# Identifying Uncertainty Shocks Using the Price of Gold*

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**Abstract**

We propose an instrument to identify uncertainty shocks in a proxy SVAR. The instrument equals the variations in the price of gold around events associated with unexpected changes in uncertainty. These variations correlate with uncertainty shocks because gold is perceived as a safe haven asset. To control for news-related effects associated with the events we identify uncertainty and news shocks jointly, developing a set-identified proxy SVAR. We find that the popular recursive approach underestimates the effects of uncertainty shocks and delivers responses for economic activity and monetary policy that have more in common with news shocks than with uncertainty shocks.

**JEL classification**: E32, C32, D81.
**Keywords**: Economic uncertainty, external proxy SVAR, safe haven assets, news shocks, set-identification.

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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, Bachmann *et al.*, 2013, Caggiano *et al.*, 2014, Jurado *et al.*, 2015, Baker *et al.*, 2016 and Scotti, 2016). 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 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. 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.

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.

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 Gurkaynak *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.

We find that 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 for the real variables and an insignificant response of monetary policy. Hence, for the real variables and for the monetary policy rate, the uncertainty shock identified with the recursive approach more closely resembles the dynamics of the news shock rather than those of 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.

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. Cesa-Bianchi *et al.* (2014) identify uncertainty shocks as the common stochastic component to the VIX index in several countries. A yet 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 simulation to study the effect of measurement errors on the estimation of impulse responses. We build 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. In comparison to Baker and Bloom (2013), we also study the response of monetary policy, finding that monetary policy responds to second-moment but not to first-moment shocks. In contrast to Carriero *et al.* (2015), we find that the responses of real variables to an uncertainty shock are not hump-shaped, and that the stock market index responds on impact to an uncertainty shock only very mildly.

## 1 The Proxy SVAR Model

We first 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

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

where $\boldsymbol{y}_t$ is a $k \times 1$ vector including the endogenous variables, $\boldsymbol{\delta}$ includes constant terms, and $\boldsymbol{A}(L)$ 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

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

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

The aim is to identify the uncertainty shock out of the $k$ structural shocks in $\boldsymbol{\epsilon}_t$. Let the scalar $\epsilon_t^u$ 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

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

where $\boldsymbol{b}^u$ is the impulse vector associated with the uncertainty shock and $\boldsymbol{B}^*$ gathers the impulse vectors of the remaining shocks. Identifying $\epsilon_t^u$ 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 $\epsilon_t^u$, because it allows for isolating variations in $\boldsymbol{u}_t$ that are driven by $\epsilon_t^u$ rather than by $\boldsymbol{\epsilon}_t^*$. By contrast, if $m_t$ correlates also with some of the structural shocks in $\boldsymbol{\epsilon}_t^*$, then the identification of $\epsilon_t^u$ requires further restrictions that prevent the estimated shock $\epsilon_t^u$ 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. 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.

## 2 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.

### *2.1 Collecting the Events*

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 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 G

[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. We use the peaks of the VXO only to identify underlying events, whose exact timing is then assessed separately.

[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

of the appendix we show that the results are not driven by this exact selection of events. Table H3 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. Bloomberg News aggregates information from several sources around the world, providing 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]

### *2.2 Computing the Proxy*

We 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 high 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 5.1). 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]

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Ravn (2013), who use 13 to 16 events for 228 quarterly observations.

