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Abstract

We propose a new instrument to identify uncertainty shocks in a SVAR model with external instruments. The instrument is constructed by exploiting variations in the price of gold around events that capture periods of changes in uncertainty. The variations in the price of gold around the events correlate with the underlying uncertainty shocks, due to the perception of gold as a safe haven asset. To control for possible news-related effects associated with the events, we identify uncertainty and news shocks jointly, developing a set-identified proxy SVAR with restrictions on the correlations between shocks and proxies. We find that the recursive approach, extensively used in the literature, underestimates the effects of uncertainty shocks and delivers shocks that have more in common with news shocks than with uncertainty shocks.

JEL-Codes: E320, C320, D810.

Keywords: economic uncertainty, external proxy SVAR, safe haven assets, news shocks, set-identification.

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1 Introduction

Economic uncertainty, broadly defined as the difficulty of economic agents to make accurate forecasts (Bloom, 2014, Jurado et al., 2015), is believed to have far reaching effects on the economy. The empirical literature studies the causal effect of uncertainty on the economy by employing Vector Autoregressive (VAR) models, and by using a recursive approach to identify uncertainty shocks (see, among others, Bloom, 2009, Baker et al., 2016, Scotti, 2013, Bachmann et al., 2013, Caggiano et al., 2014 and Jurado et al., 2015). However, the exclusion restrictions of recursive orderings are subject to criticism, because they do not fully address the simultaneity problem between uncertainty and the state of the economy (Baker and Bloom, 2013). In their investigation of the Great Recession, Stock and Watson (2012) highlight the challenge of isolating exogenous variations in uncertainty. Our paper attempts to fill this gap.

In this paper, we propose a new strategy to identify uncertainty shocks. We build on the proxy SVAR methodology developed by Stock and Watson (2012) and Mertens and Ravn (2013) to identify structural VARs using external instruments. The first contribution of our paper consists of proposing a new instrument for the uncertainty shock. We use events associated with variations in uncertainty, for example the 9/11 terrorist attack, the Iraqi invasion of Kuwait, and the fall of the Berlin Wall. We then define the instrument (or proxy) for the uncertainty shock as a vector taking value equal to the percentage variation in the price of gold around the event when an event occurred, and equal to zero otherwise. Since gold is perceived by market participants as a safe haven, unexpected variations in uncertainty are likely to affect the price of gold by affecting agents' decisions to buy or sell gold. By reflecting the agents' response to the underlying uncertainty shocks, the variations in the price of gold are correlated with such shocks, providing the basis for the proxy to work as an instrument.

As pointed out by Baker and Bloom (2013), one challenge faced in identifying uncertainty shocks consists of separating uncertainty shocks from news shocks. Baker and Bloom (2013) note that variations in uncertainty are also observed in combination with first-moment shocks that reflect news shocks about the future, rather than second-moment shocks. For example, a terrorist attack might generate higher uncertainty about future attacks, but could also be associated with the certain belief that the economy will be negatively affected by the event. By construction, the price of a safe haven asset should emphasise the uncertainty-related component of the events. To further reduce the possibility that the shocks identified as uncertainty shocks are correlated with news shocks, we do not impose that the proxy for the uncertainty shock is orthogonal to the news shock. Instead, we set-identify both the uncertainty shock and the news shock within a unified proxy SVAR framework. As a proxy for the news shock, we use the first principal component of an array of news shocks estimated in the literature. We then impose the identifying restrictions that the proxy for the uncertainty shock is more correlated with the uncertainty shock than with the news shocks, and that the proxy for the news shock is more correlated with the news shock than with the uncertainty shock.

This set-identification within a proxy SVAR model constitutes the second contribution of the paper, and extends to a multivariate setting the analysis of imperfect instruments developed by Nevo and Rosen (2012). By imposing rather agnostic restrictions on the correlation structure between the shocks and the proxies, the proposed setup does not impose zero restrictions in the impulse responses and achieves set-identification with a minimal set of assumptions. The approach explores the use of proxy SVAR models when the instruments for selected shocks of interest are also correlated with other structural shocks. In our application, it also offers a coherent and unified framework to compare uncertainty shocks and news shocks.

We find that, within the proxy SVAR, an uncertainty shock that increases uncertainty has a recessionary effect on the real economy within the month when the shock occurs, and is followed by a prolonged monetary expansion. In contrast, a recursively identified uncertainty shock features hump-shaped responses of the real economy and a statistically insignificant response from the monetary authority. Consistent with the literature, we find that the news shock generates hump-shaped responses and an insignificant response of monetary policy. Hence, the uncertainty shock identified with the recursive approach resembles more the dynamics of the news shock rather than the uncertainty shock. Forecast error variance and historical decompositions indicate that uncertainty shocks identified within the proxy SVAR have more pronounced effects on the business cycle than those identified within a standard recursive setup, and that news shocks have a relatively small role in driving the variables in the model.

The use of events to isolate exogenous variations in variables of interest has a long-standing tradition in the literature (see, for instance, Kuttner, 2001 and Gürkaynak et al., 2005). With regard to our application, this methodology permits us to build the identification of uncertainty shocks on high frequency data rather than on the monthly data used in the VAR, and allows for contemporaneous effects of both the uncertainty shock and the news shock on all variables.

There are other papers proposing identification approaches for uncertainty shocks differing from the recursive one. Alessandri and Mumtaz (2014) identify uncertainty shocks in a VAR as the exogenous variations to the variance-covariance matrix of the structural shocks. Caldara et al. (2016), instead, identify uncertainty and financial shocks as the ones that have the highest impact on the measure of uncertainty and on the financial variable in the VAR, respectively. On the contrary, Cesa-Bianchi et al. (2014) identify uncertainty shocks as the common stochastic component to the VIX index in several countries. A different approach is proposed by Ludvigson et al. (2015), who identify macroeconomic and financial uncertainty shocks using an iterative statistical approach on stock market data.

We are aware of two papers close to our paper. Baker and Bloom (2013) use dummy variables constructed on extreme events as instruments in a single equation model of GDP growth on uncertainty. In contrast, we use a VAR and explore the endogenous dynamic response of the economy. Carriero et al. (2015) also make use of a proxy SVAR setup for the identification of uncertainty shocks. As a proxy, they use a dummy variable taking value 1 when the VXO peaks, and then employ a Monte Carlo to study the effect of measurement errors on the estimation of impulse responses. We improve upon their paper by using a proxy variable that is not restricted to a dummy variable, as well as by jointly studying uncertainty and news shocks.

The remainder of the paper is structured as follows. The next section discusses the identification via external instruments in the proxy SVAR setup. Section 3 introduces the construction of the proxy for uncertainty shocks used to identify the VAR model. Section 4 discusses the identification approach of news shocks and uncertainty shocks. Section 5 discusses the model specification and the data. Section 6 reports the results. Finally, Section 7 concludes.

2 The proxy SVAR model

Before discussing how we construct the proxy for the uncertainty shock, we introduce the framework for the identification of structural VARs via external instruments and highlight the requirements that the instrument needs to satisfy. For this section we build on Stock and Watson (2012) and Mertens and Ravn (2013). A detailed discussion is available in Section D of the appendix.

Let the reduced form model be given by

$$\boldsymbol{y}_t = \boldsymbol{\delta} + A(L)\boldsymbol{y}_{t-1} + \boldsymbol{u}_t, \tag{1}$$

where $\boldsymbol{y}_t$ is a $k \times 1$ vector including the endogenous variables, $\boldsymbol{\delta}$ includes constant terms, and $A(L)$ is a lag matrix polynomial capturing the autoregressive component of the model. The reduced form shocks, captured by the $k \times 1$ vector $\boldsymbol{u}_t$, are assumed to be linearly related to the underlying structural shocks through the equation

$$\boldsymbol{u}_t = B\boldsymbol{\epsilon}_t, \tag{2}$$

where $\boldsymbol{\epsilon}_t$ is a $k \times 1$ vector of structural shocks, whose variance-covariance matrix is normalised to the identity matrix.

The aim of the paper is to identify the uncertainty shock out of the k structural shocks in $\boldsymbol{\epsilon}_t$. Let the scalar ϵ_t^u be the uncertainty shock at time t and let the $(k-1) \times 1$ vector $\boldsymbol{\epsilon}_t^*$ include the other structural shocks. Rewrite equation (2) as

$$\boldsymbol{u}_t = \boldsymbol{b}^u \epsilon_t^u + B^* \boldsymbol{\epsilon}_t^*, \tag{3}$$

where $\boldsymbol{b}^u$ is the impulse vector associated with the uncertainty shock and B^* gathers the impulse vectors of the remaining shocks. Identifying ϵ_t^u consists of estimating the column vector $\boldsymbol{b}^u$.

Call m_t the proxy for the uncertainty shock, and define the $k \times 1$ vector $\boldsymbol{\phi}$ as $\boldsymbol{\phi} = (\phi_u, \boldsymbol{\phi}^{*'})'$, with $\phi_u = E(\epsilon_t^u m_t)$ and $\boldsymbol{\phi}^* = E(\boldsymbol{\epsilon}_t^* m_t)$. If

$$E(\epsilon_t^u m_t) \equiv \phi_u \neq 0, \tag{4}$$

$$E(\boldsymbol{\epsilon}_t^* m_t) \equiv \boldsymbol{\phi}^* = \mathbf{0}, \tag{5}$$

then m_t can be used as an instrument to identify ϵ_t^u, because it allows for isolating variations in $\boldsymbol{u}_t$ that are driven by ϵ_t^u rather than by $\boldsymbol{\epsilon}_t^*$. On the contrary, if some elements of $\boldsymbol{\phi}^*$ differ from zero, or, put differently, if m_t correlates also with some of the structural shocks in $\boldsymbol{\epsilon}_t^*$, then the identification of ϵ_t^u requires further restrictions that prevent the estimated shock ϵ_t^u from being contaminated by the other structural shock(s) that m_t correlates with. Conditions (4) and (5) are referred to as the relevance and the exogeneity conditions, respectively.

