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The Real Effects of Uncertainty Shocks: New Evidence from Linear and Nonlinear SVAR Models

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Abstract

This paper applies both linear and nonlinear structural vector autoregressive (SVAR) models using two distinct identifications methods to disentangle the macroeconomic effects of uncertainty shocks for a developing country. As an application, we use macroeconomic data for the Democratic Republic of Congo (Congo), one of the largest and least developed countries in the world with a rich history of domestic political instability and high macroeconomic volatility. Our measure of uncertainty is the world uncertainty index for the Congo recently developed by Ahir et al. (2018) for a panel of developed and developing countries. Using a standard SVAR model with sign restrictions, we provide evidence that an unexpected increase in uncertainty triggers contractions in GDP and investment on impact in the Congo. We show that uncertainty shocks are among the greatest drivers of economic fluctuations. Our results are robust across alternative linear and nonlinear SVAR specifications using the Cholesky decomposition.

JEL codes: C30, D80, E32, O40

Keywords: Uncertainty, SVAR, Sign restriction, Congo.

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1 Introduction

A growing number of studies have documented the role of uncertainty shocks for the economies of many industrialized nations.[1] In contrast, evidence on the effects of uncertainty shocks for developing countries are missing. Our paper attempts to contribute to the literature by using the world uncertainty index (WUI) recently developed by Ahir et al. (2018) for a panel of developed and developing countries to shed light on the macroeconomic consequences of uncertainty shocks on economic activities in a least developed country. To do so, we basically use the WUI and macroeconomic data for the Democratic Republic of Congo (Congo). The Congo is one of the largest and less economically developed countries in the world with a rich history of domestic political instability and high macroeconomic volatility.

In reference to the economic literature, a high level in uncertainty is expected during economic downturns to significantly influence both firms' decisions to hire and invest, and households' choice to spend and may therefore be an important driver of economic fluctuations (Pindyck 1982, Bernanke 1983, Bloom 2009, 2014). The theoretical literature suggest two negative mechanisms through which uncertainty can impact the macroeconomy but also identify two positive channels of influence (Bloom, 2014).

Regarding the negative channels, one strand of the theoretical literature has focused on the effects of uncertainty shocks on real options. The real option argument posits that high uncertainty may cause both households to postpone consumption of durable goods and firms to delay investment and hiring decisions, which adjustment costs can make costly to reverse (Bernanke 1983, Dixit and Pindyck 1994, Eberly 1994). Bloom (2014) believes that the real option argument not only suggests that uncertainty may drop investment, hiring, and consumption, but it also makes economic agents less sensitive to changes in business conditions. For example, high uncertainty can make countercyclical economic policies (i.e. fiscal and monetary stabilization tools) less effective because firms and households are likely to react more cautiously to interest-rate and tax cut, thereby dampening the effect of potential stimulus policy.

Another strand of the theoretical literature examine the impact of uncertainty shocks via risk aversion and risk premia. The idea here comes from the fact that investors want to be compensated

[1]See e.g. Bloom (2009), Bachmann et al. (2013), Caggiano et al. (2014, 2017); Castelnuovo and Pellegrino (2018), Fontaine et al. (2018), Pellegrino (2018), Redl (2018), Trung (2019), Alam and Istiak (2020), Bhattarai et al. (2020), Gupta et al. (2020), Kumar et al. (2021). For a review of the recent literature on uncertainty shocks, see Castelnuovo and Pellegrino (2017), and Fernández-Villaverde and Guerrón-Quintana (2020) among others.

for higher risks, and because high uncertainty results in rising risk premia, this should increase financing costs such as borrowing costs (Arellano et al. 2011, 2019, Pástor and Veronesi 2013, Christiano et al. 2014, Gilchrist et al. 2014, Caldara et al. 2016). High uncertainty may also force households to raise their precautionary savings and reduce consumption spending (Guiso et al. 1992, Bansal and Yaron 2004, Carroll and Kimball 2008, Basu and Bundick 2017). An increase in precautionary saving may exert contrasting effects on investment and this depends on whether the environment is a closed economy or an open economy (Fernández-Villaverde et al. 2011, Leduc and Liu 2016, Basu and Bundick 2017).

In closed economies, high uncertainty would lead to a drop consumption and increases in savings and increase in investment (savings equals investment in closed economies). In open economies, high precautionary savings as a result of high uncertainty can reduce investment and consequently domestic demand since domestic money will flow abroad (Fernández-Villaverde et al., 2011). However, recent studies have argued that if prices are sticky, high uncertainty may trigger a recession even in closed economies because prices do not decrease enough to clear markets (Fernández-Villaverde et al. 2015, Leduc and Liu 2016, Basu and Bundick 2017, Cesa-Bianchi and Corugedo 2018). Precautionary effect of high uncertainty may also affect firms through managerial risk-aversion as managers may become more cautious in making long-run investments (Panousi and Papanikolaou, 2012).

Moreover, the two mechanisms through which high uncertainty can potentially have a positive effect on long-run growth are: the growth options and the Oi–Hartman–Abel effect (Bloom, 2014). The growth options argument is based on the idea that high uncertainty can boost investment if it raises the size of the potential prize. The Oi–Hartman–Abel effect introduces the idea that if firms can expand to exploit good outcomes and contract to insure against bad outcomes, they may be risk loving.

There is by now an abundant macroeconomic literature that evaluates the effects of uncertainty shocks and quantifies its relevance for economic fluctuations in developed economies within the context of dynamic stochastic general equilibrium (DSGE) models (Andreasen 2012, Bonciani and Van Roye 2016, Leduc and Liu 2016, Basu and Bundick 2017, Fasani and Rossi 2018, Fernández-Villaverde and Guerrón-Quintana 2020),[2] and structural vector autoregressive (SVAR) models (Bloom et al. 2007, Bloom 2009, Denis and Kannan 2013, Caggiano et al. 2014, 2017, 2021; Carriero

[2]Other notable studies include among others Justiniano and Primiceri 2008, Fernández-Villaverde et al. (2011), Gourio 2012, Bachmann and Bayer 2013, Fernández-Villaverde and Rubio-Ramírez (2013), Born and Pfeifer 2014, Christiano et al. 2014, Chugh 2016, Bloom et al. 2018.

et al. 2018, 2015; Ludvigson et al. 2021, Pellegrino 2021).[3]

For example, Leduc and Liu (2016) study the macroeconomic effects of uncertainty shocks and find that an uncertainty shock triggers a rise in unemployment and declines in inflation and the nominal interest rate both in the data (VAR) and in a DSGE model with search frictions and nominal rigidities. They conclude that uncertainty shocks act like an aggregate demand shock and are key contributor to economic fluctuations. Fasani and Rossi (2018) revisit the work of Leduc and Liu (2016) and examine the effects of uncertainty shocks under different Taylor-type rules. They show that under a plausible parameterization of interest rate smoothing, an uncertainty shock raises inflation and reduces output. Consequently, uncertainty shock can act as a demand or supply shock depending on monetary policy reactiveness. Basu and Bundick (2017) support that if prices adjust slowly to changing economic conditions, a standard DSGE model can replicate significant collapses in output, consumption, investment, and hours worked to an identified uncertainty shock in the data.

Empirically speaking, for instance, Bloom (2009), Carriero et al. (2015), Caggiano et al. (2017), and Ludvigson et al. (2021) apply different VAR specifications different identification methods and all ascertain that uncertainty shocks generate substantial contractions in economic activity (e.g. output and other macroeconomic variables such as investment, consumption) and are crucial drivers of economic fluctuations.

Our paper is primarily linked to the literature that evaluates the macroeconomic effects of uncertainty shocks in developed countries using both DSGE and SVAR models. We note several studies that analyze the effects of uncertainty shocks within the context of linear (Bonciani and Van Roye 2016, Leduc and Liu 2016, Basu and Bundick 2017, Fernández-Villaverde and Guerrón-Quintana 2020) and nonlinear DSGE models (Andreasen 2012, Mumtaz and Theodoridis 2018, Caggiano et al. 2021). The most relevant strand of literature for our paper uses linear (e.g. Bloom 2009, Carriero et al. 2015, and Ludvigson et al. 2021 for the US; Redl 2017 for the UK; Redl 2020 for a panel of developed countries including among others Germany, France, Italy, Japan, and Canada) and nonlinear SVAR models (Caggiano et al. 2017, Jackson et al. 2020, Pellegrino et al. 2020, 2021, Caggiano et al. 2021, Pellegrino 2021) to measure the relevance of uncertainty shocks. For example, Jackson et al. (2020) and Caggiano et al. (2021) show that the effects of uncertainty shocks are amplified in nonlinear SVARs.

[3]Others recent studies include Jones et al. (2016), Fontaine et al. (2017), Mumtaz and Theodoridis (2017, 2018), Castelnuovo and Pellegrino (2018), Pellegrino (2018), Jackson et al. (2020), Pellegrino et al. (2020), Pellegrino et al. (2020).

Regarding emerging countries, for instance Gupta et al. (2020) study the impact of US uncertainty shocks on a panel of advanced and emerging market economies, Redl (2018) examines the effects of an unanticipated increase in uncertainty on the macroeconomy in South Africa. Alam and Istiak (2020) investigate the impact of US policy uncertainty shock on Mexico. Studies in the literature rely on distinct identification strategies to identify the impact of uncertainty shocks in linear and nonlinear SVARs. For example, Bloom (2009), Leduc and Liu (2016), Basu and Bundick (2017), Redl (2018), Alam and Istiak (2020) apply linear SVAR models and use the Cholesky decomposition to identify uncertainty shocks. Caggiano et al. (2017), Jackson et al. (2020), Pellegrino (2021) develop nonlinear SVAR specifications and rely on the latter identification.

Carriero et al. 2015 apply a proxy SVAR model and identify uncertainty shocks through instrumental variables, Ludvigson et al. 2021 use a linear SVAR model with a new identification method based on inequality constraints. Redl (2017), Meinen and Roehe (2018), Shin and Zhong (2020) setup standard SVAR models and disentangle uncertainty shocks through an identification based on sign restriction. Redl (2020) specifies a factor VAR model and rely on narrative sign restriction (NSR) identification strategy à la Antolín-Díaz and Rubio-Ramírez (2018) to separately identify uncertainty shocks. Pellegrino et al. (2020, 2021) develop nonlinear SVAR models and identify uncertainty shocks using the NSR identification method à la Ludvigson et al. (2021).

As mentioned previously, despite this growing literature on the relevance of uncertainty shocks, we note very few empirical evidence on the macroeconomic effects of uncertainty shocks in emerging countries. For example, Carrière-Swallow and Céspedes (2013) examine the impact of uncertainty shocks on a large group of countries. They show that emerging economies suffer deeper and more prolonged impacts from uncertainty shocks. Using data from the US and India, Kumar et al. (2021) find that uncertainty shocks are demand shocks in the US with a contractionary output effect but they behave as supply shocks in India with an inflationary effect.