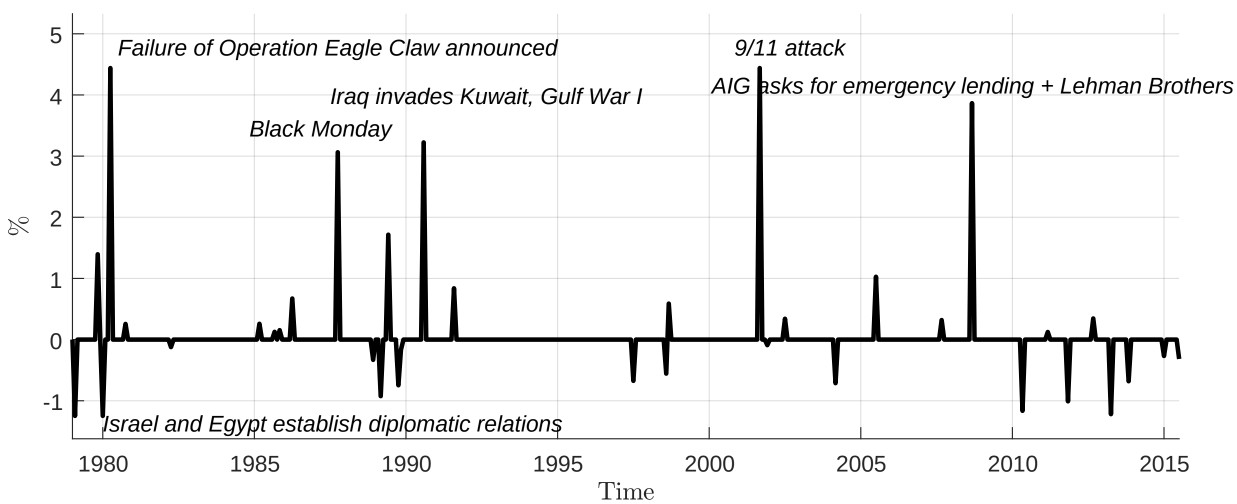
[3]The list is available on https://sites.google.com/site/michelepiffereconomics/home/research-1.

[4]For example, Bloomberg News agency releases do not cover the period when the Berlin Wall fell, November 9, 1989. Nevertheless, 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.

[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",

We use intradaily data on the London spot market of physical gold, employing prices from the two daily auctions organised 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 $\tau^j$ the time in which event $e_j$ became known to the market. For each event we compute $\Delta p^j$ as the percentage variation in the price of gold between the last available auction price before $\tau^j$ and the first available auction price after $\tau^j$. We then aggregate these $K$ realizations of $\Delta p^j$ into a monthly time series, summing up the daily proxy within a month, following the aggregation in Romer and Romer (2004).[7]

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




The final proxy $m_t^g$ for the uncertainty shock is shown in Figure 1. The realizations are well distributed across the sample. The peaks of the proxy tend to be predomi-

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.

nantly positive and of higher magnitude when positive, a feature consistent with the literature on uncertainty 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 H5 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.

### *2.3 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). We aim to establish such an assessment indirectly. The relevance condition was partly discussed with regard to the constructed proxy, and we provide additional evidence for it in Section 5.1 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 from the existing literature. 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 ($\delta_j \neq 0$) 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. 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 addition to the shocks studied by Stock and Watson (2012), the macroeconomic literature evaluates news shocks as drivers of the business cycle (Beaudry and Portier, 2014). 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) and by Kurmann and Otrok (2013), as well as on the shocks estimated by Beaudry and Portier (2014) using several of their model specifications.[8] For simplicity, with regard to the shocks by Beaudry and Portier (2014) we report in Table 1 only the results using their trivariate VAR model including consumption (see Section 3.3.2.1 in their paper). Overall, while we find no statistically significant relationship with the news shocks estimated by Barsky and Sims (2011) and by Kurmann and Otrok (2013), we find some statistically significant relationship with the news

[8] 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. Kurmann and Otrok (2013) identify statistically the shock that contributes to the maximum forecast error variance decomposition of the slope of the term structure, and interpret it as a news shock based on the dynamics of the impulse responses. 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.