The above discussion provides the basis for how we construct the proxy for the uncertainty shock in Section 3. We set up the proxy with two requirements in mind. First, the proxy should correlate with the uncertainty shock in order to ensure that the proxy is a relevant instrument. Second, the proxy should be exogenous to as many other structural shocks as possible – ideally to all other shocks – in order to ensure that the proxy is an exogenous instrument. Note that there is no need for the proxy to be free from any measurement error, to be symmetric around zero, or to cover the entire time length covered by the VAR model.

3 A proxy for the uncertainty shock

The construction of the proxy for the uncertainty shock is structured in two steps. First, we collect an array of events that potentially affected economic uncertainty in an unrelated way with respect to other macroeconomic shocks. Second, we use variations in the price of safe haven assets around the events in order to inform the proxy.

3.1 Collecting the events

To isolate periods in which uncertainty is likely to have changed exogenously with respect to the economy, we collect a vector of events that generated or reduced uncertainty, that were not anticipated, and that were exogenous with respect to other relevant macroeconomic shocks.

We start with the events already identified by Bloom (2009) through the peaks in the VXO.[1] We then extend the list using natural disaster databases and other publicly available data on armed conflicts, terrorist attacks, as well as political elections and judicial decisions. We exclude all the events that may have been anticipated by

[1] It may be noted that these peaks do not necessarily indicate an exogenous variation in uncertainty, but potentially an endogenous response to other macroeconomic shocks, or even uncertainty shocks that may have occurred earlier in the sample. Indeed, investigating the timing of the dummies, we found that the peaks of the VXO quite regularly occur with a few months delay after the events used by Bloom (2009) to interpret them. For example, the peak of the VXO in March 1980 is usually interpreted as the effect of the crisis related to the US hostages in Iran and to the Soviet invasion of Afghanistan, events that took place in November and December 1979, respectively; Black Monday occurred in October 1987, while the VXO peaked in November 1987; Iraq invaded Kuwait in August 1990, while the VXO peaked in October 1990; the Worldcom bankruptcy happened in July 1990, while the VXO peaked in September 1990. We use the peaks of the VXO only to identify underlying events, whose exact timing is then assessed separately.

economic agents and that are potentially related to other relevant macroeconomic shocks. The baseline specification of the analysis consists of 38 events.[2] In Section 6.6 we show that the results are not driven by this exact selection of events. Table E.2 in the appendix lists all 38 events, while the database available on-line lists the entire set of the events collected.[3]

To assess when the news about the events hit the market, we rely on news releases from the Bloomberg News agency. We do so because Bloomberg News is a main source of information for market participants. It aggregates information from several sources around the world and, hence, provides access to a broad set of information. We use other reliable sources whenever Bloomberg News could not be used, either because the News agency was not fully operational yet or because it is not clear which release was the relevant one.[4]

3.2 Computing the proxy

We depart from an array of candidate safe haven assets and select gold as the most favourable safe haven asset for the construction of the proxy. As discussed in Section B of the appendix, we do so for two reasons. First, because the proxy based on the price of gold Granger-causes several measures of uncertainty, suggesting a higher informational content of uncertainty dynamics. Second, because the proxy based on the price of gold is more correlated with the VXO residuals from the VAR model estimated in the paper, suggesting a stronger relation with the drivers of the data studied in the VAR model (we return to the second point in Section 6.1). We reach

[2]The use of 38 events for the identification of the VAR model estimated on about 400 monthly observations is consistent with the number of shocks per observations in the sample of Mertens and Ravn (2013), who use 13 to 16 events for 228 quarterly observations.

[3]The list is available on https://sites.google.com/site/michelepiffereconomics/home/research-1.

[4]For example, Bloomberg News agency releases do not cover the period when the Berlin Wall fell, November 9, 1989. Nevertheless, it is uncontroversial that the trigger of the event was the reply given by the GDR official Günter Schabowski at the press conference on that day, which was broadcast at 7:17 PM, Berlin time, following which East Germans rushed to the border crossing. As such, the news can be comfortably classified as having occurred before the markets opened the following day. Of the 38 events, 19 were based upon Bloomberg News, the remaining 19 using alternative sources.

these conclusions after comparing the proxy based on the price of gold with proxies based on other precious metals, on the price of Treasury bills, and on the VXO, as well as with proxies equal to dummy variables taking value 1 when events occurred, value 1 when the VXO peaked, or values 1 or -1 when the event was judged to imply an increase or a decrease in uncertainty, respectively. Additional anecdotal evidence favouring the use of gold was found in the media, which frequently comments on the response of the price of gold when discussing the unfolding of uncertainty after important events.[5]

We use intradaily data on the London spot market of physical gold, employing prices from the two daily auctions organized at 10:30 and 15:00 by the London Bullion Market.[6] We compute the proxy for the uncertainty shock as the percentage variation of the price of gold around the selected events. Given an event e_j, with $j = 1, ..., K$ and K the total number of events considered, call τ^j the time in which event e_j became known to the market. For each event we compute Δp^j as the percentage variation in the price of gold between the last available auction price before τ^j and the first available auction price after τ^j. We then aggregate these K realizations of Δp^j into a monthly time series, summing up the daily proxy within a month, following the aggregation in Romer and Romer (2004).[7]

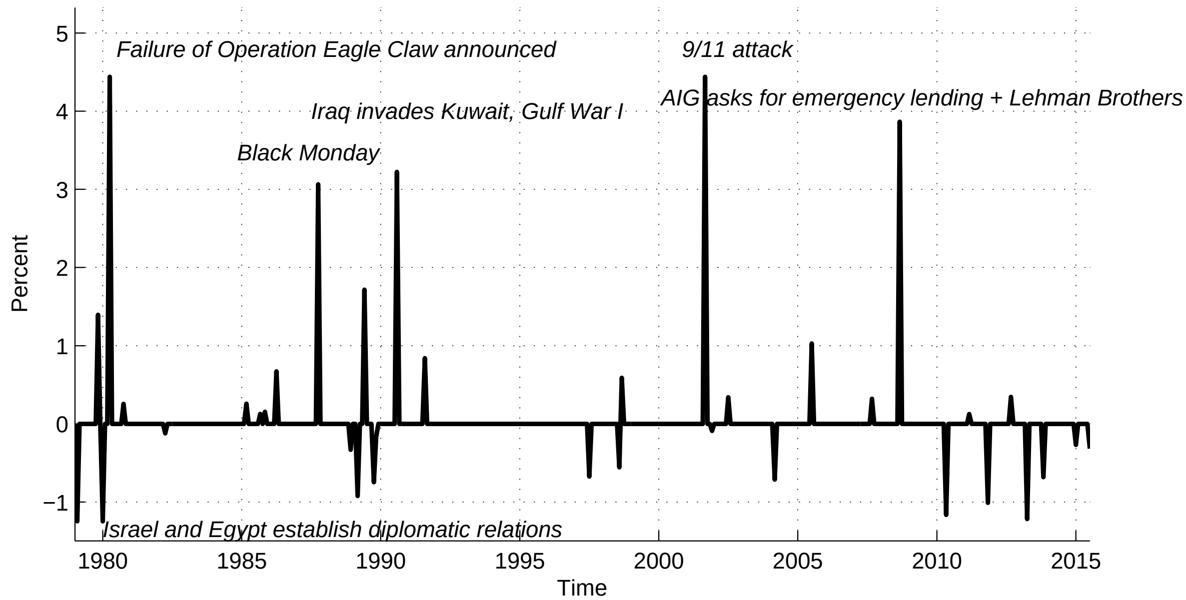
The final proxy for the uncertainty shock is shown in Figure 1. We will refer to this proxy as m_t^g, highlighting that it is based on gold. The realizations are well distributed among the sample. The peaks of the proxy tend to be predominantly positive and of higher magnitude when positive, a feature consistent with the literature on uncertainty

[5]For example, on November 16, 2015, the *Wall Street Journal* titled an article "Gold Prices Rise as Paris Attacks Spark Safe-Haven Demand", and CNBC titled "Safe haven assets gain after Paris attacks". Similarly, BBC News titled "Gold price climbs to new record on debt uncertainty", July 19, 2011. Along these lines, the *International Business Times* titled "Gold prices set to rise on financial markets uncertainty" on January 24, 2015, Bloomberg released a TV discussion titled "Gold driven by geopolitical, QE uncertainty", May 15, 2011, and the *Nikkei Asian Review* titled "As risks, uncertainty grow, so does reliance on gold", October 29, 2015.

[6]A discussion on the London Bullion Market is available in Section A of the appendix.

[7]To avoid having the results driven by outliers, the proxy is winsorised at the one percent level. However, this does not affect the results. Winsorisation eliminates outliers in the distribution by replacing values in the tails with those of the respective percentiles.

Figure 1: Proxy for the uncertainty shock based on the price of gold



shocks (Bloom, 2014). The peaks are intuitive with respect to the nature of the underlying event, as indicated by the labels in Figure 1. Figure E.2 in the appendix shows the histogram for the variations of the price of gold along the events, while Section C of the appendix discusses a number of illustrative events in greater detail in order to provide further intuition behind the proxy.

3.3 Exogeneity of the proxy

Since structural shocks are not observable, it is not possible to test directly whether the proxy for the uncertainty shock satisfies the relevance and exogeneity conditions from equations (4) and (5).[8] For this reason, we aim to establish such assessment indirectly. The relevance condition was partly discussed with regard to the constructed proxy, and we provide additional evidence for it in Section 6.1 and in Section B of the appendix. Instead, we investigate the exogeneity condition by documenting the relationship between our proxy and several measures of structural shocks available

[8]This is in contrast to the application of instrumental variable estimation in microeconometric univariate models, where the validity of the instruments can be tested as the relationship between the instrument and the endogenous regressor.

from the existing literature. In particular, we estimate the models

$$m_t^g = \gamma + \delta_j \cdot z_{jt} + \theta_{jt}, \tag{6}$$

where z_{jt} indicates a proxy for the structural shock j. Rejecting the null hypothesis of no correlation ($\delta_j = 0$) suggests that the proxy for the uncertainty shock correlates with the structural shock proxied by measure j.

