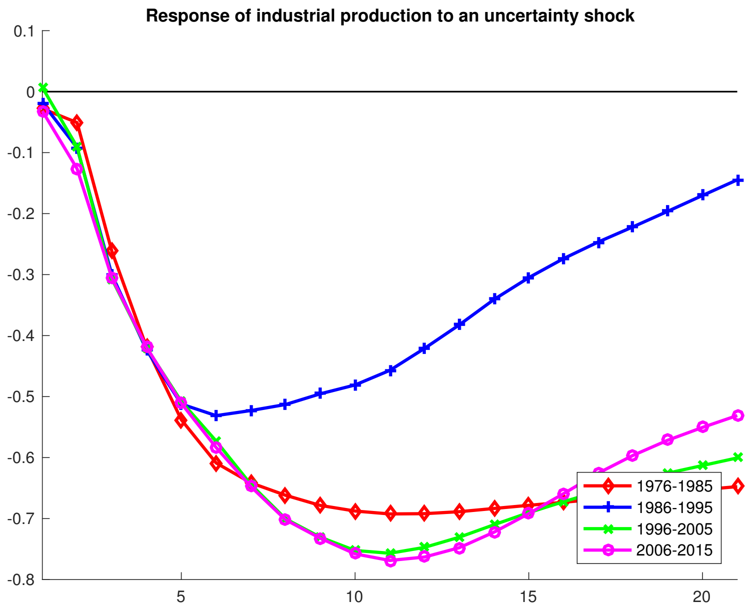


Figure 3.1: Average responses of industrial production to an uncertainty shock for selected periods.

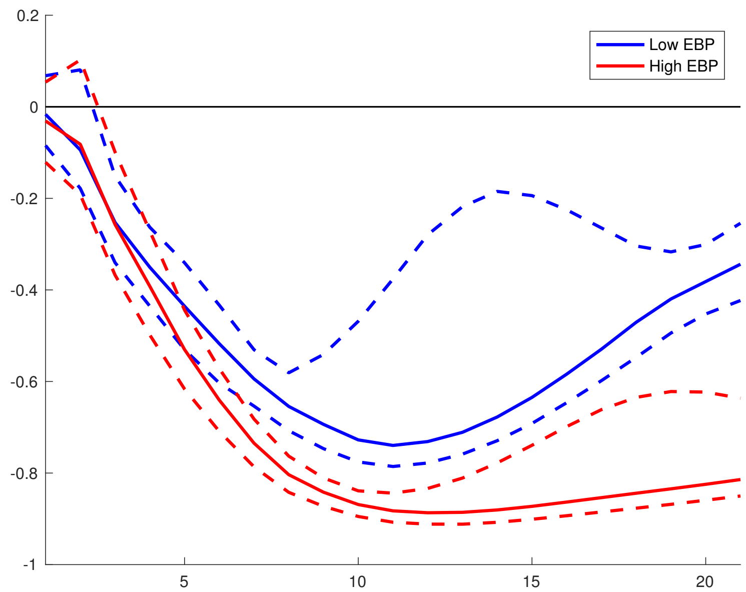


Figure 3.2: Impulse responses of industrial production to an uncertainty shock at the highest and lowest observed levels of the EBP.

Conclusions

This thesis empirically investigates the role of nonlinearities in the transmission of macroeconomic shocks, within a nonlinear macroeconometric framework. This is the common thread of the three chapters herein, in which we address the issue along two dimensions. On the one side, we explore different types of shocks, and investigate the effects of uncertainty and fiscal policy shocks. On the other side, we employ different nonlinear time series models, an Interacted VAR (I-VAR) and a time-varying parameter VAR with stochastic volatility (TVP-VAR). In chapter 1 and chapter 3, we analyze the effects of uncertainty shocks by means of an I-VAR and of a TVP-VAR respectively, whereas in chapter 2 we investigate the effects of government spending shocks within a TVP-VAR framework.