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

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

| Shock | Source | $\beta$ | S.E. | P-value | Obs | Sample |
|---|---|---|---|---|---|---|
| *Oil* | Hamilton (2003) | 0.106 | 0.119 | 0.37 | 393 | 1979M1 to 2011M9 |
| | Kilian (2008) | -0.039 | 0.299 | 0.90 | 103 | 1979Q1 to 2004Q3 |
| | Ramey and Vine (2010) | 0.918 | 1.355 | 0.5 | 397 | 1979M1 to 2012M1 |
| *Monetary Policy* | Romer and Romer (2004) | -3.810 | 2.822 | 0.18 | 216 | 1979M1 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 | 1979M1 to 2003M3 |
| | Gurkaynak *et al.* (2005) | 0.049 | 0.050 | 0.33 | 60 | 1990Q1 to 2004Q4 |
| *Productivity* | Basu *et al.* (2006) | -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) residual of VIX | 0.302 | 0.165 | 0.07 | 394 | 1979M1 to 2011M10 |
| | Baker *et al.* (2016) | 0.016 | 0.012 | 0.18 | 325 | 1985M1 to 2012M1 |
| *Financial* | Gilchrist and Zakrajšek (2012) | 0.583 | 0.554 | 0.29 | 127 | 1979Q1 to 2010Q3 |
| | TED spread | 0.903 | 0.628 | 0.15 | 394 | 1979M1 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 | $\beta$ | S.E. | P-value | Obs | Sample |
|---|---|---|---|---|---|---|
| *News* | Barsky and Sims (2011) | -0.181 | 0.379 | 0.63 | 115 | 1979Q1 to 2007Q3 |
| | Kurmann and Otrok (2013) | 0.387 | 0.383 | 0.31 | 106 | 1979Q1 to 2005Q2 |
| | Beaudry and Portier (2014) | -0.901 | 0.428 | 0.04 | 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 updated series of the productivity shocks by Basu *et al.* (2006) were made available by the authors. The shocks by Beaudry and Portier (2014) used in the table refer to the trivariate VAR models including a measure of TFP, the stock market index and consumption.

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 shock 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.

## 3 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 identify the uncertainty shock by imposing that the proxy for the uncertainty shock is more correlated with the uncertainty 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 direct restriction on impulse responses.

Rewrite equation (3) as

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

where $\boldsymbol{b}^u$ represents the impulse vector to the uncertainty shock, $\boldsymbol{b}^n$ is the impulse vector to the news shock, and $\tilde{\boldsymbol{B}}^*$ collects the impulse vectors of the remaining shocks. Define $\tilde{\boldsymbol{\epsilon}}_{\boldsymbol{t}t} = (\epsilon_t^u, \epsilon_t^n)'$, $\boldsymbol{m}_t = (m_t^g, m_t^n)'$ and $E(\tilde{\boldsymbol{\epsilon}}_t \boldsymbol{m}_t') = \boldsymbol{\Phi}$, i.e.

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

with $\phi_{ij}$ the $i, j$ entry of $\boldsymbol{\Phi}$. Assume that $E(\tilde{\boldsymbol{\epsilon}}_t^* m_t^g) = E(\tilde{\boldsymbol{\epsilon}}_t^* m_t^n) = \boldsymbol{0}$. Under the normalization of $E[(\epsilon_t^u)^2] = E[(\epsilon_t^n)^2] = 1$ and ensuring $E[(m_t^g)^2] = E[(m_t^g)^2] = 1$, $\Phi$

can be interpreted as the correlation structure between the shocks of interest and the instruments. We set-identify $\epsilon_t^u$ and $\epsilon_t^n$ by imposing restrictions on $\mathbf{\Phi}$.

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. We then use the following restrictions on $\mathbf{\Phi}$:

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

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

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. 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 $\Phi$. 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 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. Section E of the appendix discusses the results of a Monte Carlo simulation, showing that the identification strategy applied in this paper correctly identifies the TFP and the monetary shocks within the New Keynesian model by An and Schorfheide (2007).

In the baseline analysis we measure $m_t^n$ as the first principal component computed over 15 series of productivity news shocks estimated in the literature, reflecting the identification approaches by Barsky and Sims (2011), by Kurmann and Otrok (2013) and by Beaudry and Portier (2014). This first component explains about 58 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.[9]

## 4 Data, Model Specification and Inference

We consider a vector of eight endogenous variables that enter the VAR model in the following order: $\Delta log$(S&P 500), VXO, federal funds rate, $\Delta log$(wages), $\Delta log$(CPI),

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

hours, $\Delta log$(employment), and $\Delta log$(industrial production). 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 H6 in the appendix.