As measures for z_{jt}, we first draw on the 15 external instruments used in Stock and Watson (2012) to identify oil, monetary policy, productivity, financial, and fiscal policy shocks.[9] We also add their proxies for uncertainty shocks, which they derive as the residual of a univariate autoregression with two lags on the VIX, and the common component of the different countries' policy uncertainty indexes from Baker and Bloom (2013). We use each shock at the original frequency available in the dataset provided by the authors, and aggregate our proxy m_t^g to such frequency when necessary. The results, reported in Table 1, indicate that our proxy for the uncertainty shock is not mistakenly picking up oil shocks, productivity shocks, financial shocks, or fiscal policy shocks. The monetary policy shock taken from Smets and Wouters (2007) and the financial shock from Bassett et al. (2014) are not far from being borderline cases. Reassuringly, a significant correlation is found with one of the two uncertainty shock instruments, namely the residual from an AR(2) regression on the VIX. In Section 6.2 we revisit the assessment of potential exogeneity towards these shocks using the estimated shocks rather than the proxies, and confirm the exogeneity of our proxy with respect to these shocks.

In addition to the shocks studied by Stock and Watson (2012), the macroeconomic literature evaluates news shocks as potential drivers of business cycles (Beaudry and Portier, 2014). Uncertainty and news shocks are potentially related, because several

[9]These variables are either constructed variables from observables, or estimated shocks from separate papers. See pages 108-110 of Stock and Watson, 2012 for a detailed description of each instrument.

Table 1: Assessing the exogeneity of the proxy for the uncertainty shock

A) Using the external instruments by Stock and Watson (2012)

Shock	Source	β	S.E.	P-value	Obs	Sample
Oil	Hamilton (2003)	0.106	0.119	0.37	393	1979M01 to 2011M09
	Kilian (2008)	-0.039	0.299	0.90	103	1979Q01 to 2004Q3
	Ramey and Vine (2010)	0.918	1.355	0.5	397	1979M01 to 2012M01
Monetary Policy	Romer and Romer (2004)	-3.810	2.822	0.18	216	1979M01 to 1996M12
	Smets and Wouters (2007)	0.232	0.144	0.11	104	1979Q1 to 2004Q4
	Sims and Zha (2006)	-0.052	0.040	0.2	291	1979M01 to 2003M03
	Gürkaynak et al. (2005)	0.049	0.050	0.332	60	1990Q1 to 2004Q4
Productivity	Basu et al. (2006)[10]	-0.103	0.113	0.36	132	1979Q1 to 2011Q4
	Smets and Wouters (2007)	0.268	0.191	0.16	104	1979Q1 to 2004Q4
Uncertainty	AR(2) resid. of VIX	0.302	0.165	0.07	394	1979M01 to 2011M10
	Baker et al. (2016)	0.016	0.012	0.18	325	1985M01 to 2012M01
Financial	Gilchrist and Zakrajšek (2012)	0.583	0.554	0.29	127	1979Q1 to 2010Q3
	TED spread	0.903	0.628	0.15	394	1979M01 to 2011M10
	Bassett et al. (2014)	0.597	0.392	0.13	76	1992Q1 to 2010Q4
Fiscal Policy	Ramey (2011)	5.638	20.207	0.78	128	1979Q1 to 2010Q4
	Fisher and Peters (2010)	0.400	4.362	0.93	120	1979Q1 to 2008Q4
	Romer and Romer (2010)	0.820	0.604	0.18	116	1979Q1 to 2007Q4

B) Using estimates of news shocks

Shock	Source	β	S.E.	P-value	Obs	Sample
News	Barsky and Sims (2011)	-0.181	0.379	0.63	115	1979Q1 to 2007Q3
	Beaudry and Portier (2014) (1)	-0.901	0.428	0.04	132	1979Q1 to 2011Q4
	Beaudry and Portier (2014) (2)	-0.942	0.364	0.01	132	1979Q1 to 2011Q4
	Beaudry and Portier (2014) (3)	-0.842	0.385	0.03	132	1979Q1 to 2011Q4
	Beaudry and Portier (2014) (4)	-0.673	0.389	0.08	132	1979Q1 to 2011Q4

Notes: The tests are run by regressing m_t^g on z_{jt} (see equation (6)), where m_t^g is the proxy for the uncertainty shock and z_{jt} is indicated in the rows of the table. Reported standard errors are white heteroscedasticity-consistent standard errors. If the instrument z_{jt} is available on quarterly frequency, then m_t^g is aggregated by averaging across months. The shocks estimated by Beaudry and Portier (2014) and used in the table refer to the trivariate VAR models including a measure of TFP and of the stock market index, and adding (1) consumption; (2) investment; (3) output; and (4) hours worked.

variations in uncertainty could also be associated with first-moment shocks of the type of news shocks (Baker and Bloom, 2013). The theoretical literature explores news shocks along several dimensions, for example news about future productivity shocks, future monetary shocks, future investments shocks, and others (see, for example, Schmitt-Grohé and Uribe, 2012). The empirical literature, however, focuses mainly on news about future productivity. We run the tests from model (6) on the news shocks on future productivity estimated by Barsky and Sims (2011), as well as on the shocks estimated by Beaudry and Portier (2014) using several model specifications. For simplicity, in Table 1 we report the results from the shocks estimated by Barsky and Sims (2011), and for the shocks estimated by Beaudry and Portier (2014) using the four trivariate VAR models from Section 3.3.2.1 of their paper.[11] Overall, while we find no statistically significant relationship with the news shocks estimated by Barsky and Sims (2011), we find some statistically significant relationship with the news shocks estimated by Beaudry and Portier (2014), indicating some correlation between the proxy for the uncertainty shock and the news shocks estimated in the literature.

The correlation between our proxy for the uncertainty shock and some estimates of the news shocks bears different interpretations. One possibility is that our proxy for the uncertainty shock also detects news shocks. An alternative possibility is that the identification strategy by Beaudry and Portier (2014) fails to fully disentangle news shocks from uncertainty shocks and, hence, reflects uncertainty shocks. To minimise the risk of contaminating uncertainty shocks with news shocks, we identify both uncertainty and news shocks in a unified framework, as is now discussed.

4 Set identification of the model

We refer to m_t^n as the proxy variable for the news shock, whose construction is described below. We build an approach that set-identifies the uncertainty shock and the news shock using m_t^g and m_t^n as proxies for such shocks, without restricting any proxy to correlate with only one shock. Specifically, we identify the uncertainty shock by imposing that the proxy for the uncertainty shock is more correlated with the uncer-

[11] Barsky and Sims (2011) identify the news shock as the shock that maximises the forecast error variance decomposition of TFP over a ten year horizon after the shock. Beaudry and Portier (2014) identify the news shock as the only shock other than the productivity shock that affects TFP in the long run, and disentangle the news shock from the productivity shock using the assumption that the latter is the only shock affecting all variables contemporaneously.

tainty shock than with the news shock, and identify the news shock by imposing that the proxy for the news shock is more correlated with the news shock than with the uncertainty shock. These identifying restrictions on correlations provide a minimal set of assumptions and flexibly identify the structural model without imposing any restriction on impulse responses.

More precisely, depart from the decomposition of the reduced form shocks from equation (3) into

$$\boldsymbol{u}_t = \boldsymbol{b}^u \epsilon_t^u + \boldsymbol{b}^n \epsilon_t^n + \tilde{B}^* \tilde{\boldsymbol{\epsilon}}_t^*, \tag{7}$$

where $\boldsymbol{b}^u$ represents the impulse vector to the uncertainty shock, $\boldsymbol{b}^n$ is the impulse vector to the news shock, and $\tilde{B}^*$ collects the impulse vectors of the remaining shocks. Define $\tilde{\boldsymbol{\epsilon}}_{\boldsymbol{tt}} = (\epsilon_t^u, \epsilon_t^n)'$, $\boldsymbol{m}_t = (m_t^g, m_t^n)'$ and $E(\tilde{\boldsymbol{\epsilon}}_t \boldsymbol{m}_t') = \Phi$, i.e.

$$\begin{pmatrix} E(\epsilon_t^u m_t^g) & E(\epsilon_t^u m_t^n) \\ E(\epsilon_t^n m_t^g) & E(\epsilon_t^n m_t^n) \end{pmatrix} = \begin{pmatrix} \phi_{11} & \phi_{12} \\ \phi_{21} & \phi_{22} \end{pmatrix}. \tag{8}$$

Assume that $E(\tilde{\boldsymbol{\epsilon}}_t^* m_t^g) = E(\tilde{\boldsymbol{\epsilon}}_t^* m_t^n) = \mathbf{0}$, implying that the two proxies are not detecting any other structural shock than the shocks of interest. Under the normalization of $E[(\epsilon_t^u)^2] = E[(\epsilon_t^n)^2] = 1$ and ensuring $E[(m_t^g)^2] = E[(m_t^g)^2] = 1$, Φ can be interpreted as the correlation structure between the shocks and the instruments. We set-identify ϵ_t^u and ϵ_t^n by imposing restrictions on Φ.

We adopt the sign convention that both an increase in the proxy for the uncertainty shock and a positive uncertainty shock imply an increase in uncertainty. Similarly, we adopt the sign convention that both an increase in the proxy for the news shock and a positive news shock imply the occurrence of unfavourable news. Building on these sign patterns, which are further discussed in Section D of the appendix, we use the following restrictions on Φ:

$$\phi_{11} > 0 \quad ; \quad \phi_{22} > 0, \tag{9a}$$

$$\phi_{11} - \phi_{21} > \psi \quad ; \quad \phi_{22} - \phi_{12} > \psi. \tag{9b}$$

Equation (9a) implies that each proxy is positively correlated with the shock that it aims to capture, while equation (9b) implies that each proxy is more correlated with the shock that it targets, rather than with the other shock. We provided evidence in support of restriction (9a) for the proxy for uncertainty shock, while we rely on the literature regarding the validity of the same restriction for the proxy for the news shock. For the restrictions in equation (9a) we impose that the correlation is statistically different from zero to ensure a sufficiently strong relationship between each instrument and the respective shock. For the restrictions in equation (9b), we set $\psi = 0.10$ in the baseline specification, and consider alternative values in the range from 0 to 0.20 to assess the robustness of the results.