To the best of our knowledge, evidence on the macroeconomic effects of uncertainty shocks for developing countries are missing and are yet to be documented. In fact, uncertainty should be of a great concern to policymakers in developing countries for three main reasons (Koren and Tenreyro 2007, The World Bank 2013). First, developing countries tend to be less diversified and export a small number of products. consequently, they are more exposed to fluctuations in the output and price of these products. Second, most of the commodities (e.g. rubber, sugar, oil, and copper) that developing countries produce have volatile prices. Finally, developing countries seem to have more domestic political shocks such as coups, revolutions and wars; are more vulnerable to natural disasters like epidemics and floods, and have less effective fiscal and monetary stabilization policies. According to Bloom (2014), low-income countries in African and South America tend to have the most volatile GDP growth rates, stock markets and exchange rates. Using a panel of 60 countries with available growth and financial data, Bloom (2014) finds that low income countries had 50 percent higher volatility of growth rates, 12 percent higher stock-market volatility and 35 percent higher bond-market volatility and concludes that developing countries experience about one-third higher macro uncertainty.

In this paper, we basically address the following issues: What are the macroeconomic effects of uncertainty shocks in developing economies? What is the contribution of uncertainty shocks in explaining economic fluctuations in developing countries? To what extent do uncertainty shocks explain deviations in output from its predicted path over time in developing countries? Examining these questions would provide a better understanding of the macroeconomic consequences of uncertainty shocks on economic activities a developing countries.

More specifically, our paper contributes to this literature in two fashions. First, it uses the WUI for the Congo, an uncertainty index recently developed by Ahir et al. (2018) for a panel of countries including developing countries such as the Congo, to formally document key episodes of uncertainty in the Congo. For instance, we document that spikes in WUI for the Congo have occurred near the Second Congo war, the decision by the Independent National Electoral Commission to delay Congo's 2016 presidential elections, and the coronavirus pandemic. Second, we investigate the macroeconomic effects of uncertainty shocks in the Congo, a developing country, and quantify their relevance for economic fluctuations. As in Alam and Istiak (2020), we use both linear and nonlinear SVAR specifications and we rely on different identification strategies. We disentangle the effects of uncertainty shocks using two identification strategies (i.e. the sign restrictions and the Cholesky decomposition). Results from the standard linear SVAR model with sign-restriction identification suggest that uncertainty shocks lead to substantial drops in investment and GDP. The decrease in GDP is about 6 percent after 2 years in response to an uncertainty shock. Uncertainty shocks are among the largest contributor to economic fluctuations both at short and long horizons. Importantly, we also show that our findings are robust across alternative linear and nonlinear SVAR specifications.

The remainder of this paper is structured as follows. Section 2 describes data. Section 3 presents the standard VAR model and the sign restriction identification strategy. Section 4 discusses the results of the baseline model and those of the robustness checks. Section 5 analyzes the effects of uncertainty shocks in a small open economy setup. Section 6 applies a nonlinear VAR to study the macroeconomic effects of uncertainty shocks conditional on uncertainty states. Section 7 concludes.

2 Data and Application to the Congo

2.1 Measuring Uncertainty

Since uncertainty cannot be directly observed, a key challenge in the literature has been to devise a reasonable proxy. Researchers have relied on different uncertainty proxies to disentangle the effects of uncertainty shocks. According to Fernández-Villaverde and Guerrón-Quintana (2020), the three popular approaches to measure uncertainty have been to use some proxy of uncertainty (e.g. Bloom 2009, Baker et al. 2016, Baker et al. 2020), to construct surveys of subjective expectations of uncertainty (Bachmann et al. 2013, Scotti 2016, Bloom et al. 2019, Altig et al. 2020), or to estimate a formal econometric model and use it to measure uncertainty (e.g. Fernández-Villaverde et al. 2015, 2011). We refer the reader to Cascaldi-Garcia et al. (2020) for a survey of several measures of risk, uncertainty, and volatility .

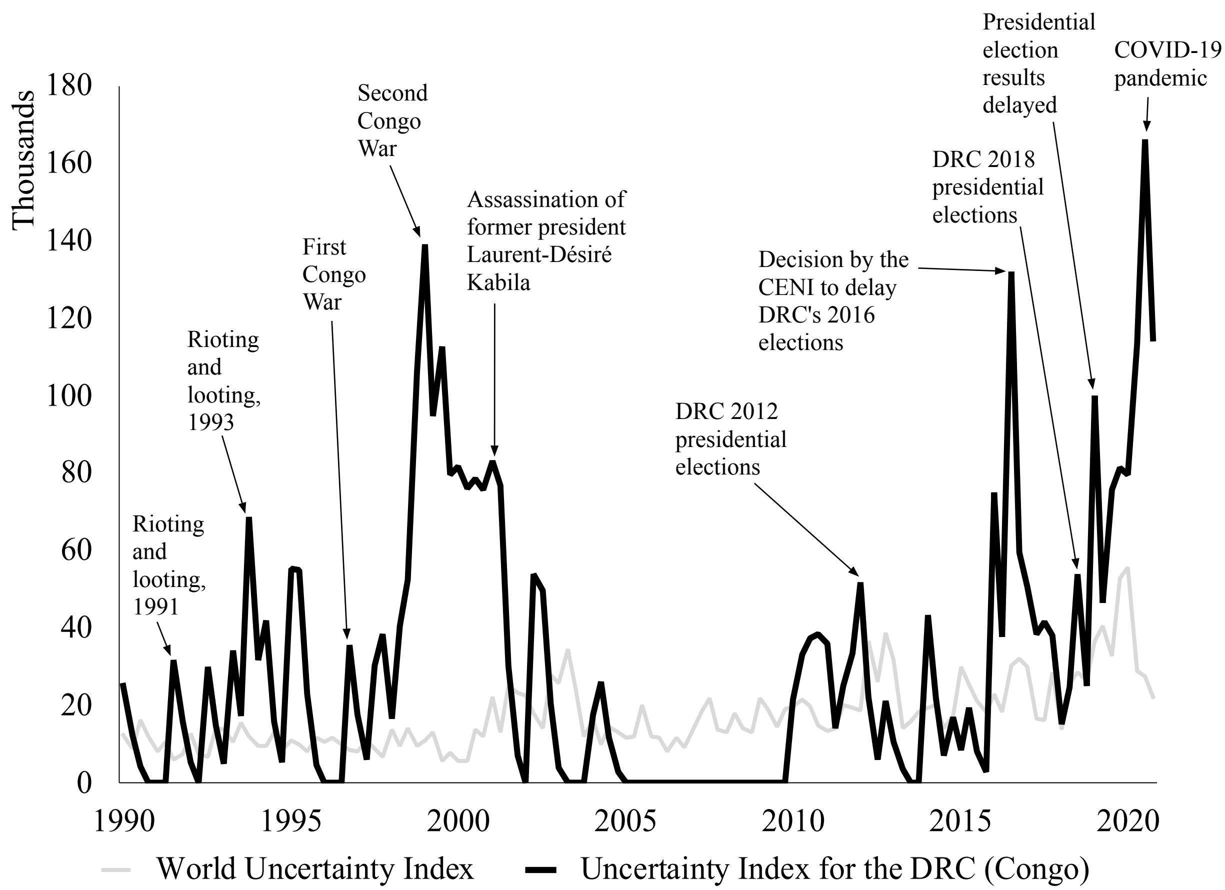
For example, the seminal study by Bloom (2009) use actual and implied stock market volatility (i.e. the VIX index of 30-day implied volatility on the S&P 500 stock market index) to measure uncertainty. Baker et al. (2016) build policy uncertainty indexes by (i) counting the frequency of uncertainty words in newspaper articles (e.g. Economic Policy Uncertainty index), (ii) counting the number of federal tax code provisions set to lapse in future years, and (iii) disagreement among economic forecasters as a proxy for uncertainty (Fernández-Villaverde and Guerrón-Quintana, 2020). Jurado et al. (2015) construct several series, using the common variation in forecast errors as a measure of uncertainty. Rossi and Sekhposyan (2015) rely on the Survey of Professional Forecasters (SPF) to measure uncertainty.[4]

For our paper, we use the world uncertainty (WUI) index recently developed by Ahir et al. (2018). The latter covers a panel of developed and developing countries (143 countries) and is developed by counting the frequency of words related to uncertainty in the Economist Intelligence Unit (EIU) country reports. The index captures uncertainty related to economic and political developments, regarding both near-term and long-term concerns (see Ahir et al. 2018, p. 5). A good alternative

[4]Recently, Redl (2020) used a data rich environment to produce a refined version of macroeconomic and financial uncertainty á la Jurado et al. (2015). Using a historical perspective, Shen (2020) provides a new macroeconomic uncertainty proxy for the US and other 14 major industrial countries using 100 years of data.

index for our study would be the EPU index which relies on a large set of newspapers. But to the best of our knowledge, there is no EPU index for the Congo. Figure 1 presents the evolution of the WUI index for the globe and for the Congo. On a global scale, historical evidence suggests that uncertainty spikes up after major health crisis, political tensions, economic shocks such as the recent COVID-19 pandemic, the trade escalations between US and China or the 2007 financial crisis.

Figure 1: Evolution of the world uncertainty index for the Congo



Note: Figure 1 displays the uncertainty index developed by Ahir et al. (2018). The gray line plots the global uncertainty using the World Uncertainty Index (WUI). The WUI measures overall uncertainty across the globe. The WUI index is an unbalanced GDP weighted average for 142 countries. The black line plots the WUI index for the Congo. Each index is rescaled by multiplying by 1,000,000. A higher number means higher uncertainty and vice versa.

The level of uncertainty is significantly higher in Congo and is positively associated with global uncertainty. The spikes in the WUI index for the Congo have occurred near: the 1991 and 1993 rioting and looting respectively; the first Congo war (1996-1997); the second Congo war (1998-2003); the assassination of former president L.-D. Kabila; the 2012 and 2018 presidential elections;

and the coronavirus pandemic (see e.g. Koyame and Clark 2002, McCalpin 2002, Prunier 2008, Reyntjens 2010, Tsasa 2018, Moshonas 2020 among others).