Our specification of the model deviates from Bloom (2009) in three ways. Firstly, we update the sample up to 2015M6. Secondly, we let the variables enter in log differences rather than in deviations from HP trends. 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 a model specification using the variables as in 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 extend 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 3, drawing a single orthogonal matrix $\boldsymbol{Q}$ from the uniform distribution with respect to the Haar measure. 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.

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. Whenever we discuss the recursive identification we refer to the recursive identification applied to each bootstrapped data.

## 5 Results

### 5.1 *Tests on the Strength of the Instruments*

**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.) |
|---|---|---|---|---|---|---|---|---|
| $\beta$ | $-0.80^{**}$ | $166.4012^{***}$ | $-5.582$ | $-0.026$ | $0.020$ | $-4.133^{*}$ | $-0.066^{***}$ | $-0.182^{***}$ |
| 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.) |
|---|---|---|---|---|---|---|---|---|
| $\beta$ | $-0.0051^{***}$ | $0.2983^{***}$ | $0.0059$ | $0.000$ | $0.0001^{***}$ | $-0.0055^{**}$ | $-0.0001^{*}$ | $0.000$ |
| T | 170 | 170 | 170 | 170 | 170 | 170 | 170 | 170 |
| F | 135.631 | 45.345 | 0.593 | 0.492 | 19.452 | 4.340 | 3.336 | 0.116 |
| $R^2$ | 0.446 | 0.212 | 0.003 | 0.003 | 0.103 | 0.025 | 0.019 | 0.001 |

Notes: The models estimated are $\hat{u}_{it} = \alpha + \beta_i m_t + \eta_{it}$ with $\hat{u}_{it}$ 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.

Following Gertler and Karadi (2014), we first test the strength of the instruments.

$m_t^g$ and $m_t^n$ are strong instruments if they sufficiently correlate with the estimated reduced form shocks $\boldsymbol{u}_t$ from equation (1). Formally, call $\hat{u}_{it}$ 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

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

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

Table 2 reports the results of the tests. 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 tends to increase when the price of gold increases, confirming the intuition behind the proxy constructed in Section 2. 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 (Beaudry and Portier, 2014, Caldara *et al.*, 2016). 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 135. 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 one third of the $F$ statistic related to the residual of the stock market index.