The above set-identification, which is discussed in detail in Section D of the appendix, builds on the work by Mertens and Ravn (2013). Mertens and Ravn (2013) identify two structural shocks using two instruments correlated with both shocks, and then separate the two shocks with a recursive ordering of the correlation matrix Φ. We propose an alternative strategy that combines external instruments with set-identifying restrictions on correlations in a flexible and tractable way. The approach can be extended to alternative restrictions, for example restrictions on the sign and shape of the impulse responses. The set-identification proposed relates to Nevo and Rosen (2012), who identify univariate models using imperfect instruments, defined as instruments whose correlation with the error term is lower than the correlation with the error term of the endogenous regressor. We extend their analysis to VAR models by imposing restrictions on the correlation between the instruments and the structural shocks driving the model. Last, our approach relates to Ludvigson et al. (2015), who use two instruments to identify three shocks by restricting the size of the VAR model to three variables and using the covariance restrictions to identify the third shock.

We conclude this section by discussing the proxy used for the news shocks. In the baseline analysis we measure m_t^n as the first principal component computed over an array of productivity news shocks estimated in the literature, reflecting both the identification approach by Beaudry and Portier (2014) and the identification approach by Barsky and Sims (2011).[12] This first component explains about 60 percent of the total variance. We use the estimated productivity news shocks because productivity is an important driver of the future state of the economy, and hence news about the economy is correlated with news about future productivity. The instrument is available only at quarterly frequency due to the frequency of the data on total factor productivity. As discussed in Section D of the appendix, the identification that we use allows accommodating different frequencies for the proxies, while still estimating monthly shocks for both uncertainty shocks and news shocks.[13]

5 Data, model specification and inference

To facilitate comparison with the recursive identification used in Bloom (2009), we use a specification of the VAR model very similar to his one. We consider a vector of eight endogenous variables that enter the VAR model in the following order:

[12]The identification strategies by Barsky and Sims (2011) and Beaudry and Portier (2014) is outlined in footnote 11. For the approach by Beaudry and Portier (2014), we use the shocks estimated by the authors in Sections 3.3.2.1 and 3.3.2.2 from five trivariate and five quadrivariate VAR models. For the approach by Barsky and Sims (2011) we use the original estimates from the authors as well as the three specifications provided by Beaudry and Portier (2014) in Section 3.3.2.4 using the identification approach by Barsky and Sims (2011). Overall, this implies that the principal component is computed on 14 series of estimated shocks. Section 6.6 shows that the results are robust to alternative specifications of the proxy for the news shock.

[13]For consistency, we apply the same winsorization used for the proxy for the uncertainty shock to the proxy for the news shock, see footnote 7.

$$\boldsymbol{y}_t = \begin{pmatrix} \Delta log(\text{S\&P } 500_t) \\ \text{VXO}_t \\ \text{federal funds rate}_t \\ \Delta log(\text{wages}_t) \\ \Delta log(\text{CPI}_t) \\ \text{hours}_t \\ \Delta log(\text{employment}_t) \\ \Delta log(\text{industrial production}_t) \end{pmatrix}.$$

In the baseline specification, variables either enter in levels or in log differences in order to ensure the stationarity of the system. Based on information criteria, we estimate a reduced form VAR with five lags, considering alternative lag lengths in the robustness section. The sample spans from 1962M8 to 2015M6. The data included in the VAR model is plotted in Figure E.3 in the appendix.

Our specification of the model deviates from Bloom (2009) in three ways. Firstly, we update the sample up to 2015M6 in order to include more recent uncertainty related events in our database. Secondly, we let the variables enter in log differences rather than in deviations from HP trends (Hodrick and Prescott, 1997), since such a detrending might distort the dynamics in the underlying time series.[14] Thirdly, we use the entire dynamics of the VXO as a measure of uncertainty instead of a dummy series that takes the value of unity in correspondence to the peaks of the series. For robustness, we also consider the same model specification from Bloom (2009), as well as a specification in levels.

The reduced form model is estimated equation by equation using Ordinary Least Squares. To compute confidence intervals that account for both estimation and identification uncertainty, we build on Mertens and Ravn (2013) and Gertler and Karadi (2014) in using the wild bootstrap developed by Gonçalves and Kilian (2004), and ex-

[14] See King and Rebelo (1993), Harvey and Jaeger (1993), Guay and St-Amant (2005) and Meyer and Winker (2005) for a discussion of potential distortionary effects induced by using of HP filtered data.

tend the bootstrap to account for set-identification. The wild bootstrap resamples the data by changing the sign of the estimated vectors of reduced form shocks at randomly-selected periods, and by changing the sign of the instruments in correspondence to the same periods. For each draw of pseudo data, we identify the model as discussed in Section 4 and in Section D of the appendix, drawing a single orthogonal matrix Q. We keep the draw if the estimates of the reduced form model from the pseudo data and the orthogonal matrix imply that the restrictions are satisfied, otherwise we repeat the draw of both the pseudo data and the orthogonal matrix.[15]

For the results shown in the rest of the paper, we repeat the bootstrap procedure until 1000 draws are generated satisfying the identifying restrictions. We then compute the median target model by Fry and Pagan (2011), targeting the median impulse responses to both the uncertainty shock and the news shock from the proxy SVAR, jointly. We also report 90 percent confidence bands on the 1000 models generated, given that the median target model is probabilistically not more valid than other draws. Whenever we discuss the recursive identification we refer to the recursive identification applied to each bootstrapped data. This procedure makes the results from the proxy SVAR and from the recursive identification more comparable, because they refer to the same reduced form estimates within each bootstrapped draw.

6 Results

This section discusses the results of the analysis across five dimensions: tests on the strength of the proxies, estimated shocks, impulse responses, forecast error variance decompositions, and historical decomposition.

[15] For the bootstrap of pseudo data, Brüggemann et al. (2016) propose using a residual block bootstrap, arguing that the fourth moments are not properly bootstrapped in a wild bootstrapping approach. Given that the distortions for the point wise confidence bands are minor, we follow the literature and deploy a wild bootstrapping to obtain confidence bands.

6.1 Tests on the strength of the instruments

Following Gertler and Karadi (2014), we first test the strength of the instruments. m_t^g and m_t^n are strong instruments with regard to the application of the paper if they sufficiently correlate with the estimated reduced form shocks $\boldsymbol{u}_t$ from equation (1). This requirement follows from the fact that, given equation (2), the absence of a relation between the instruments and the VAR residuals indicates the possible absence of a relation between the instruments and the underlying structural shocks driving the VAR model. Formally, call $\hat{u}_{i,t}$ the estimated reduced form shock in equation i at time t and call m_t either m_t^g or m_t^n. We run the regressions

$$\hat{u}_{it} = \alpha + \beta_i \cdot m_t + \eta_{it} \quad , \quad i = 1, 2, ..., k. \tag{10}$$

for each of the eight equations of the model and for each proxy variable used.[16]

Table 2 reports the results of the tests. Consider first the proxy for the uncertainty shock. The VXO is the only measure positively related to the proxy for the uncertainty shock in a statistically significant way. This correlation suggests that uncertainty, as measured by the VXO, tends to increase when the price of gold increases, confirming the intuition behind the proxy constructed in Section 3. The F statistic on the null hypothesis $\beta_i = 0$ is above 10 for the residual on the VXO equation, and is much higher for the residual in this equation than for the residual in the equation of the stock market index. This further suggests that the proxy is picking up uncertainty shocks rather than financial shocks or news shocks, as the latter are argued to have a strong impact on financial variables (Caldara et al., 2016, Beaudry and Portier, 2014). As expected, the residuals from the equations of the stock market index, hours worked, employment and industrial production are negatively related to the proxy in a

[16]For comparability to Gertler and Karadi (2014) we assess the hypothesis $\beta_i = 0$ using an F test rather than a t test. The univariate nature of the test implies that the results of the test are identical to the ones obtained from a t test. We follow the literature and consider a threshold value for the F statistic of 10 as a value below which statistical significance is considered weak (Stock and Yogo, 2005).

Table 2: Tests on the strength of the instruments

Proxy for uncertainty shocks

	S&P 500 (log dif.)	VXO (level)	Fed funds rate (level)	Wage (log dif.)	CPI (log dif.)	Hours (levels)	Employment (log dif.)	Industrial production (log dif.)
β	-0.80^{**}	166.4012^{***}	-5.582	-0.026	0.020	-4.133^{*}	-0.066^{***}	-0.182^{***}
T	438	438	438	438	438	438	438	438
F	4.336	19.380	1.324	1.076	0.779	3.654	9.224	8.035
R^2	0.0098	0.042	0.003	0.002	0.002	0.008	0.020	0.018

Proxy for news shocks

	S&P 500 (log dif.)	VXO (level)	Fed funds rate (level)	Wage (log dif.)	CPI (log dif.)	Hours (levels)	Employment (log dif.)	Industrial production (log dif.)
β	-0.0050^{***}	0.2969^{***}	0.0045	0.000	0.0001^{***}	-0.0052^{**}	-0.0000^{*}	0.000
T	179	179	179	179	179	179	179	179
F	140.938	48.1266	0.3821	0.4361	14.468	4.0476	3.3607	0.0580
R^2	0.443	0.213	0.002	0.002	0.075	0.022	0.018	0.003

Notes: The models estimated are $\hat{u}_{i,t} = \alpha + \beta_i m_t + \eta_{i,t}$ with $\hat{u}_{i,t}$ the residual in the equation of the VAR corresponding to the variable indicated in each column of the table and m_t the proxy variable for either the uncertainty shock or the news shock. The null hypothesis refers to $\beta_i = 0$. The statistical significance of $\hat{\beta}_i$ indicated in the table is constructed using the asymptotic distribution of the OLS estimator. For the proxy for the news shock we run the regressions on a quarterly frequency due to the frequency of the instrument.

statistically significant way, while the residuals from the equations of the federal funds rate, wages and the consumer prices are unrelated to the proxy.