The macroeconomic environment of the Congo is naturally characterized by high level of uncertainty triggered mainly by political tensions, armed conflicts and economic factors (Doevenspeck and Mwanabiningo 2012, Larmer et al. 2013). According to the October 2019 edition of the IMF's World Economic Outlook (IMF 2020, p. 22), the Congolese economy was projected to register a negative growth rate of -2.2 percent in 2020, down from 4.4 percent in 2019. Several developments have prompted the downward revision of the Real GDP Growth. A key element is a rising "uncertainty" due to the COVID-19 pandemic. Moreover, in a joint analysis (The World Bank and IMF 2019, p. 3), the World Bank and IMF point out that from 2014 to 2017, the Congolese economy deteriorated sharply in the wake of commodity price shock and political crises. The sharp fall in the price of copper between 2014 and 2016 and the uncertainty caused by the delay in holding general elections hurt badly economic growth, exports, and fiscal revenues, unleashing a spiral of currency depreciation and inflation. Globally speaking, as argued by Mukwiza Ndahinda (2016, pp. 141-142), the uncertainty in the Congo is also reflected in the multiple changes of the country's official name: it has successively been known as the Congo Free State (1885-1908); Belgian Congo (1908-1960); Republic of Congo (1960-1964); Democratic Republic of Congo (1964-1971); Republic of Zaire (1971-1997); before regaining the current "Democratic Republic of Congo" denomination in 1997.

Recently, Félix-Antoine Tshisekedi, an opposition leader, was declared the winner of the 2018 presidential elections. The transfer of power from former President Joseph Kabila, in January 2019, marked the first peaceful transfer of power in the Congo's history. However, two years after, the country still faces high political uncertainty (see e.g. the recent Human Rights Watch report, HRW 2020) and macroeconomic instability amplified by the COVID-19 pandemic.[5]

2.2 Macroeconomic Data

In addition to the WUI index for the Congo, we use the following variables of interest: Real GDP (GDP), real private investment (investment) and the consumer price index (prices). We extract our macroeconomic variables from the World development indicators database. Our sample runs

[5] After the recent peaceful political transition, the IMF has approved a loan under its Rapid Credit Facility (RCF) combined with a Staff-Monitored Program, in order to help the Congo strengthen its economy. The previous IMF financial arrangement with the Congo ended in 2012. See IMF (2019a,b) for more details.

from 1995 to 2019 and the frequency of our data is annual. Our data are expressed in logs except the WUI index. Further details about data can be found in the appendix B.

3 SVAR Model and Identification

We consider the following reduced form VAR:

$$Y_t = C + \sum_{i=1}^{P} \Psi_i Y_{t-i} + \varepsilon_t \quad (1)$$

where in equation (1), Y_t is a $(n \times 1)$ vector containing all endogenous variables, C is a $(n \times 1)$ vector of constants, Ψ_i for $i = 1, ..., P$ are $(n \times n)$ matrices of parameters associated with P lags and ε_t is a $(n \times 1)$ vector of reduced form residuals with $\varepsilon_t \sim \mathcal{N}(0, \Omega)$ where Ω is a $(n \times n)$ variance-covariance matrix. We estimate our model using Bayesian methods with flat priors as in Furlanetto et al. (2019) so that the information contained in the likelihood becomes dominant. Our priors give rise to a Normal-Inverse Wishart posterior with the mean and variance parameters corresponding to OLS estimates. Our model is estimated in level since Bayesian technique can be used regardless of non-stationarity in data (Sims et al., 1990).

Let the mapping between the reduced-form residuals and the structural disturbances be $\varepsilon_t = D\eta_t$ with $\eta \sim \mathcal{N}(0_n, \mathbb{I}_t)$ is a $n \times 1$ vector of structural disturbances. Applying the Cholesky decomposition on D restricts the latter to become a unique lower triangular matrix such that the variance-covariance admits the following $\Omega_t = DD'$. For our baseline model, we rely on the identification based on sign restrictions to disentangle our uncertainty shock from supply and demand shocks (Faust 1998, Uhlig, 2005, Canova and Paustian 2011, Fry and Pagan 2011).

In the Cholesky decomposition, the variance-covariance of structural disturbances admits the following structure $\mathbb{I} = QQ'$ where Q denotes orthonormal matrices. Relying on sign restriction identification implies specifying a set of admissible Q matrices. To implement this strategy, we use the algorithm proposed by Rubio-Ramirez et al. (2010). We impose sign restrictions on impact only since this is sufficient to disentangle several shocks (Canova and DeNicoló, 2002). Further details about the model and the identification method can be found in the appendix A.1. Table 1 summarizes the restrictions imposed on the responses of our variables in the baseline specification.

Table 1: Sign Restrictions

	Uncertainty	Supply	Demand
Uncertainty	+	/	/
Investment	–	–	–
GDP	–	–	–
Prices	/	+	–

Note: Table shows restrictions for each variable (in rows) to identified shocks (in columns). + and – denote positive and negative restriction respectively. / denotes unrestricted.

Our baseline model includes four endogenous variables namely real GDP, real investment, CPI prices and our uncertainty index. We identify three shocks. The identifying restrictions of the uncertainty shock are taken from recent empirical studies that analyze the role of uncertainty shocks for business cycle fluctuations (see e.g. Bloom 2009, Carriero et al. 2015, Redl 2020 among others). We normalize the responses of GDP to all shocks. We model collapses in GDP in response to all shocks as uncertainty is most likely to burst during economic downturns. We restrict our positive temporary uncertainty shock to trigger a rise in the uncertainty index and a collapse in investment and GDP. We leave the response of prices to the uncertainty shock unrestricted as the effect is not clear in the literature (Basu and Bundick, 2017). We impose that a negative temporary supply shock generates declines in investment and GDP. We identify a negative demand shock as a disturbance that leads to slumps in investment and GDP. To separately identify the supply shock from the demand shock, we impose that the supply shock drives prices and GDP in opposite direction whereas the demand shock generates procyclical co-movement between the two variables. We leave unrestricted the responses of our uncertainty index to supply and demand shocks since their effects are not clear in the literature.

4 Empirical Results

4.1 Baseline Model

In what follows we present the results that emerge from the estimation of our baseline model. We present our results through the lens of impulse responses (IRFs), forecast error variance decompositions, and historical decomposition (Stock and Watson, 2001). First, we show the results of the forecast error variance decomposition. Second, we present the impulses responses to the temporary uncertainty shock. Third, we exhibit the historical decomposition of our structural shocks.

Table 2 reports the forecast error variance decomposition implied from our baseline model. The variance decomposition is computed at each horizon on the median draw that satisfies our sign restrictions. One horizon corresponds to one year. Results show that the uncertainty shock explains more than two-third of business cycle fluctuations at short horizons and 20 percent at long horizons. It accounts for more than 20 percent of investment volatility both at short and long horizons. It represents less than 10 percent of prices fluctuations both at short and long horizons. The significance of the uncertainty shock for output volatility in the long-run is consistent with the results of Meinen and Roehe (2018) for the US and the euro area.

Figure 2 plots the impulse responses to a temporary one standard error uncertainty shock. A positive uncertainty shock generates statistically significant contractions in investment and GDP. The drops in investment and GDP are persistent as they last for the entire horizons. The decrease in investment is around 6 percent on impact. The uncertainty shock triggers a contraction in GDP of about 2 percent on impact. The large fall in GDP is consistent with the results of Redl (2018) for South Africa and Carrière-Swallow and Céspedes (2013) for emerging economies. Our results reflect the macroeconomic environment surrounding developing economies where macroeconomic variables are highly volatile. The uncertainty shock leads to an increase in prices although we do not impose any restriction.

Table 2: Median Forecast Error Variance Decomposition-Sign Restriction

	Horizon	Uncertainty	Supply	Demand
Uncertainty	1	0.12	0.81	0.03
	5	0.12	0.75	0.07
	15	0.15	0.46	0.31
Investment	1	0.20	0.17	0.51
	5	0.21	0.16	0.55
	20	0.19	0.14	0.60
Real GDP	1	0.86	0.04	0.09
	5	0.35	0.11	0.46
	20	0.23	0.12	0.58
Prices	1	0.09	0.17	0.73
	5	0.06	0.15	0.76
	20	0.06	0.12	0.78

Figure 3 depicts the historical decomposition of GDP in which we show the contribution of each structural shock to the deviation of GDP from its forecasted path at each point in time. Supply and uncertainty shocks emerge as two crucial drivers that have considerable importance in explaining the deviation of GDP from its predicted path across horizons. Supply and uncertainty shocks together contribute to explain the contraction in GDP between 1995 and 2005. Then, they help accelerate output between 2012 and 2015, a period characterized by low macroeconomic volatility and political uncertainty. After 2015, the two shocks accelerate the collapse in GDP. Our findings move in tandem with the relatively high macroeconomic volatility observed during this period. During the period 2016-2019, large uncertainty bursts due to high political tensions caused by the delay in the organization of the presidential election, have been registered.

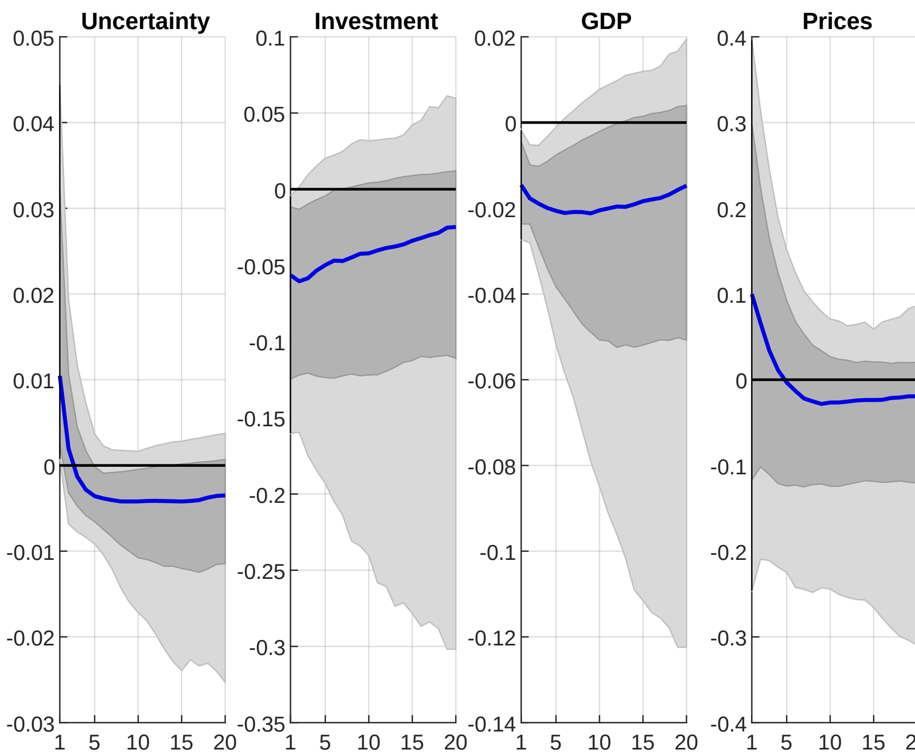


Figure 2: Impulse responses to the uncertainty shock. The blue line represents the median response at each horizon. The grey shaded area indicates the 68th confidence intervals while the light shaded area shows the 90th confidence intervals.