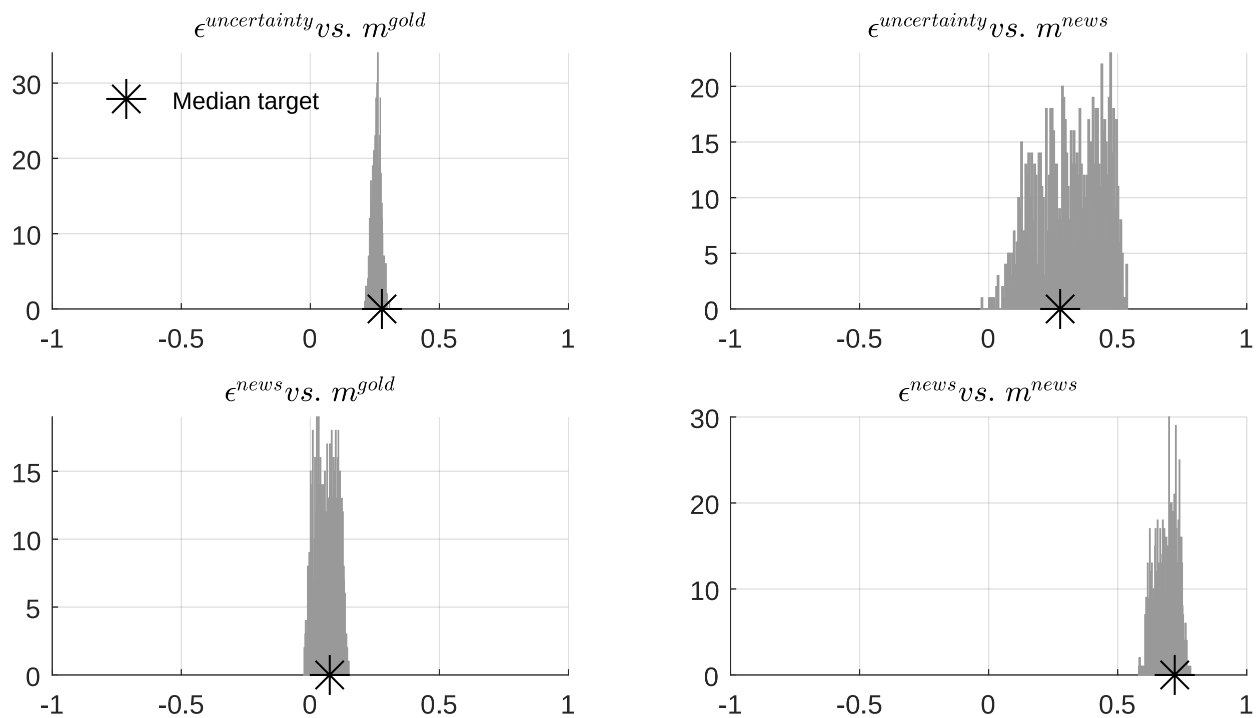
### *5.2 Estimated Shocks*

As discussed in Section 3, 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 draws which set-identify the model under these restrictions. Figure 2 shows the correlation structure $\mathbf{\Phi}$ from equation (8), based on the 1000 draws, that is implicit in the restricted structural models. 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 $\psi$, with $\psi = 0.10$ in the baseline specification.

Figure 3 plots the estimated shocks. The top panel shows the proxy for the uncertainty shock, while the middle panel plots the estimated uncertainty shocks corresponding to the median target specification and the pointwise 90% confidence band. 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 indicate a number 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.[10]

[10] 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 shock attributes a strongly positive peak to that period. The estimated uncertainty shock also peaks in August and in October 1982. These peaks do not correspond to any of the 117 events collected in our database.