In detail, in the first chapter we explore the effects of a global uncertainty shock on output and the exchange rate in a group of developed economies and ask whether and how countries' relative risk exposure affects the transmission of the shock. The I-VAR model allows to detect nonlinear effects of the shock through the computation of state-conditional impulse response functions, where the two states of the economy that we consider are high and low relative risk exposure. In chapter 2 we investigate the evolution over time of government spending multipliers and devote special attention to the size of multipliers at the zero lower bound in a TVP-VAR framework, which allows both shocks and transmission mechanisms to change over time. We ask whether and how the conduct of monetary policy affects fiscal policy effectiveness. Finally, in the third chapter we aim at estimating time-dependent finance-uncertainty multipliers, to assess whether and how frictions in financial markets affect the transmission of uncertainty shocks to the economy.

Overall, the results presented in each of the chapters point to substantial variation over time of the effects of both uncertainty and fiscal shocks. In chapter 1, we find that relative risk exposure matters and that the effects of a global uncertainty shock on the economy are different depending on whether the economy is in high or low risk regime. In chapter 2, we find that the size of fiscal multipliers varies over time and that the monetary policy regime plays an important role for fiscal policy effectiveness. In chapter 3, our findings point to substantial variation of uncertainty multipliers over time and suggest that financial markets conditions matter for the transmission of uncertainty shocks. These results provide supporting evidence of the importance of nonlinear models for exploring the effects of macroeconomic shocks, by highlighting how the same shock can differently affect the economy depending on the state of the economy itself, and on the time-varying interactions among different economic sectors.

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Estratto per riassunto della tesi di dottorato

Studente: Silvia Delrio Matricola: 956078

Dottorato: Economia

Ciclo: XXIX

Titolo della tesi: **Empirical Essays on Uncertainty and Fiscal Shocks**

Abstract (english):

This thesis investigates the macroeconomic effects of uncertainty and fiscal shocks, particularly focusing on the role of nonlinearities in the transmission mechanisms.

Chapter 1 investigates the effects of global uncertainty shocks in open economies and explores the role that different levels of country risk exposure might have in the transmission of the shock through an I-VAR. We find evidence for the presence of nonlinear effects of global uncertainty shocks on economic activity.

Chapter 2 evaluates the evolution over time of fiscal spending multipliers in the U.S. through a TVP-VAR, particularly focusing on their size at the ZLB. Estimated spending multipliers display substantial variability over the investigated period. The effects of changes in government spending on output are larger in periods with passive monetary policy stance and at the ZLB.

Chapter 3 estimates time-dependent finance-uncertainty multipliers in the U.S. using a TVP-VAR. Our results point to substantial variations in the finance-uncertainty multipliers over the investigated period. Uncertainty shocks always have recessionary effects, although with time-varying persistence, and those effects are amplified in periods of financial distress.

Abstract (italiano):

Questa tesi analizza gli effetti macroeconomici di shock di incertezza e di shock di politica fiscale, con particolare attenzione alla presenza di non linearità nei meccanismi di trasmissione.

Il primo capitolo esplora gli effetti di shock di incertezza globale in economia aperta e il ruolo che diversi livelli di esposizione al rischio possono avere nella trasmissione dello shock, utilizzando un modello I-VAR. I risultati delle stime

indicano la presenza di effetti non lineari di shock di incertezza globali sull'economia reale.

Il secondo capitolo si propone di valutare l'evoluzione del tempo dei moltiplicatori fiscali negli Stati Uniti, attraverso un TVP-VAR, con particolare attenzione al valore dei moltiplicatori allo ZLB. I moltiplicatori stimati mostrano notevole variabilità durante il periodo considerato. Variazioni della spesa pubblica hanno effetti maggiori sull'attività economica in periodi di politica monetaria passiva e allo ZLB.

Il terzo capitolo analizza l'impatto delle condizioni finanziare sulla trasmissione di shock di incertezza, attraverso un TVP-VAR. I risultati mostrano sostanziale variabilità nel tempo degli effetti di shock di incertezza, condizionatamente allo stato dei mercati finanziari. Uno shock di incertezza ha sempre effetti recessivi, tuttavia tali effetti sono amplificati durante periodi di turbolenze finanziarie.

Firma dello studente