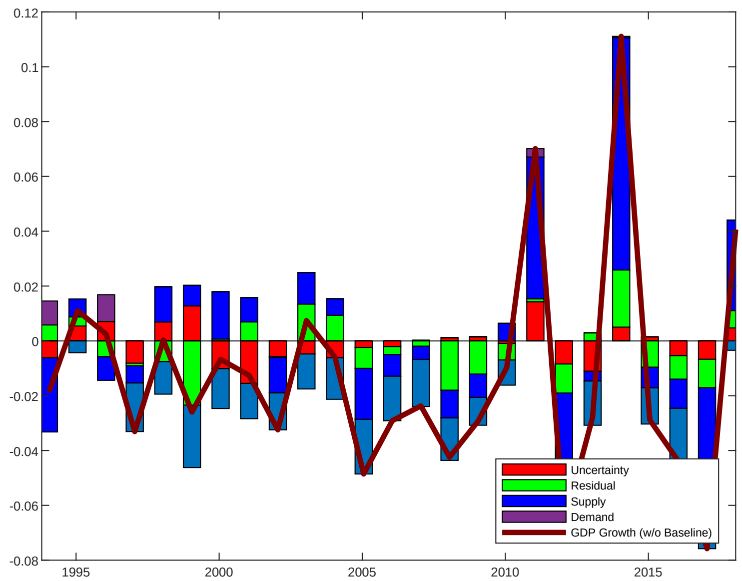


Figure 3: Historical decomposition of GDP for the baseline model (1995-2019). The bars represent deviations in GDP from its predicted path.

4.2 Baseline-Robustness Checks

In this subsection, we test the validity of our baseline results to a battery of sensitivity analysis. We check the robustness of our results by (i) choosing another lag specification, (ii) specifying a parsimonious SVAR model with three variables (uncertainty, GDP and prices), (iii) replacing GDP with investment in the trivariate SVAR, and finally (iv) identifying the uncertainty shock with Cholesky decomposition. We present the results in terms of the impulse responses and the forecast error variance decomposition.

In subsection 4.1, we have estimated the baseline model with one lag. We re-estimate the model with two lags and presents the forecast error variance decomposition in Table 6. It clearly emerges that the role of the uncertainty shock remains substantial for all the endogenous variables. The uncertainty shock accounts for at least 10 percent of investment variability both at short and long horizons. It represents more than half of output fluctuations at short horizons and around 20 percent at long horizons. Its contribution in explaining prices volatility remains unchanged in this specification.

Figure 10 exhibits the impulse responses to an uncertainty shock in this modified model. The reactions of investment and GDP are hump-shaped, prolonged and statistically significant after an uncertainty shock. The peak of the declines remains around 6 percent for investment and 2 percent for GDP. We now specify a parsimonious SVAR that includes our uncertainty index, GDP and prices. Table 3 illustrates the identifying restrictions for this modified model. In general, we keep the restrictions imposed in the baseline model. However, we further restrict the uncertainty shock to generate a drop in prices (Leduc and Liu, 2016).

Table 3: Sign Restrictions

	Uncertainty	Supply	Demand
Uncertainty	+	/	/
GDP	−	−	−
Prices	−	+	−

Table 7 summarizes the forecast error variance decomposition for this model. The role of the uncertainty shock is amplified in this specification. It accounts for more than 50 percent of GDP volatility across horizons. It contributes to explain half of prices fluctuations at short horizons and more than half at long horizons. Figure 11 displays the impulse responses to the uncertainty shock in the first trivariate model. The uncertainty shock triggers statistically significant collapses in GDP and prices. The contraction in GDP reaches a peak of about 3.7 percent around the fifth quarter. The fall in prices is close to 3 percent on impact. The next sensitivity analysis consists of replacing GDP by investment in the trivariate model. The restrictions imposed on the response of GDP in Table 7 are the same for investment. The results of the forecast error variance decomposition are reported in Table 8. The relevance of the uncertainty shock is magnified in this model. It is a major driver of investment volatility both at short and long horizons. It explains an important fraction of prices fluctuations across horizons. Figure 12 portrays the impulse responses to the uncertainty shock in this modified specification. The uncertainty leads to statistically significant declines in investment and prices. The peak of the fall in investment is doubled (more than 12 percent) compared to the baseline model and it is achieved around the second quarter. The peak of the decrease in prices is comparable to the first trivariate model.

Finally, we re-estimate the baseline model and we use the Cholesky decomposition to identify the uncertainty shock. The Cholesky decomposition is a recursive identification and puts a strong emphasis on the ordering of variables in the SVAR. The ordering of the uncertainty index remains a controversial issue in the literature. We place the uncertainty index as the first variable in our SVAR model. This is followed by investment, GDP, and prices. Ordering the uncertainty index as the first variable in the SVAR implies that the uncertainty index does not react contemporaneously to macroeconomic disturbances. This resembles treating the uncertainty index as an exogenous variable, consistent with Carriero et al. (2018).

Table 9 presents the forecast error variance decomposition with the Cholesky decomposition. The contribution of the uncertainty shock is relatively modest in this specification. The uncertainty shock accounts for less than 20 percent of investment variability at short horizons and around 20 percent long horizons. The uncertainty shock represents around 20 percent of output fluctuations in the long-run. The importance of the uncertainty shock is very marginal for prices volatility. Figure 13 plots the impulse responses to the uncertainty shock. The uncertainty shock triggers persistent and statistically significant drops in investment and GDP. The fall in investment reaches a peak of 6 percent while that of GDP is around 2 percent.

5 Uncertainty Shocks in a Small Open Economy

In this section, we analyze the transmission mechanism of global uncertainty shocks on macroeconomic dynamics in the Congo. As a small open economy, macroeconomic developments in the Congo are prone to external disturbances. Therefore, it is important to account for the impact of external shocks on domestic macroeconomic development. We specify a small open economy SVAR model in the spirit of Moran et al. (2020). We slightly modify the baseline model by including a proxy of global uncertainty (i.e the US uncertainty index) in order to account for the small open economy feature of the Congolese economy. The US uncertainty index comes from the world uncertainty index developed by Ahir et al. (2018).

We order the US uncertainty index as the first variable in Y_t. This is followed by the domestic uncertainty index, investment, GDP, and prices. Placing the US uncertainty index before the domestic uncertainty index helps to capture the small open economy nature of the Congo whose macroeconomic developments are contemporaneously affected by global uncertainty shock and the reverse is not true, consistent with Carriero et al. (2018).

In another specification, we order the domestic uncertainty index as the last variable in Y_t. By doing so, we treat the domestic uncertainty index as an endogenous variable which reacts immediately to foreign and domestic macroeconomic shocks, consistent with Ludvigson et al. (2015). We use the Cholesky decomposition to disentangle the US uncertainty shock from the domestic uncertainty shock and other structural shocks.

Table 4 summarizes the forecast error variance decomposition for the first small open economy

SVAR model. The domestic uncertainty shock remains an important contributor to investment and GDP fluctuations. It accounts for about 20 percent of investment volatility in the short-run and 30 percent in the long-run. It explains around 20 percent of output volatility at medium and long horizons. Figure 4 plots the impulse responses to the domestic uncertainty shock for this extended specification. The uncertainty shock triggers statistically significant declines in investment and GDP. The contractions in investment and GDP are persistent and of the same magnitude as in the model without the US uncertainty index. The uncertainty index leads to a persistent fall in prices which is statistically insignificant.

Table 5 presents the forecast error variance decomposition for the second small open economy SVAR model. The relevance of the domestic uncertainty shock in accounting for investment and output fluctuations is only marginal in this specification. Figure 5 shows the impulse responses to the uncertainty shock for this modified specification. The uncertainty shock generates persistent but statistically insignificant contractions in investment and GDP. It triggers a temporary rise in prices which is also statistically insignificant.

Table 4: Median Forecast Error Variance Decomposition-SOE I

	Horizon	US Uncertainty	Uncertainty	Investment	Technology	Prices
US Uncertainty	1	0.00	0.00	0.00	0.00	0.00
	5	0.90	0.03	0.07	0.01	0.01
	15	0.87	0.03	0.08	0.01	0.01
Uncertainty	1	0.06	0.94	0.00	0.00	0.00
	5	0.07	0.88	0.04	0.01	0.00
	15	0.07	0.68	0.22	0.01	0.02
Investment	1	0.00	0.16	0.84	0.00	0.00
	5	0.05	0.26	0.68	0.00	0.02
	15	0.06	0.26	0.64	0.00	0.04
GDP	1	0.00	0.01	0.04	0.96	0.00
	5	0.07	0.17	0.52	0.23	0.01
	15	0.07	0.24	0.60	0.05	0.60
Prices	1	0.00	0.00	0.06	0.08	0.84
	5	0.07	0.00	0.13	0.07	0.73
	15	0.07	0.03	0.25	0.06	0.60

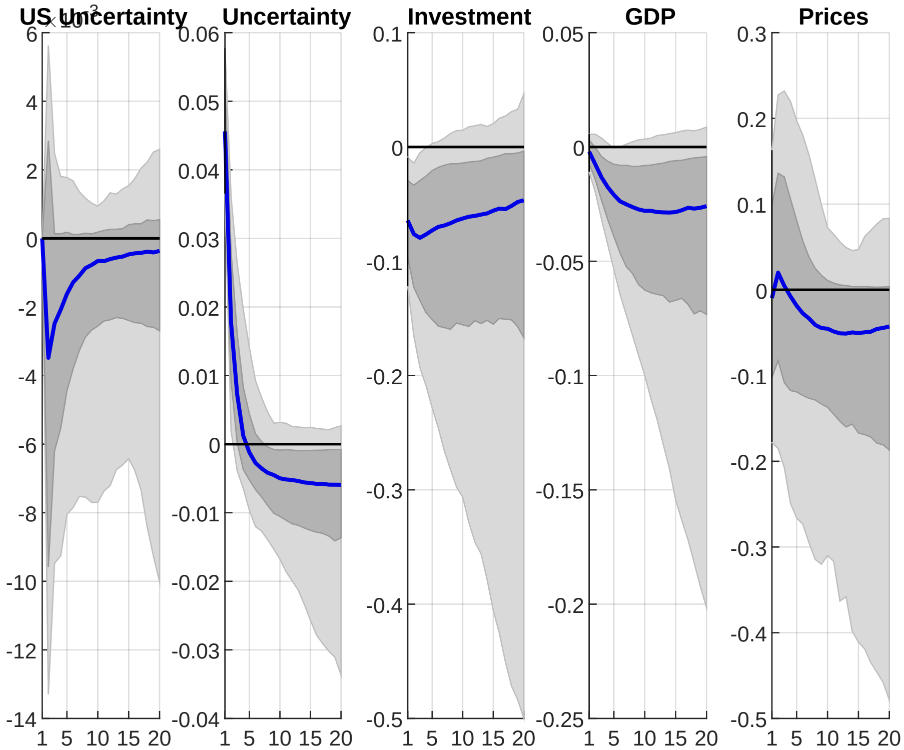


Figure 4: Impulse responses to the uncertainty shock. The blue line represents the median response at each horizon. The grey shaded area indicates the 68th confidence intervals while the light shaded area shows the 90th confidence intervals.