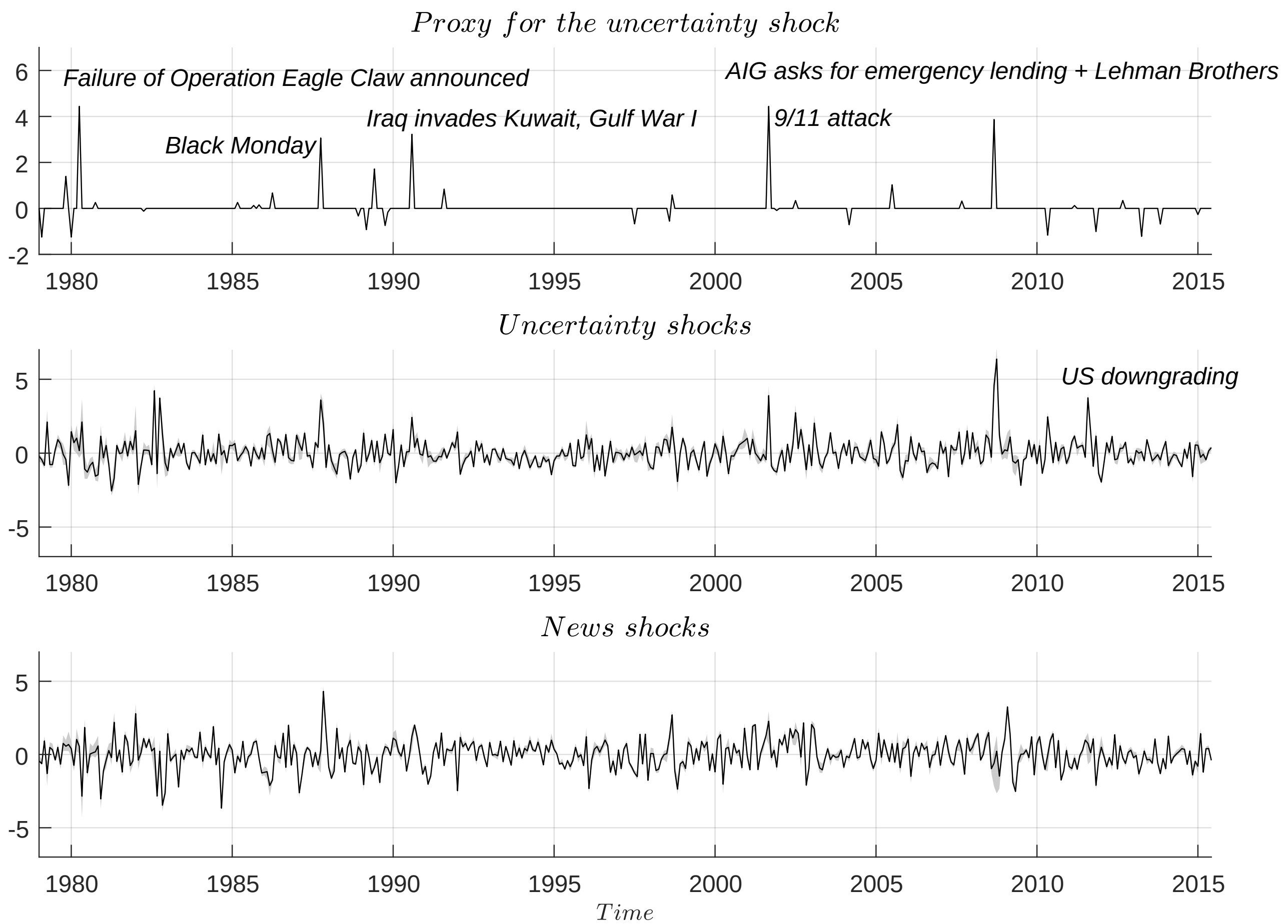
**Figure 2:** Correlation structure between proxies and shocks




The lower panel of Figure 3 shows the median target specification and the pointwise 90% confidence bands of the estimated news shocks. The comparison of the three plots allows us to study 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 Black Monday, the invasion of Kuwait by Iraq and the 9/11 terrorist attack were associated with both an unfavourable news shock and an exogenous increase in uncertainty, of the size greater than two standard deviations.

We replicate Table 7 from Stock and Watson (2012) and study the correlations between their estimated shocks and the shocks estimated in our paper. Table H4 in the appendix reports the average absolute correlation between the different groups of shocks, while Table H5 reports the correlations among the individual shocks underlying Table H4. The correlation between the oil shocks estimated by Stock and Watson

**Figure 3:** Estimated shocks and proxy for 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.

(2012) and our uncertainty and news shocks are always 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).