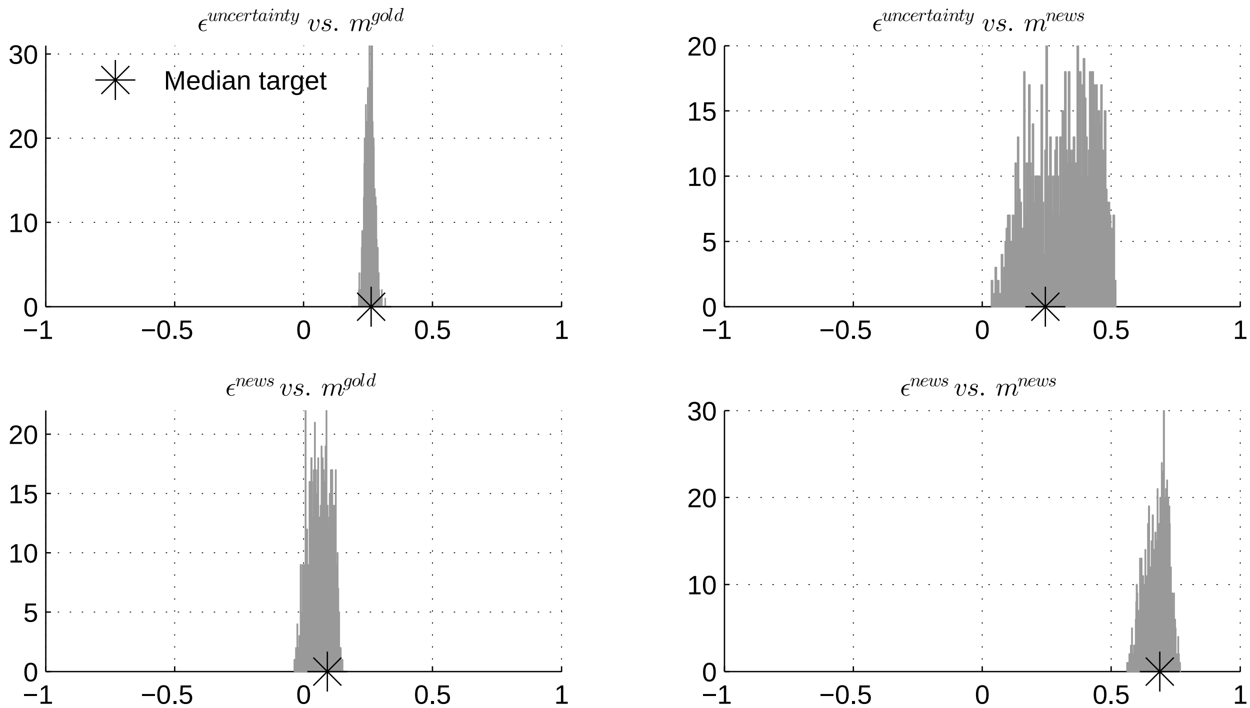
Consider now the proxy for the news shock. The residual on the stock market index has a strong and negative correlation with the proxy for the news shock, delivering an F statistic as high as 140. This finding indicates that unfavourable news, as captured by an increase in the proxy for the news shock, is associated with decreases in the S&P500. While we find that increases in the proxy for the news shock are also associated with increases in the residuals in the VXO, the F statistic corresponding to the latter equation equals less than one third of the F statistic related to the residual of the stock market index. This further suggests that the proxy for the news shock is predominantly capturing news shocks. In line with the findings in Barsky and Sims (2011) the proxy associates unfavourable news with increases in inflation. Consistent with what might be expected for an unfavourable news shock, the residuals from the equations of hours worked and employment are negatively related to the proxy in a statistically significant way, while the residuals from the equations of the remaining variables are unrelated to the proxy.

6.2 Estimated shocks

As discussed in Section 4, the identification of the uncertainty shock and of the news shock mainly relies on two restrictions: that the proxy for the uncertainty shock is more correlated with the uncertainty shock than with the news shock, and that the proxy for the news shock is more correlated with the news shock than with the uncertainty shock. We generate 1000 candidate draws which set-identify the model under these restrictions. The correlation structure Φ from equation (8) based on the 1000 draws and implicit in the restricted structural models is shown in Figure 2. The plots on the diagonal of the figure show the distribution of the estimated correlations between each proxy and the shock that it is supposed to proxy for. The off-diagonal plots, instead, show the distribution of the estimated correlations between each proxy and the shock that it is potentially contaminated by. The diagonal plots show a distribution that is positive and significantly far from zero, reflecting the restriction imposed by equation (9a). In accordance with the restriction from equation (9b), for each draw the difference between the correlation in the diagonal plots and the correlation in the off-diagonal plot from the same column of the figure is never below ψ, with $\psi = 0.10$ in the baseline specification.

Figure 3 plots the estimated shocks. The top panel plots the estimated shocks corresponding to the median target specification and the pointwise 90% confidence band, and overlaps them with the proxy for the uncertainty shock. The proxy and the estimated shocks share several peaks including, most notably, Black Monday, the 9/11 attack, and the collapse of Lehman Brothers. This holds not only for the median target model but for the entire set. The estimated uncertainty shocks also detect a number

Figure 2: Correlation structure between proxies and shocks

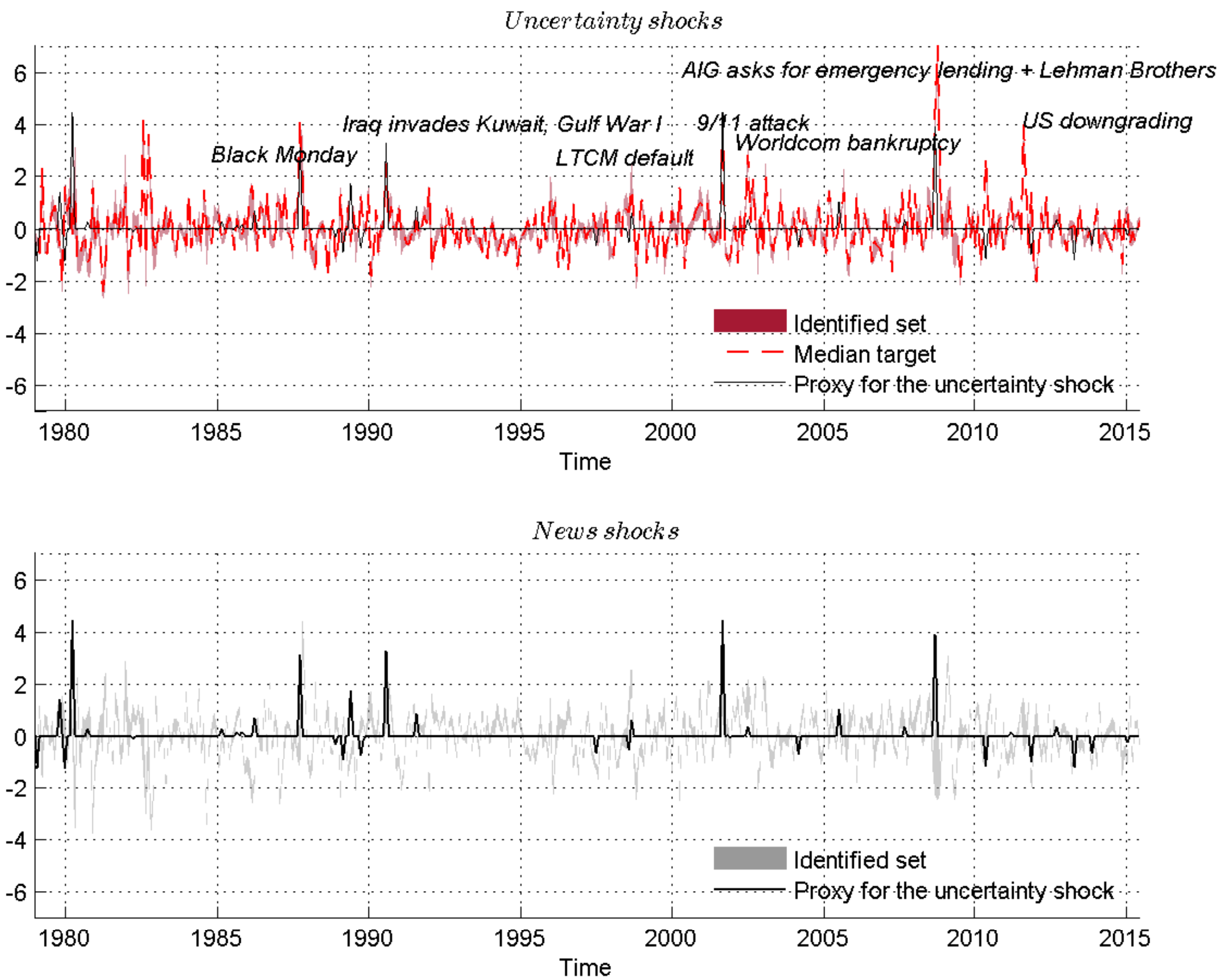


of events that were not incorporated in the construction of the proxy variable, such as the downgrading of the credit rating of the US federal government that occurred on August 5, 2011.[17]

The lower panel of Figure 3 shows the band of the estimated news shocks. To improve readability, we plot neither the estimated news shocks from the median target model nor the proxy for the news shock, but overlap the figure with the proxy for the uncertainty shock. This allows studying which of the events used for the construction of the proxy for the uncertainty shock were also associated with a strong news shock. We see that the 9/11 terrorist attack and the invasion of Kuwait by Iraq were associated with both an unfavourable news shock and an exogenous increase in uncertainty, of the size greater than two standard deviations. On the contrary, we find that Black Monday

[17]We did not include this event in the proxy variable, because within the same window (which extends from Friday to Monday) the European Central Bank reactivated the Securities Markets Programme, and we could not control for this monetary event. Nevertheless, the estimated uncertainty shocks attribute a strongly positive peak to that period.