Table 5: Median Forecast Error Variance Decomposition-SOE II

	Horizon	US Uncertainty	Investment	Technology	Prices	Uncertainty
US Uncertainty	1	0.00	0.00	0.00	0.00	0.00
	5	0.90	0.09	0.01	0.00	0.00
	15	0.88	0.11	0.01	0.01	0.00
Investment	1	0.00	1	0.00	0.00	0.00
	5	0.05	0.92	0.00	0.01	0.02
	15	0.07	0.88	0.00	0.03	0.02
GDP	1	0.00	0.04	0.96	0.00	0.00
	5	0.07	0.68	0.24	0.01	0.01
	15	0.07	0.82	0.05	0.03	0.02
Prices	1	0.02	0.06	0.08	0.84	0.00
	5	0.07	0.11	0.07	0.74	0.01
	15	0.07	0.26	0.06	0.61	0.01
Uncertainty	1	0.07	0.16	0.00	0.01	0.76
	5	0.08	0.15	0.02	0.01	0.74
	15	0.07	0.38	0.02	0.02	0.50

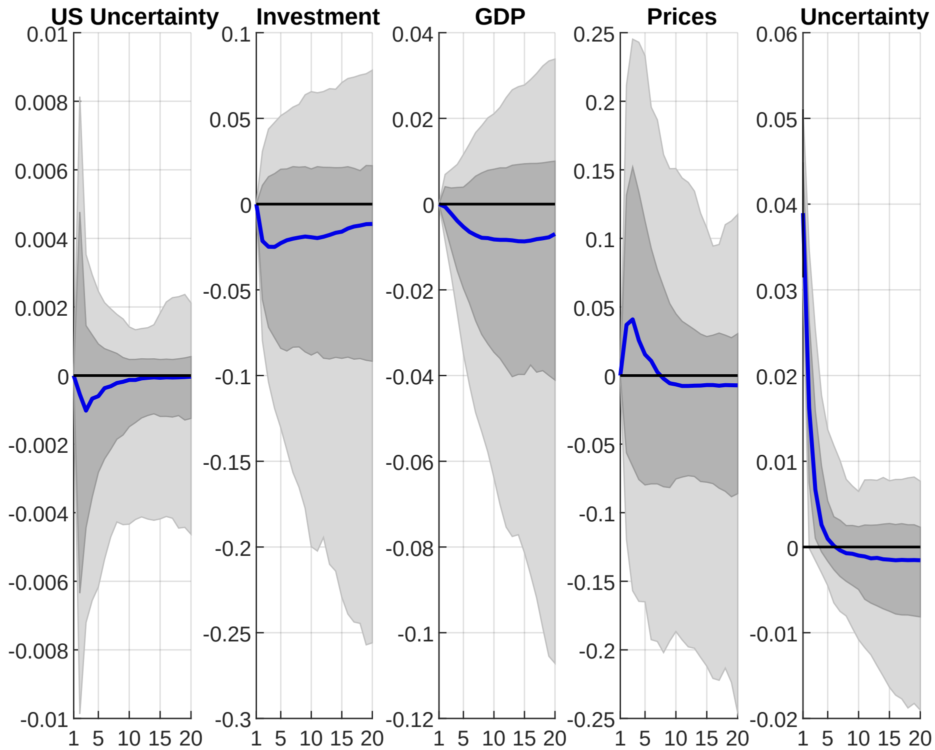


Figure 5: Impulse responses to the uncertainty shock. The blue line represents the median response at each horizon. The grey shaded area indicates the 68th confidence intervals while the light shaded area shows the 90th confidence intervals.

Finally, we conduct an additional robustness check by assuming that the small open economy (i.e. the Congo) takes the proxy of global uncertainty index as exogenously given (Schmitt-Grohé and Uribe, 2018). We order the US uncertainty index as the first variable in the SVAR model. This is followed subsequently by the domestic uncertainty index, investment, and prices. Shocks are identified using the Cholesky decomposition. By assuming strict exogeneity of the US uncertainty index, we imposes that $\Psi_{1,j} = 0$ for $j = 2, \ldots, 5$ in our SVAR model.

Figure 6 plots the impulse responses to the domestic uncertainty shock in this specification. The US uncertainty response reflects our exogeneity assumption. A one standard deviation increase in domestic uncertainty leads to substantial drops in investment and GDP. The uncertainty shock leads to a temporary rise in prices. The forecast error variance decomposition of this model shows that the uncertainty shock represents 17 percent and 15 percent of investment and output fluctuations respectively. It accounts for 6 percent of price volatility.

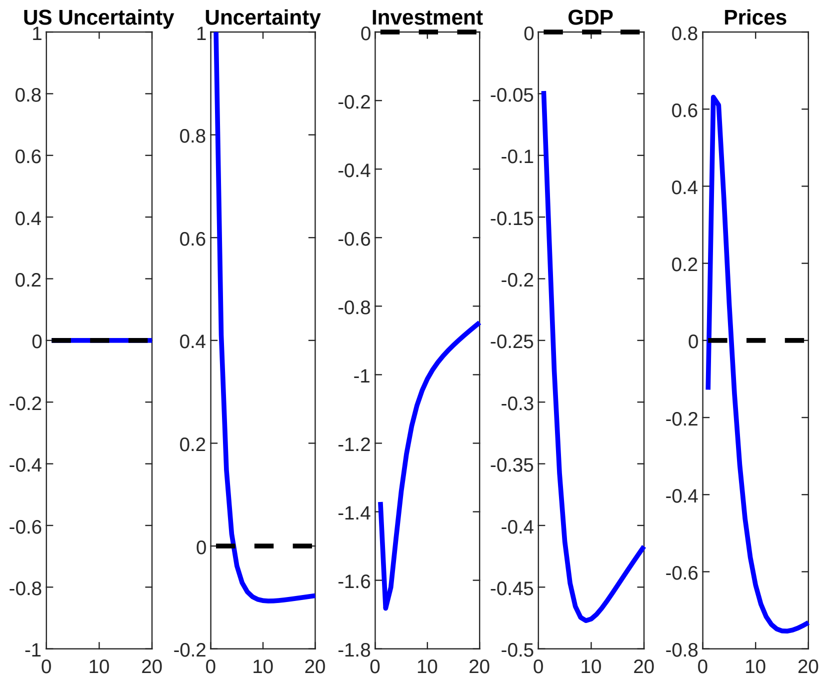


Figure 6: Impulse responses to the uncertainty shock assuming exogeneity of US uncertainty. The blue line represents the median response at each horizon.

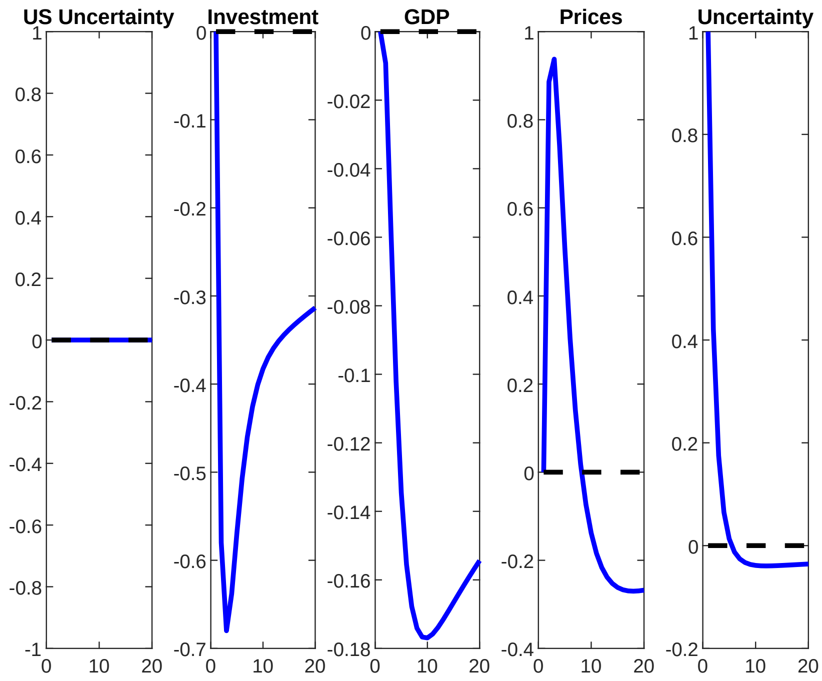


Figure 7: Impulse responses to the uncertainty shock assuming exogeneity of US uncertainty. The blue line represents the median response at each horizon.

Figure 7 exhibits the impulse responses to the domestic uncertainty shock when we order the domestic uncertainty index as the last variable in the SVAR model while preserving the order of other variables. The responses are qualitatively similar although they are different in magnitudes. The forecast error variance decomposition of this specification confirms that the relevance of the uncertainty shock is amplified as it explains around 58 percent and 54 percent of investment and output volatility respectively and 24 percent of price fluctuations.

6 Uncertainty Shocks in a Nonlinear Environment

Another strand of the recent empirical literature takes into non-linearity when analyzing the macroeconomic effects of uncertainty shocks (Nodari 2014, Jones et al. 2016, Caggiano et al. 2017, Fontaine et al. 2017, Alessandri and Mumtaz 2019, Alam and Istiak 2020, Caggiano et al. 2020, Jackson et al. 2020, Pellegrino et al. 2020, Caggiano et al. 2021, Pellegrino 2021). For example, Pellegrino (2021) examines whether the real effects of uncertainty shocks are different in times of tranquil and high uncertainty and finds that monetary policy shocks are significantly less powerful during uncertain times. Caggiano et al. (2017) explore whether the real effects of uncertainty shocks are higher when the economy is at the Zero Lower Bound (ZLB). They discover that the contractionary effects of uncertainty shocks are statistically greater when the ZLB is binding, with differences that are economically meaningful.

We follow Pellegrino (2021) and employ a fully nonlinear or Self-Exciting Interacted VAR model to empirically evaluate whether the real effects of uncertainty shocks are different in low and high growth times.