### 5.3 Impulse Responses

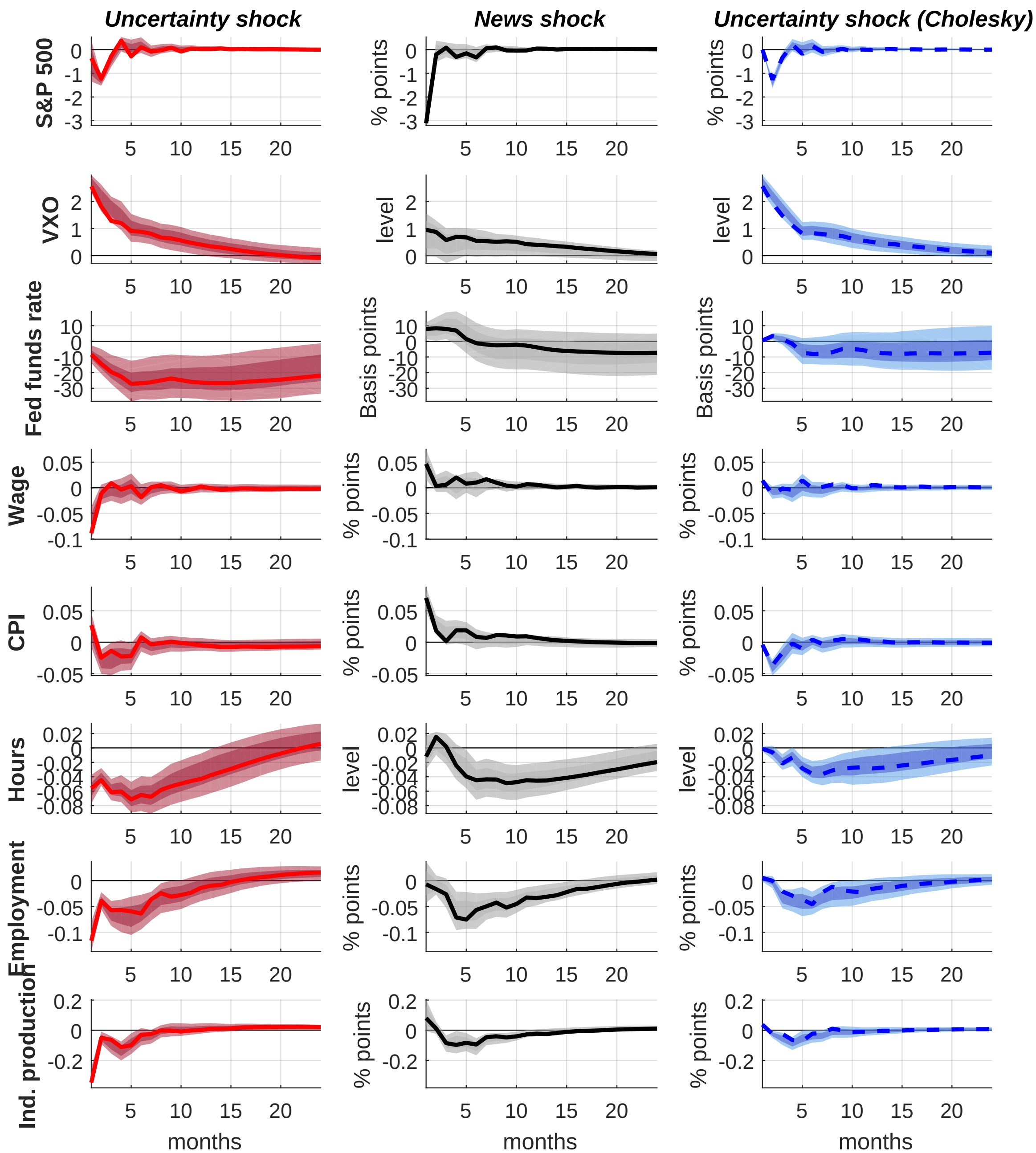
The impulse responses are shown in Figure 4 and refer to one standard deviation shocks.[11] An uncertainty shock affects financial markets, monetary policy, and the real economy, while it has a rather limited effect on nominal variables. The real economy reacts on impact with a drop in industrial production 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.

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. Monetary policy does not react to the news shock.

We compare the above results with the response to the uncertainty shock identified

[11]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 for the recursive identification 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 H18 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.

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. 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 impulse responses to the recursively identified uncertainty shock share several features of the responses to both the news shock and the uncertainty shock from the proxy SVAR. The recursively identified impulse responses for the stock market index, the VXO and CPI somewhat resemble dynamics of the uncertainty shock identified in the proxy VAR, in particular at shorter horizons. However, for the remaining five variables, which include the real variables as well as the monetary policy rate, the impulse responses to the recursively identified uncertainty shock is more similar to the news shock response. Section F in the appendix confirms this pattern of similarity in a more formal manner by constructing a measure of relative impulse response distance that builds on the metric employed by Rotemberg and Woodford (1997) and by Christiano *et al.* (2005) for impulse response matching.