Figure 3: Estimated shocks and proxy of the uncertainty shock



Note: Positive values of the uncertainty shock (and of the proxy for the uncertainty shock) are associated with increases in uncertainty. Positive values of the news shock (and of the proxy for the news shock) are associated with unfavourable news.

was associated with an exogenous increase in uncertainty, but with no significant news shock within the same month. An unfavourable news shock, instead, hit the economy within the following month.

We complement the assessment of the exogeneity of the proxy from Table 1 in Section 3 by replicating Table 7 from Stock and Watson (2012) and studying the correlations between their estimated shocks and the shocks estimated in our paper. Table 3 reports the average absolute correlation between the different groups of shocks,

Table 3: Average absolute correlation among groups of estimated shocks

	This paper		Stock and Watson (2012)					
	Uncertainty	*News*	*Oil*	*Monet.*	*Prod.*	*Uncert.*	*Financ.*	*Fiscal*
Uncertainty	1.00							
News	0.05 *(.01/.12)*	1.00						
Oil	0.21 *(.11/.24)*	0.08 *(.05/.15)*	0.45					
Money	0.24 *(.17/.32)*	0.10 *(.06/.19)*	0.28	0.37				
Productivity	0.11 *(.06/.17)*	0.10 *(.06/.16)*	0.51	0.31	0.67			
Uncertainty	0.42 *(.32/.55)*	0.44 *(.24/.47)*	0.36	0.35	0.22	0.78		
Financial	0.38 *(.28/.51)*	0.42 *(.24/.45)*	0.24	0.34	0.16	0.73	0.66	
Fiscal	0.22 *(.16/.32)*	0.14 *(.07/.22)*	0.20	0.51	0.24	0.12	0.21	0.59

Notes: The table is a summary of Table E.3 in the appendix. Table E.3 in the appendix shows the correlations among each of the shocks estimated in Stock and Watson (2012) and the shocks estimated in our paper. The table here, instead, summarises the individual correlations in Table E.3 by averaging the absolute values of correlations among the different groups of shocks. Since the factor model by Stock and Watson (2012) estimates shocks at a quarterly frequency, we first aggregate to this frequency the uncertainty and news shocks estimated in our paper.

while Table E.3 in the appendix reports the correlations among the individual shocks underlying Table 3. The correlation between the oil shocks estimated by Stock and Watson (2012) and our uncertainty and news shocks equals, on average, 0.21 and 0.08, respectively. These correlations are always equal to or smaller than the average correlation between the oil shocks and all the other shocks estimated by Stock and Watson (2012). The same holds for monetary shocks, productivity shocks, and, in part, fiscal shocks. The uncertainty and news shocks estimated in the proxy SVAR are instead relatively correlated with the uncertainty and the financial shocks estimated by Stock and Watson (2012). Stock and Watson (2012) discuss the close relation between financial and uncertainty shocks, arguing, for example, that the TED spread (used by the authors as a proxy for the financial shock) and the AR(2) residual of the VIX (used by the authors as a proxy for the uncertainty shock) do not identify a specific shock and, hence, may pick up similar dynamics (see page 116 in their paper). We find that their estimated uncertainty and financial shocks reflect both uncertainty shocks and news shocks.

6.3 Impulse Responses

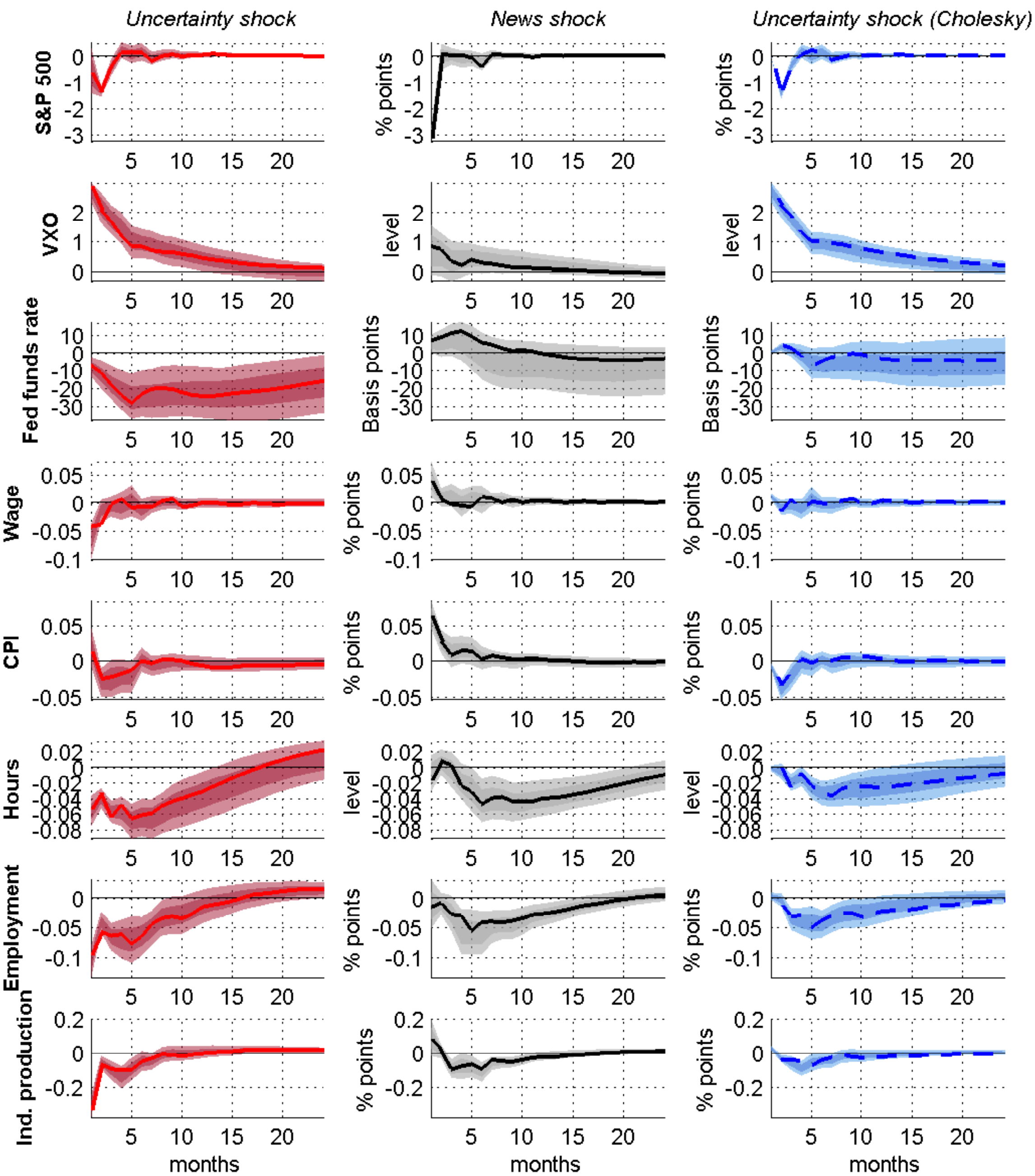
We now discuss the response of the variables in the model to an uncertainty shock and to a news shock identified in the proxy SVAR. To facilitate comparison with the literature, we also report the response to an uncertainty shock identified with the recursive identification. The impulse responses are shown in Figure 4 and refer to one standard deviation shocks.[18]

An uncertainty shock identified within the proxy SVAR affects financial markets, monetary policy, and the real economy, while it has a rather limited effect on nominal variables. The real economy reacts on impact with a drop in industrial production as well as a reduction in employment and hours worked. The stock market index, the monetary policy rate and consumer prices follow with a significant reduction in the period after the shock hit. While the recovery of the financial markets is rather rapid, it takes the real economy about four quarters to return to pre-shock levels. This recovery is supported by a loose monetary policy.

Unlike the uncertainty shock, an unfavourable news shock causes a sharp but short-lived decline in the stock market index, indicating a fast pricing of the news. However, it causes no impact effect on the real economy, which responds with a hump-shaped contraction, peaking after about half a year. The news shock has a significantly stronger impact effect on the stock market index than on the VXO, while the uncertainty shock affects more the VXO than the stock market index. The responses of the nominal variables, wages and consumer prices indicate upward pressure, in line with the empirical findings in Barsky and Sims (2011), but do not adjust strongly to the negative news shock, in line with the presumption of rigidity of those variables.

[18]Within the proxy SVAR, the impulse responses are computed after generating a shock of one standard deviation, which equals unity under the normalization used. The response under the recursive identification, instead, is computed by applying the recursive identification to each of the bootstrapped draws, and giving a shock such that the VXO increases on impact by just as much as in the case of the proxy SVAR in each draw. The point estimate reported is the one corresponding to the recursive identification of the median target specification. The results are quite similar when also studying a one standard deviation shock under the recursive identification, as shown in Figure E.10 in the appendix.

Figure 4: Impulse responses



Note: impulse response of the median target model, together with the pointwise 95% and 68% bands summarising the 1000 bootstrap replications generated. The impulse responses are non-cumulative responses and represent the responses of the variables as they enter the model.

Monetary policy does not react to the news shock.

We compare the above results with the response to the uncertainty shock identified using the popular recursive identification. Having ordered the VXO as the second variable, the response to an uncertainty shock under the recursive setting is constrained to zero on impact for the stock market index, and is unrestricted for the remaining variables. Relative to the uncertainty shock from the proxy SVAR, the uncertainty shock from the recursive approach generates very different dynamics. Firstly, employment, industrial production and hours worked respond on impact to the uncertainty shock identified in the proxy SVAR, while not in the recursive model. Secondly, monetary policy responds with a stronger decrease of the federal funds rate in the proxy SVAR, reflecting the response to a more pronounced depression of the real economy as compared to the recursively identified model. Finally, the reduction of employment and hours worked is accompanied by an adjustment in wages, whereas wages do not respond in the recursively identified setup. Overall, the response to an uncertainty shock identified with the recursive approach resembles more the dynamics of the responses attributed by the proxy SVAR to a news shock rather than to an uncertainty shock. This can be seen in the pronounced hump-shaped response of several variables to a news shock and to an uncertainty shock identified recursively, as well as in the muted response of the policy rate.