The Self-Exciting Interacted VAR. The nonlinear model augments the standard linear VAR as in section 3 with an interaction term, which involves two endogenously modeled variables: the variable via which we identify the uncertainty shock, i.e. the uncertainty index and the variable on which we measure the real effects of the uncertainty shock, i.e. GDP. The latter variable serves as a conditioning variable that helps us to measure the impact of the uncertainty shock depending on the state of the business cycle (i.e. in low versus high growth times). In addition to the interaction term, we consider all the endogenous variables used in the baseline model.

The estimated Self-Exciting Interacted VAR (SEIVAR) model is the following:

$$Y_t = \alpha + \varphi.lineartrend + \sum_{i=1}^{P} B_i Y_{t-i} + \left[\sum_{i=1}^{P} a_i \Delta \ln GDP_{t-i}. \ln unc_{t-i}\right] + \epsilon_t \tag{2}$$

$$\ln GDP_t = u'_{GDP} Y_t \tag{3}$$

$$\ln unc_t = u'_{unc} Y_t \tag{4}$$

where Y_t is a $(n \times 1)$ vector of the endogenous variables, α is a $(n \times 1)$ vector of constants, φ is a $(n \times 1)$ vector of slope coefficients for the time trend included, B_i for $i = 1, ..., P$ are $(n \times n)$ matrices of parameters associated with P lags and ϵ_t is a $(n \times 1)$ vector of error terms whose Ω is a $(n \times n)$ variance-covariance matrix. The interaction term in the bracket makes the standard VAR a SEIVAR model. It includes a $(n \times 1)$ vector of coefficients a_i, a measure of uncertainty, $\ln unc_t$ and an indicator of the business cycle $\Delta \ln GDP_{t-i} \equiv \ln GDP_{t-i} - \ln GDP_{t-i-1}$ which is the annual growth rate of GDP. u'_y is a selection vector for the endogenous variable y in Y_t. This means that the uncertainty index and GDP are treated as endogenous variables. We estimate the model in first difference using OLS as in Pellegrino (2021). We opt for one lag specification, consistent with the baseline model in section 3.

The SEIVAR presents many advantages over alternatives non-linear specifications that also feature an observed conditioning variable such as the Smooth transition (ST-) VAR and the Threshold (T-) VAR (see Pellegrino 2021 for an in-depth-discussion). As in Pellegrino (2021), we identify the short-run effects of the uncertainty shock using the Cholesky decomposition. We follow Pellegrino (2021) and order the vector of endogenous variables in the following way $Y = [Unc, Inv, GDP, P]'$ where in order, we have the uncertainty index, investment, GDP, and the price index, consistent with Carriero et al. (2018). As a robustness check, we maximize the degree of endogeneity of the uncertainty index, consistent with Ludvigson et al. (2015).

Generalized Impulse Response Functions. Given that the conditioning variable, i.e. the uncertainty index, is included in the vector of endogenous variables, it is crucial to compute impulse responses that are conditional on low versus high growth. Not accounting for the uncertainty endogenous movement would generate biased responses as the feedbacks from the uncertainty movement on macroeconomic dynamics would be disregarded. In order to correctly estimate responses from a nonlinear model in the presence of an endogenous conditioning variable, we calculate Generalized Impulse Response Functions (GIRF) à la Koop et al. (1996) and we account for orthogonal structural shocks as in Kilian and Vigfusson (2011). Theoretically, the GIRF at horizon h of the vector Y to a shock in date t, ψ_t computed conditional on initial conditions $\Theta_{t-1} = \{Y_{t-1}, \cdots, Y_{t-p}\}$ is given by the difference between the conditional expectations between the shocked and the non-shocked paths of Y:

$$GIRF_{Y,t}(h, \psi_t, \Theta_{t-1}) = \mathbb{E}[Y_{t+h}|\psi_t, \Theta_{t-1}] - \mathbb{E}[Y_{t+h}|\Theta_{t-1}] \tag{5}$$

In principle, we have many history-dependent GIRFs with a reference to a generic initial year $t-1$ as there are annual data in the estimation sample. Once these GIRFs are averaged, per horizon, over a specific subset of initial conditions, we obtain state-dependent GIRFs, which represent average response of endogenous variable to a shock in a given state. Keeping up with Bloom et al. (2007) and Vavra (2014), we assume that the *low growth times* state is characterized by initial horizons with uncertainty around the first decile of its empirical distribution while the *high growth times* state by initial horizons around its ninth decile (a five percentage tolerance band around the top and bottom deciles is used). Theoretically, the state-dependent GIRFs can be defined in the following way:

$$GIRF_{Y,t}\left(h, \psi_t, \Omega_{t-1}^{high\ growth\ times}\right) = \mathbb{E}\left[GIRF_{Y,t}\left(h, \psi_t, \left\{\Theta_{t-1} \in \Omega_{t-1}^{high\ growth\ times}\right\}\right)\right] \tag{6}$$

$$GIRF_{Y,t}\left(h, \psi_t, \Omega_{t-1}^{low\ growth\ times}\right) = \mathbb{E}\left[GIRF_{Y,t}\left(h, \psi_t, \left\{\Theta_{t-1} \in \Omega_{t-1}^{low\ growth\ times}\right\}\right)\right] \tag{7}$$

where Ω_{t-1}^{j} denotes the set of histories characterizing regime $i = \{high\ growth\ times, low\ growth\ times\}$. For further details regarding the GIRFs, the algorithm used to compute them and alternative methodologies, we refer the reader to Pellegrino (2021). Figure 8 displays the point estimates for the state-conditional GIRFs of endogenous variables together with the impulse responses from the linear SVAR nested in our SEIVAR to a one percent temporary uncertainty shock.

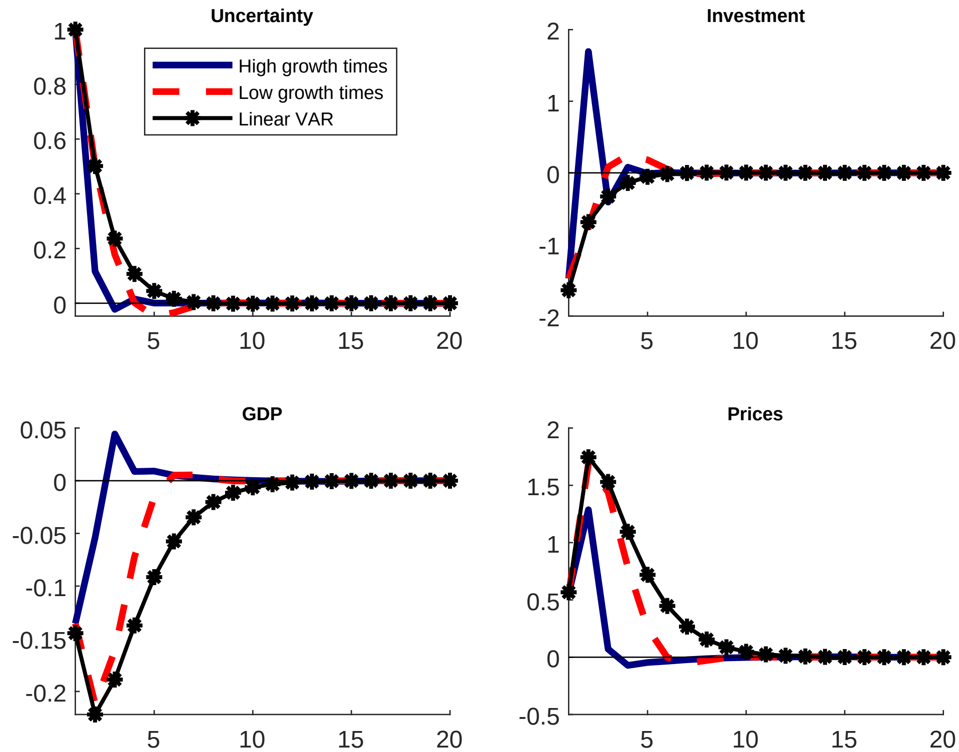


Figure 8: High growth vs. Low growth times to state-conditional responses in comparison to linear responses. Solid blue (red dotted) line: state conditional GIRF for the low growth times (high growth times) state. Black starred line: IRF from the nested linear VAR.

In other words, we examine the state-dependent effects of uncertainty by computing the average effects of the latter in our 'high growth times' or 'low growth times'(which refer to the extremes deciles explained previously). Two important findings emerge from this analysis. First, our results show great disparities between the state-dependent GIRFs (low vs high growth times). In fact, the GIRFs confirm that the uncertainty shock is on average more effective during low growth times. The uncertainty shock triggers an increase in prices and collapses in investment and GDP during low growth times. Second, linear responses are larger than the state-conditional responses especially for GDP and prices. In order words, the standard linear VAR model does well in capturing the impact of the uncertainty shock on the macroeconomy during low growth times, thereby supporting our baseline results. Figure 9 produces the same dynamics when maximizing the endogeneity of the uncertainty index, consistent with Pellegrino (2021). The state-dependent GIRFs are similar to those in Figure 8. Once again, the effectiveness of the uncertainty shock is strengthened during low growth times. Furthermore, as in Pellegrino (2021) we notice that the linear responses are within the state-conditional responses at short horizons.

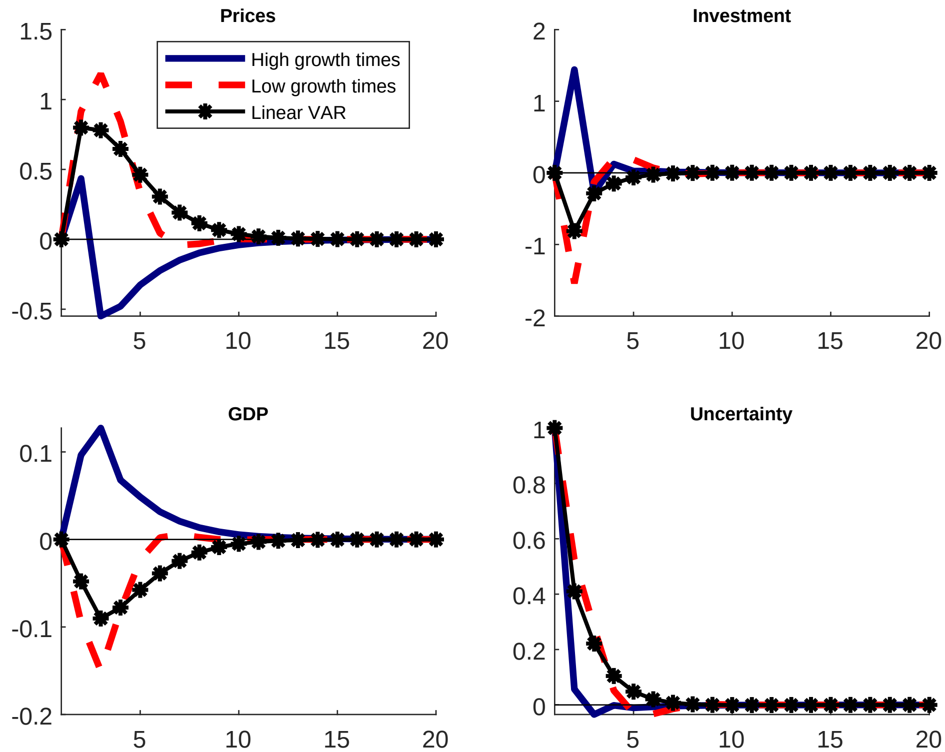


Figure 9: High growth vs. Low growth times to state-conditional responses in comparison to linear responses. Solid blue (red dotted) line: state conditional GIRF for the low growth times (high growth times) state. Black starred line: IRF from the nested linear VAR.