6.4 Forecast error variance decomposition

Table 4 reports the forecast error variance decomposition of the uncertainty shock and of the news shock. The uncertainty shock from the proxy SVAR explains around 50% of the forecast error variance of the VXO and only about 10% of the forecast error variance of the stock market index. The situation reverts for the news shock, which explains up to 77% of the forecast error variance of the stock market index after one month, and around 12% of the forecast error variance of the VXO along the horizons considered. This result is consistent with the impulse response analysis,

Table 4: Forecast Error Variance Decomposition

h	S&P 500 (log dif.)	VXO (level)	Fed funds (rate level)	Wage (log dif.)	CPI (log dif.)	Hours (levels)	Employment (log dif.)	Industrial production (log dif.)
				Uncertainty shock				
1	0.00	0.58	0.02	0.07	0.00	0.07	0.10	0.20
	.00/.14	*.40/.67*	*.00/.10*	*.02/.12*	*.00/.04*	*.04/.14*	*.08/.22*	*.14/.34*
6	0.12	0.54	0.13	0.06	0.02	0.20	0.18	0.20
	.09/.21	*.36/.67*	*.02/.24*	*.02/.11*	*.02/.11*	*.13/.32*	*.13/.33*	*.16/.32*
12	0.12	0.50	0.23	0.06	0.02	0.24	0.20	0.20
	.09/.21	*.31/.65*	*.03/.32*	*.02/.11*	*.02/.11*	*.12/.38*	*.11/.34*	*.15/.31*
24	0.12	0.47	0.28	0.06	0.03	0.19	0.19	0.19
	.09/.21	*.27/.62*	*.02/.38*	*.02/.11*	*.02/.12*	*.09/.32*	*.11/.32*	*.15/.31*
				News shock				
1	0.77	0.12	0.01	0.01	0.09	0.01	0.00	0.01
	.57/.78	*.00/.19*	*.00/.06*	*.00/.07*	*.04/.16*	*.00/.02*	*.00/.03*	*.00/.11*
6	0.56	0.12	0.01	0.02	0.08	0.04	0.07	0.08
	.41/.57	*.00/.21*	*.00/.07*	*.01/.07*	*.04/.13*	*.01/.10*	*.02/.18*	*.04/.13*
12	0.55	0.12	0.02	0.02	0.08	0.09	0.11	0.08
	.40/.56	*.00/.23*	*.00/.06*	*.01/.07*	*.04/.13*	*.03/.22*	*.04/.24*	*.05/.15*
24	0.54	0.12	0.03	0.02	0.08	0.09	0.11	0.08
	.40/.56	*.01/.22*	*.00/.11*	*.01/.06*	*.04/.12*	*.03/.23*	*.04/.24*	*.05/.15*
				Uncertainty shocks (Cholesky)				
1	0.00	0.90	0.00	0.00	0.00	0.00	0.00	0.00
6	0.20	0.90	0.01	0.01	0.06	0.04	0.07	0.05
12	0.20	0.87	0.02	0.01	0.06	0.06	0.09	0.05
24	0.20	0.83	0.03	0.01	0.05	0.05	0.09	0.05

Notes: the table shows the forecast error variance decompositions at horizons 1, 6, 12 and 24 months. The top and middle panels report the decomposition of the uncertainty shock and of the news shock, respectively, indicating the value corresponding to the median target specification and to the pointwise 90% bands, based on 1000 bootstrap replications. The lower panel shows, for the uncertainty shock, the decomposition corresponding to the recursive identification of the median target specification.

which documents both a stronger effect of an uncertainty shock on the VXO and a stronger effect of the news shock on the stock market index. Both uncertainty and news shocks from the proxy SVAR explain very little of the forecast error variance of nominal variables, while real variables are affected more by the uncertainty shock than by the news shock.

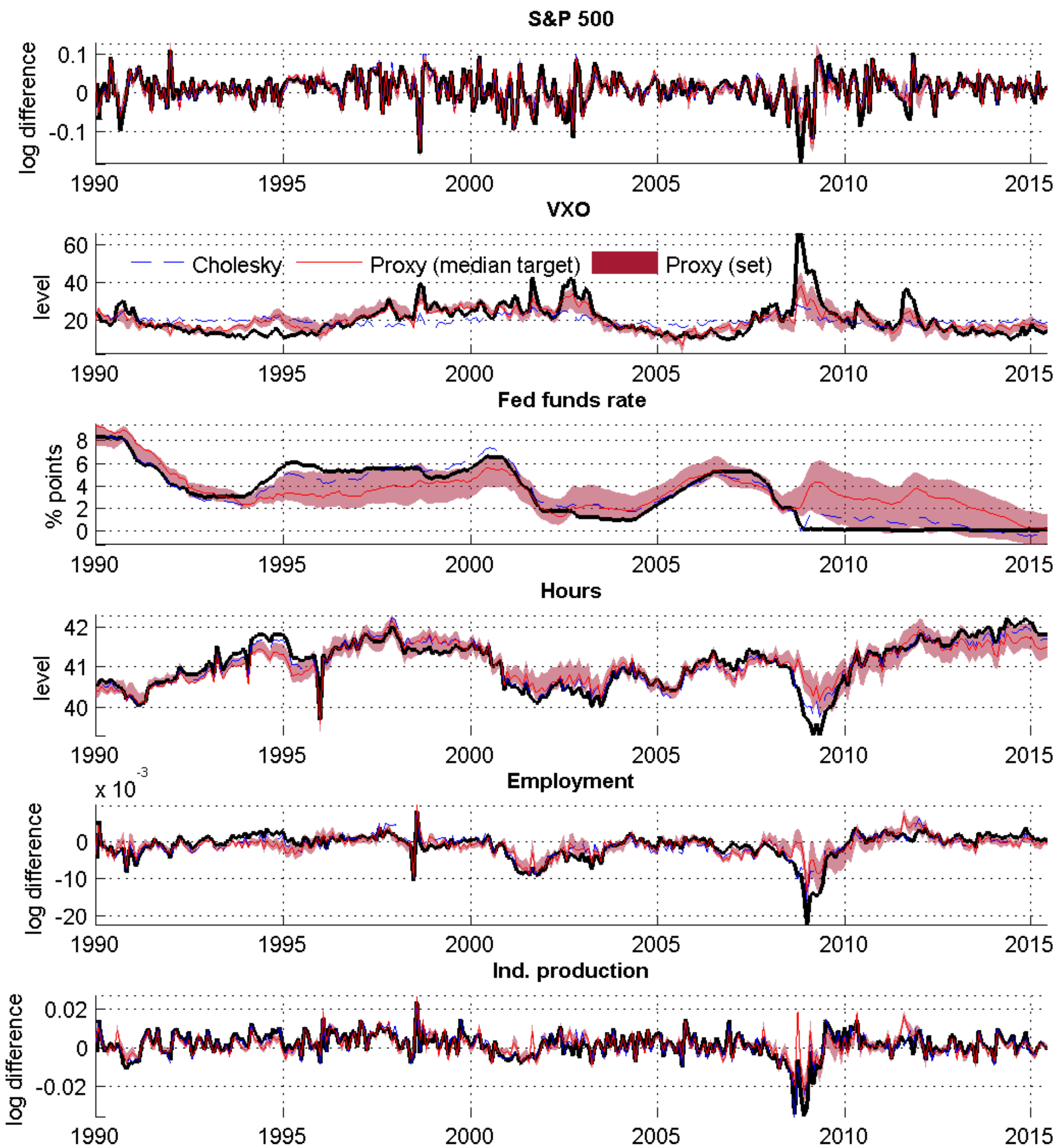
When comparing the above results with the results from the recursive approach, we find that under the recursive identification the uncertainty shock explains close to the full variance of the forecast error of the VXO and only a minor part of the variance of forecast error of the policy rate. On the contrary, the uncertainty shock identified in the proxy SVAR explains less than the full variance of the forecast error of the VXO and a relatively large part of the variance of the forecast error of the policy rate. Overall, when considering wages, consumer prices, hours worked, employment, and industrial production, the forecast error variance decomposition of the uncertainty shock under recursive identification resembles more the decomposition that the proxy SVAR associates with the news shock than with the uncertainty shock. Finally, the variance of the forecast error of the stock market index explained by the recursively identified uncertainty shock is substantially larger than that of the uncertainty shock from the proxy SVAR and somewhat smaller than that of the news shock from the proxy SVAR.

6.5 Historical decomposition

Last, we investigate the cumulative role played by the estimated uncertainty and news shocks in driving the variables of the model. We report historical decompositions for all variables in the VAR except wages and consumer prices, given that they are hardly affected by any of the shocks considered in this analysis.