7 Conclusions

Higher levels of volatility in developing countries, compared to developed nations (Agénor 2002), suggests that disturbances in uncertainty are important drivers of economic fluctuations in these countries. Despite a growing literature documenting the role of uncertainty shocks for developed countries, evidence on the effects of uncertainty shocks for developing countries are missing. Our paper contributes to the literature by shedding light on the macroeconomic consequences of uncertainty shocks on economic activities in developing countries. Our contribution is twofold. First, we use a new uncertainty index recently developed by Ahir et al. (2018) to formally document the key episodes of uncertainty in the Democratic Republic of Congo (Congo) —The Congo is one of the largest and least developed countries in the world (in reference to the *UNCTAD list*) with a rich history of domestic political instability and high macroeconomic volatility. Second, we evaluate the effects of uncertainty shocks by applying both linear and nonlinear SVAR models and using two distinct identification strategies. Using a standard SVAR model with sign restriction identification, our results confirm that: First, uncertainty shocks generate collapses in investment and GDP. Second, uncertainty shocks are among the largest contributors to economic fluctuations. We have checked the robustness of our results by (i) choosing another lag specification, (ii) specifying a parsimonious SVAR model with three variables (uncertainty, GDP and prices), (iii) replacing GDP with investment in the trivariate SVAR, and finally (iv) identifying the uncertainty shock with Cholesky decomposition. In addition, we have also conducted an additional robustness check by assuming a small open economy setup and a nonlinear SVAR model. We find that our results are robust across theses alternative linear and nonlinear SVAR specifications. Our message to the policymakers is to try by all means to minimize uncertainty as this hurts badly the economy and the application of macroeconomic stabilization policies during economic downturns.

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A Econometric procedure

In this appendix, we explain thoroughly the econometric procedure we apply for the estimation of our model. Data sources and additional empirical results are presented in Appendices B and C, respectively.

A.1 The Model and the Identification Strategy

We consider the following reduced-form VAR representation:

$$Y_t = C + \sum_{i=1}^{P} \Psi_i Y_{t-i} + \epsilon_t \tag{8}$$

where Y_t is a $(n \times 1)$ vector containing all endogenous variables, C is a $(n \times 1)$ vector of constants, Ψ_i for $i = 1, ..., P$ are $(n \times n)$ matrices of parameters. P denotes the number of lags and ϵ_t is a $(n \times 1)$ vector of reduced form residuals with $\varepsilon_t \sim \mathcal{N}(0, \Omega)$ where Ω is the $(n \times n)$ variance-covariance matrix. Because of great parameter uncertainty, we use the Bayesian estimation method. The model is specified and estimated in level since the Bayesian estimation technique can be applied irrespective of non-stationarity in data (Sims et al., 1990).

Bayesian Estimation

We can write our model in (3) in seemingly unrelated regression (SUR) representation as follows:

$$Y = X\Pi + E \tag{9}$$

where $Y = [y_{p+1} \dots y_T]^{'}$, $\Pi = [C \ \Psi_1 \dots \Psi_P]^{'}$, $E = [\varepsilon_1 ... \varepsilon_T]^{'}$ and

$$X = \begin{bmatrix} 1 & y_0^{'} & \dots & y_{-P}^{'} \\ \vdots & \vdots & \vdots & \vdots \\ 1 & y_{T-1}^{'} & \dots & y_{T-P}^{'} \end{bmatrix}$$

By vectorizing (9), we obtain the following:

$$y = (\mathbb{I}_n \otimes X)\pi + \varepsilon \tag{10}$$

where $y = vec(Y)$, $\pi = vec(\Pi)$, $\varepsilon = vec(E)$ and $vec()$ denotes columwise vectorization. Given the normality assumption of the error term ε with a mean zero and variance-covariance $\Omega \otimes \mathbb{I}_{T-P}$, the likelihood function conditional on the parameters of the model π and Ω and the regressors X can be written as follows:

$$L(y|X, \pi, \Omega) \propto |\Omega \otimes \mathbb{I}_{T-P}|^{-\frac{T-P}{2}} \exp\left\{\frac{1}{2}(y - \mathbb{I}_n \otimes X\alpha)^{'}(\Omega \otimes \mathbb{I}_{T-P})^{-1}(y - \mathbb{I}_n \otimes X\pi)\right\} \tag{11}$$

where y denotes the available data. Denoting $\hat{\pi} = vec(\hat{\Pi})$ where $\hat{\Pi} = (X^{'}X)^{-1}X^{'}Y$ denotes the OLS estimate and letting $\Lambda = (Y - X\hat{\Pi})^{'}(Y - X\hat{\Pi})$ be the sum of squared errors, then the likelihood function in (11) can be rewritten as follows:

$$L(y|X, \pi, \Omega) \propto |\Omega \otimes \mathbb{I}_{T-P}|^{-\frac{T-P}{2}} \exp\left\{\frac{1}{2}(\pi - \hat{\pi})^{'}(\Omega^{-1} \otimes X^{'}X)(\pi - \hat{\pi})\right\} \exp\left\{-\frac{1}{2}tr(\Omega^{-1}\Lambda)\right\} \tag{12}$$

We then specify diffuse priors for π and Ω that are proportional to $|\Omega|^{-\frac{n+1}{2}}$ namely:

$$p(\Pi|\Omega) \propto 1$$
$$p(\Omega) \propto |\Omega|^{-\frac{n+1}{2}}$$

By combining our diffuse priors with the likelihood function using Bayes rule, we then obtain Normal-Inverse Wishart posterior:

$$L(\pi, \Omega|y, X) \propto L(y|X, \pi, \Omega)p(\Pi|\Omega)p(\Omega) \tag{13}$$
$$= |\Omega|^{-\frac{T-P+n+1}{2}} \exp\left\{\frac{1}{2}(\pi - \hat{\pi})^{'}(\Omega^{-1} \otimes X^{'}X)(\pi - \hat{\pi})\right\} \exp\left\{-\frac{1}{2}tr(\Omega^{-1}\Lambda)\right\} \tag{14}$$

The likelihood function in (14) is a product of a normal distribution for π given Ω and an inverse Wishart distribution for Ω. Thus, we draw π conditional on Ω from

$$\pi|\Omega, y, X \sim \mathcal{N}(\hat{\pi}, \Omega \otimes (X^{'}X)^{-1}$$

and Ω from

$$\Sigma|y, X \sim \mathcal{IW}(\Lambda, v)$$

where $v = T - P - (nP + 1) - n - 1$; $\mathcal{IW}$ denotes an inverse-Wishart distribution.

Sign Identification

In order to recover the impact of structural disturbances from our reduced-form residuals, we assume that the latter ϵ_t is a linear combination of structural disturbances η_t such that:

$$\epsilon_t = D\eta_t \tag{15}$$

where $\eta_t \sim \mathcal{N}(0, \mathbb{I}_{\ltimes})$ denotes the $(n \times n)$ variance-covariance (VCV) matrix of structural disturbances. The variance-covariance matrix in (15) is given by $\Omega = DD^{'}$. The Cholesky decomposition restricts D to be lower triangular, thereby implying a recursive identification. However, in the Cholesky decomposition, the VCV matrix admits that $\Omega = D\mathbb{I}_n D^{'}$ where $\mathbb{I}_n = QQ^{'}$ and Q denotes an orthonormal matrix. To identify shocks through sign restrictions, we must specify a set of admissible Q matrices (Caldara et al., 2016).

To implement this strategy, we follow the algorithm proposed by Rubio-Ramirez et al. (2010). This algorithm works as follows. First, we draw from a $\mathcal{MN}(0_N, \mathbb{I}_n)$ and perform a QR decomposition of D with the diagonal of R normalized to be positive, where $QQ^{'} = \mathbb{I}_n$. Second, we impose the Cholesky decomposition on D so that $\Omega = DD'$ where D denotes a Cholesky factor. We then compute candidate impulse responses from $DQ^{'}$ and Ψ_i for $i = 1, \ldots, P$ and check if the generated impulse responses satisfy the sign restrictions or not. If they satisfy the sign restrictions, store them, otherwise, discard them and return to the initial step. We repeat the same procedure until we obtain 500 impulse responses which satisfy our sign restrictions.

B Data sources

In this section, we discuss in detail our macroeconomic data. We transform the quarterly world uncertainty index (WUI) index data into annual terms by taking the annual averages of the latter. All data are expressed in logs except the WUI index. Our source is the world development indicators from the World Bank database.

- GDP: annual real gross domestic product(GDP).
- Investment: annual real gross fixed capital formation.
- Prices: annual consumer price index.
- The US uncertainty index (see section 5)

C Additional results

The appendix C presents additional empirical results.