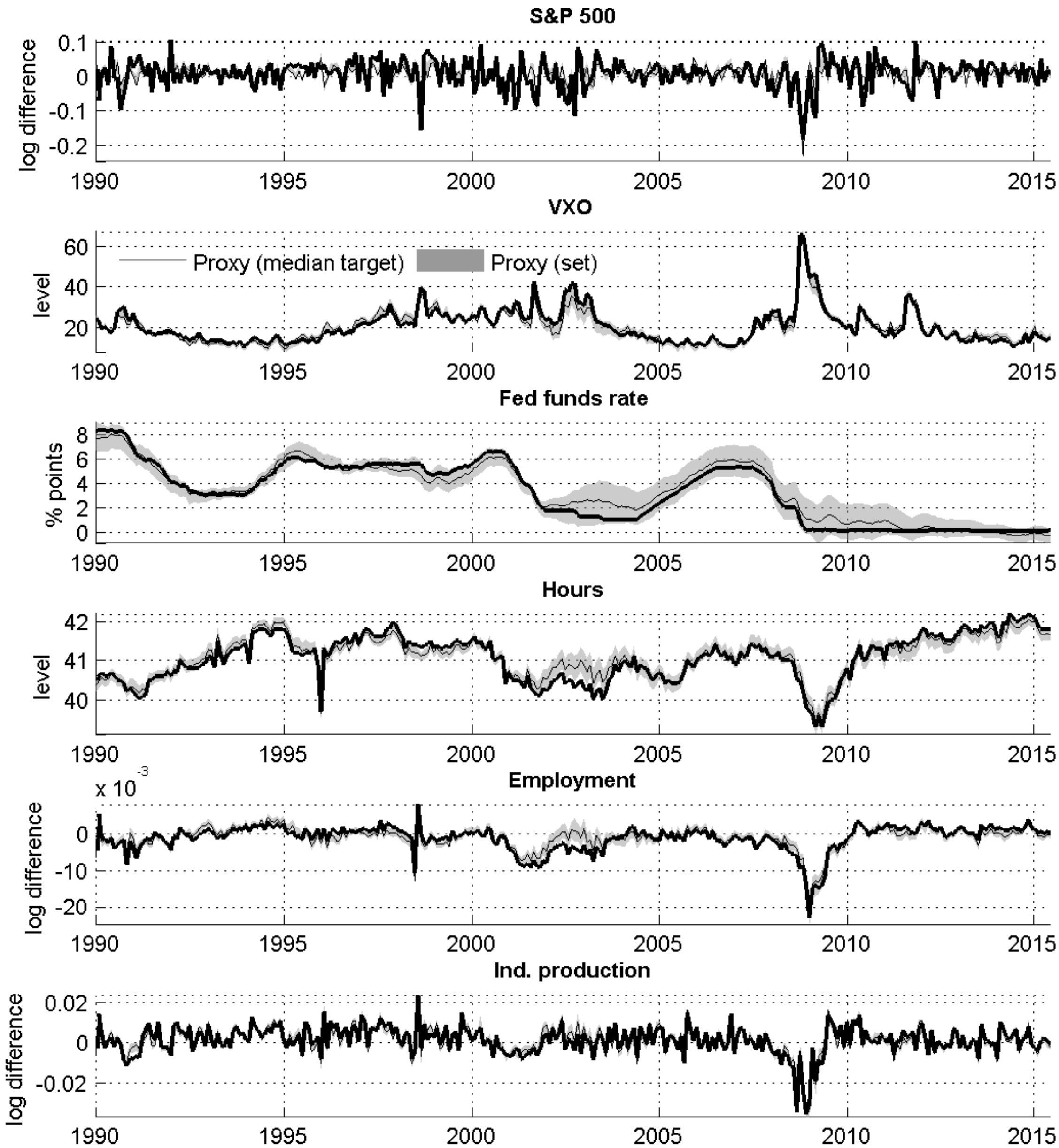
Figure 5 reports the historical decomposition for the uncertainty shocks identified in the proxy SVAR and in the recursive setup. Both identification approaches attribute the peaks in the VXO during the financial crisis and the European sovereign bond crisis as the endogenous response to the uncertainty shocks that cumulatively hit the economy before or during the financial crisis. While Figure 5 shows that under both identification approaches uncertainty shocks contributed to the depth of the recession and to the historically loose monetary policy from 2009 onwards, the effect is smaller under the recursive identification. Consistent with the analysis of impulse responses and the forecast error variance decomposition, the proxy SVAR model attributes a

Figure 5: Historical decomposition for uncertainty shocks



Notes: The decomposition is based on the full sample (1962M8 through 2015M6). At each time t, the difference between each historical decomposition and the data is attributed to the cumulative effect of the uncertainty shocks between 1962M8 and time t.

Figure 6: Historical decomposition for news shocks



Notes: The decomposition is based on the full sample (1962M8 through 2015M6). At each time t, the difference between each historical decomposition and the data is attributed to the cumulative effect of the news shocks between 1962M8 and time t.

larger role to uncertainty shocks in driving the great recession.

Figure 6 plots the historical decomposition for the identified news shocks. The decomposition further supports the insights from the forecast error variance decomposition. Compared to uncertainty shocks, news shocks have been less important in driving the business cycle during the time period analysed. This is especially true for the variables capturing real economic activity, namely hours worked, employment, and industrial production. While some models within the set of admissible models in the proxy SVAR indicate a role of news shocks in driving the federal funds rate, the median target model does not.

6.6 Robustness analysis

We assess the robustness of the results along three main dimensions. First, we consider alternative specifications of the reduced form models, adding variables in levels or in the specification by Bloom (2009), replacing the VXO with other measures of uncertainty, adding a measure of financial frictions, and changing the number of lags in the autoregression. Second, we consider variations in the identification approach, studying exact-identification rather than set-identification, changing the order of the variables for the recursive identification and changing the threshold value used for the restriction from equation (9b). Last, we use modifications of the baseline proxies by considering alternative computations of both proxies.

The robustness analysis, reported for simplicity only for the impulse responses (see Section E of the appendix), shows that the results discussed in Section 6 are largely robust to the alternative dimensions considered. We find that the results hold when specifying the reduced form model as in Bloom (2009) (Figure E.5), suggesting that the difference between our results and the results in his contribution are largely due to the alternative identification strategy rather than to the alternative specification of the reduced form model. Adding the Excess Bond Premium by Gilchrist and Zakrajšek (2012) as a measure of financial frictions (Figure E.7) only mildly attenuates the impact response of the real economy to the uncertainty shock. Replacing the VXO with the measure by Jurado et al. (2015) (Figure E.8) does not change the results, while the use of the measure by Bachmann et al. (2013) made the results even more pronounced (Figure E.9).

When identifying the model using the instruments in isolation under the additional assumption that each proxy is orthogonal to all structural shocks except the shock that it aims to proxy (equivalently, setting $\phi_{12} = \phi_{21} = 0$ in equation, (8)), we find that the results are somewhat more pronounced, and qualitatively very similar (Figure E.10). When changing the order of the variables and allowing for the uncertainty shock to affect all variables under the recursive identification (Figure E.11), we find that the recursive approach still falls short of detecting an impact effect of the real economy, and still delivers the hump-shaped responses displayed also by the news shock.

The results are also robust to alternative specification of the proxies. In particular, the results are not affected by dropping the events that were associated with decreases in the price of gold (Figure E.13) and, hence, dropping events partly associated with a counterintuitive variation of the price of gold given the nature of the event (see Table E.2). The results are also not affected by randomly dropping 20% of the baseline events multiple times (Figure E.14), nor by aggregating the daily proxy as in Gertler and Karadi (2014) (Figure E.15). Confirming the intuition that identification can be improved using data on safe haven assets, we find that the results hold also when using the price of silver rather than gold in constructing the proxy for the uncertainty shock (Figure E.16). When using the proxy constructed on Treasury bonds we find that the restrictions were never satisfied, possibly reflecting the very limited strength of these candidate proxies, as documented in Section B of the appendix. Dummy variables fail to detect the difference between uncertainty and news shocks documented by the proxy SVAR by predicting a more hump-shaped response to the uncertainty shock (Figure E.19 and Figure E.20). This might be due to the more limited ability of a simple dummy to control for first-moment effects associated with the events, relative to the price of a safe haven asset. Turning to the instruments used by Stock and Watson (2012), the result that the uncertainty shock affects the real variables already on impact also hold when using as proxy for the uncertainty shock the component of the policy uncertainty index by Baker et al. (2016) (Figure E.22). On the contrary, using as proxy for the uncertainty shock the residual on the AR(2) on the VIX delivered dynamics of the uncertainty shock that resembled the ones associated with the news shock (Figure E.21).

We conclude the discussion by noticing that the correlation among the estimated uncertainty shocks when using alternative proxies for the uncertainty shock are overall very high (Table E.4). In particular, the correlation between the uncertainty shock estimated using the baseline proxy and using alternative proxies like the dummy variables or the instruments by Stock and Watson (2012) is on the order of magnitude of 0.80. This correlation remains high and around 0.60 when using the price of silver, while it becomes relatively small (0.17) when using the price of platinum. These high correlations suggest that the estimated uncertainty shock is overall robust to alternative specifications.

7 Conclusion

In this paper we identify a proxy SVAR model to assess the economic impact of uncertainty shocks. We propose a new proxy for the uncertainty shock by exploiting the variations in the price of gold around selected events. For the construction of the proxy, we set up a database of events that are likely to have impacted on economic uncertainty. We then inform our proxy variable about the relevance of the event for economic uncertainty via the variations in the price of gold around those events. Our proxy covers the time period from 1979 to 2015 and has a monthly frequency.

Since events potentially reflect not only variations in uncertainty but also first moments changes related to news shocks, we study uncertainty shocks in a unified framework that identifies uncertainty shocks and news shocks jointly. In particular, we use the literature on news shocks to derive a proxy for the news shock, and set-identify both shocks within the proxy SVAR considered. In doing so, we extend the identification approach proposed by Mertens and Ravn (2013) building on the work on imperfect instruments developed by Nevo and Rosen (2012) for univariate models.

We find that the uncertainty shock identified within the proposed proxy SVAR triggers a larger and more rapid response of the real economy when compared to the recursive setup. In addition, the proxy SVAR suggests that uncertainty shocks are followed by a significant and prolonged monetary policy response that is not present in the recursively identified setup. On the contrary, the dynamics displayed by the uncertainty shocks under the recursive identification resemble much more the behaviour of what the proxy SVAR identifies as news shock. The recursively identified uncertainty shock displays a hump-shaped response for most of the variables, and an almost negligible effect on the policy rate.

The relationship between uncertainty shocks and news shocks has so far received limited attention within frameworks that study such shocks jointly. Most of the attention, instead, is devoted to studying each shock in isolation. Future theoretical work should shed light on the inter-linkages between first-moment and second-moment shocks, and on how to refine the joint identification of the two effects.

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