Table 6: Median Foreign Error Variance Decomposition Using Two Lags

	Horizon	Uncertainty	Supply	Demand
Uncertainty	1	0.26	0.43	0.10
	5	0.24	0.43	0.13
	15	0.21	0.33	0.30
Investment	1	0.11	0.49	0.37
	5	0.17	0.26	0.56
	15	0.14	0.17	0.68
GDP	1	0.74	0.04	0.05
	5	0.26	0.15	0.49
	15	0.17	0.10	0.69
Prices	1	0.06	0.23	0.65
	5	0.13	0.31	0.47
	15	0.11	0.29	0.53

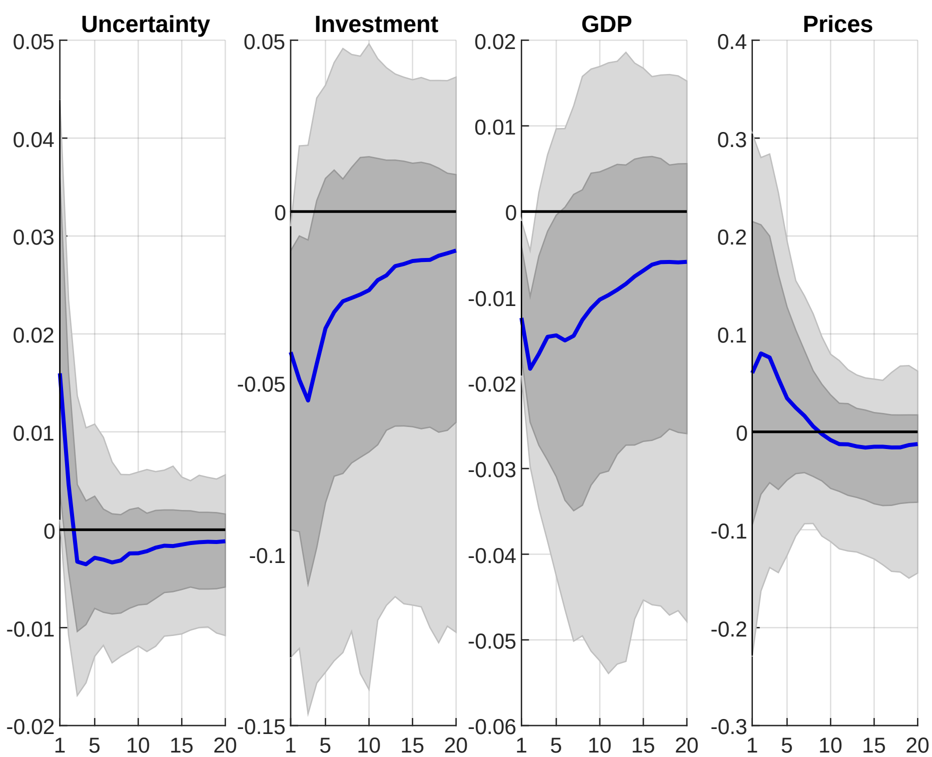

Figure 10: Impulse responses to the uncertainty shock using two lags. The blue line represents the median response at each horizon. The grey shaded area indicates the 68th confidence intervals while the light shaded area shows the 90th confidence intervals.

Table 7: Median Foreign Error Variance Decomposition-Trivariate I

	Horizon	Uncertainty	Supply	Demand
Uncertainty	1	0.85	0.02	0.13
	5	0.65	0.02	0.33
	15	0.50	0.17	0.33
GDP	1	0.54	0.35	0.11
	5	0.79	0.15	0.05
	15	0.88	0.09	0.04
Prices	1	0.49	0.40	0.12
	5	0.53	0.36	0.11
	15	0.58	0.32	0.11

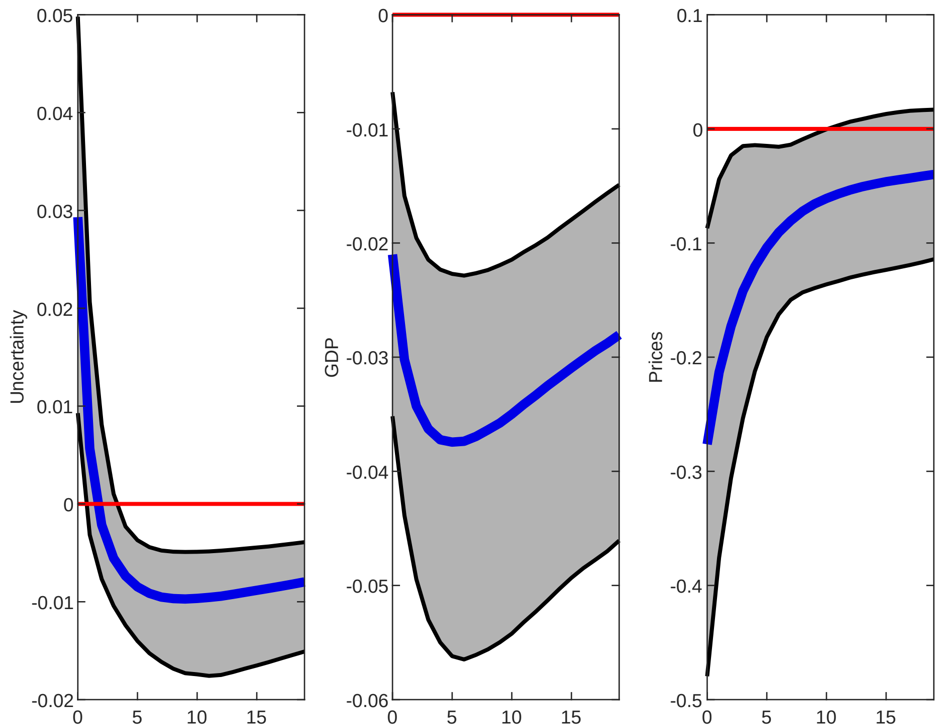

Figure 11: Impulse responses to the uncertainty shock. The blue line represents the median response at each horizon. The grey shaded area indicates the 68th confidence intervals.

Table 8: Median Foreign Error Variance Decomposition-Trivariate II

	Horizon	Uncertainty	Supply	Demand
Uncertainty	1	0.86	0.06	0.08
	5	0.68	0.03	0.30
	15	0.33	0.12	0.55
Investment	1	0.70	0.18	0.12
	5	0.76	0.13	0.10
	15	0.80	0.11	0.10
Prices	1	0.59	0.25	0.17
	5	0.62	0.19	0.19
	15	0.67	0.16	0.18

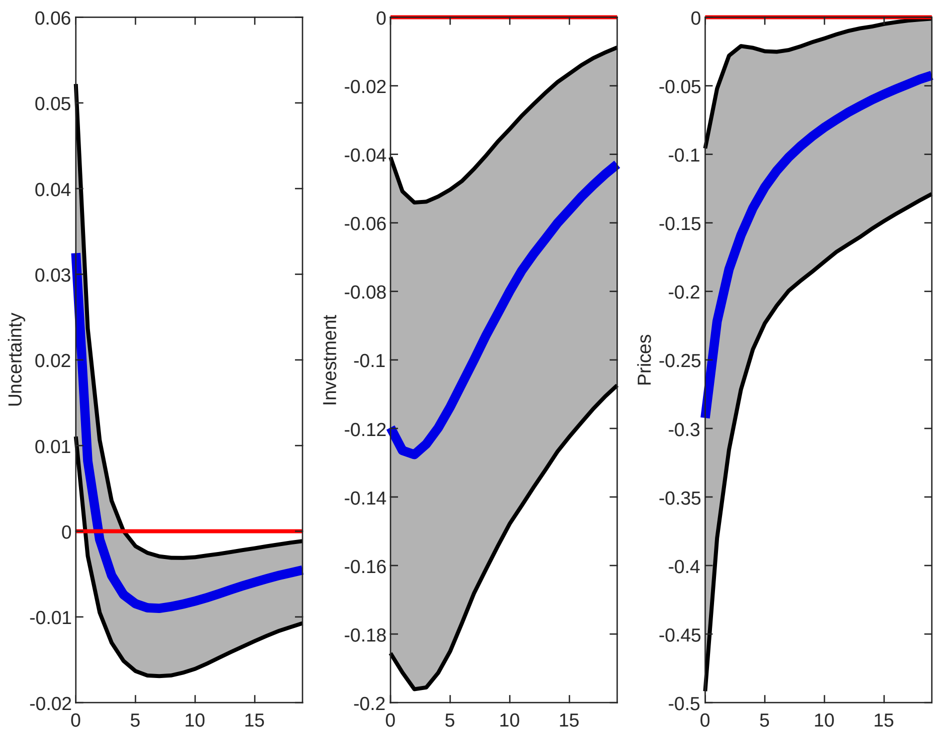

Figure 12: Impulse responses to the uncertainty shock. The blue line represents the median response at each horizon. The grey shaded area indicates the 68th confidence intervals.

Table 9: Median Foreign Error Variance Decomposition-Cholesky Identification

	Horizon	Uncertainty	Supply	Demand
Uncertainty	1	1	0.00	0.00
	5	0.95	0.02	0.00
	15	0.66	0.02	0.01
Investment	1	0.14	0.00	0.00
	5	0.19	0.00	0.01
	15	0.17	0.00	0.02
GDP	1	0.01	0.95	0.00
	5	0.13	0.19	0.01
	15	0.16	0.03	0.03
Prices	1	0.00	0.08	0.83
	5	0.00	0.09	0.68
	15	0.03	0.07	0.53

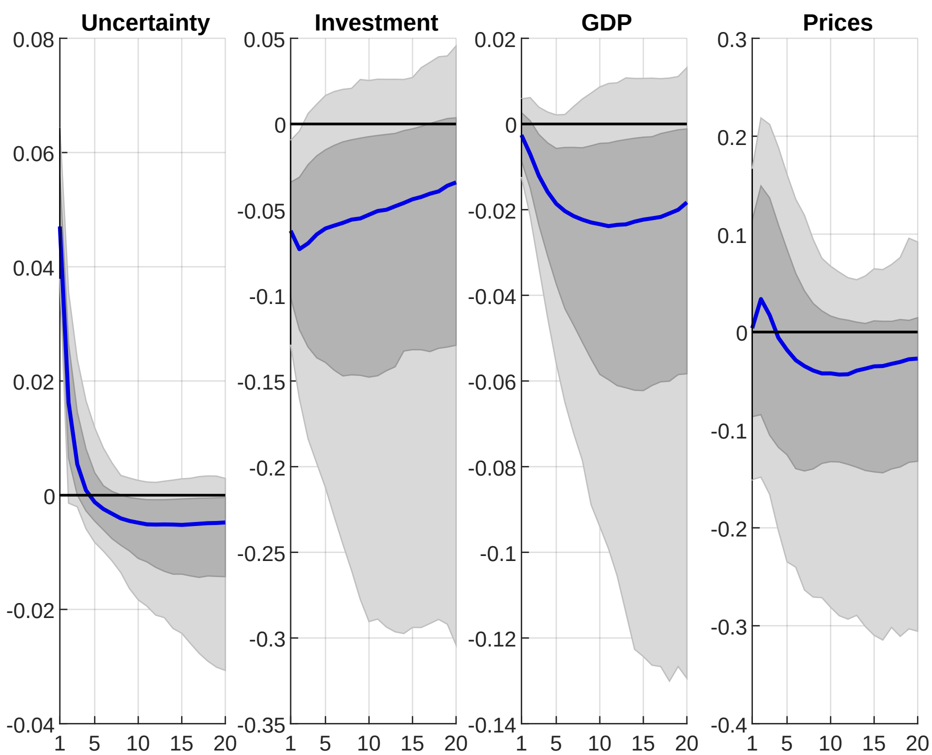

Figure 13: Impulse responses to the uncertainty shock using Cholesky identification. The blue line represents the median response at each horizon. The grey shaded area indicates the 68th confidence intervals while the light shaded area shows the 90th confidence intervals.