Section G in the appendix shows that the results are robust to a large array of alternative specifications of the reduced form model, including using alternative measures of uncertainty, changing the ordering of the variables for the recursive identification, and adding a measure of credit spread to the model. The results are also robust to the use of alternative proxies for the uncertainty shock built on other safe haven assets.

### *5.4 Forecast Error Variance Decomposition*

**Table 3:** 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 | 0.50 | 0.05 | 0.06 | 0.01 | 0.07 | 0.14 | 0.26 |
| | *.00/.13* | *.40/.67* | *.00/.10* | *.02/.12* | *.00/.04* | *.03/.14* | *.08/.22* | *.14/.34* |
| *6* | 0.10 | 0.47 | 0.15 | 0.06 | 0.02 | 0.20 | 0.20 | 0.26 |
| | *.09/.21* | *.35/.67* | *.03/.25* | *.02/.11* | *.02/.11* | *.12/.31* | *.12/.32* | *.16/.32* |
| *12* | 0.10 | 0.44 | 0.18 | 0.06 | 0.02 | 0.20 | 0.20 | 0.24 |
| | *.09/.20* | *.31/.65* | *.03/.33* | *.02/.11* | *.02/.11* | *.11/.38* | *.11/.34* | *.15/.30* |
| *24* | 0.10 | 0.39 | 0.19 | 0.05 | 0.02 | 0.12 | 0.17 | 0.12 |
| | *.09/.21* | *.28/.61* | *.03/.39* | *.02/.11* | *.02/.12* | *.09/.31* | *.11/.32* | *.15/.30* |
| | | | | *News shock* | | | | |
| *1* | 0.73 | 0.10 | 0.01 | 0.02 | 0.10 | 0.00 | 0.00 | 0.02 |
| | *.57/.76* | *.00/.19* | *.00/.07* | *.00/.07* | *.05/.17* | *.00/.03* | *.00/.03* | *.00/.10* |
| *6* | 0.52 | 0.09 | 0.02 | 0.02 | 0.08 | 0.06 | 0.08 | 0.07 |
| | *.40/.56* | *.00/.20* | *.00/.08* | *.01/.07* | *.05/.14* | *.01/.11* | *.02/.17* | *.04/.13* |
| *12* | 0.51 | 0.08 | 0.01 | 0.02 | 0.07 | 0.09 | 0.13 | 0.07 |
| | *.40/.55* | *.00/.22* | *.00/.06* | *.01/.07* | *.05/.14* | *.03/.23* | *.04/.24* | *.05/.15* |
| *24* | 0.51 | 0.07 | 0.02 | 0.02 | 0.06 | 0.11 | 0.10 | 0.07 |
| | *.40/.55* | *.01/.22* | *.00/.11* | *.01/.07* | *.05/.13* | *.04/.24* | *.04/.24* | *.05/.15* |
| | | | | *Uncertainty shocks (Cholesky)* | | | | |
| *1* | 0.00 | 0.89 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 |
| *6* | 0.18 | 0.84 | 0.01 | 0.01 | 0.05 | 0.06 | 0.06 | 0.04 |
| *12* | 0.18 | 0.81 | 0.02 | 0.01 | 0.04 | 0.11 | 0.08 | 0.04 |
| *24* | 0.18 | 0.76 | 0.04 | 0.01 | 0.04 | 0.11 | 0.08 | 0.04 |

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.

Table 3 reports the forecast error variance decomposition of the uncertainty shock and of the news shock. The uncertainty shock from the proxy SVAR explains around

45% of the forecast error variance of the VXO and only about 10% of the forecast error variance of the stock market index. The situation is reverse for the news shock, which explains up to 73% of the forecast error variance of the stock market index after one month and around 9% of the forecast error variance of the VXO along the horizons considered. 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.

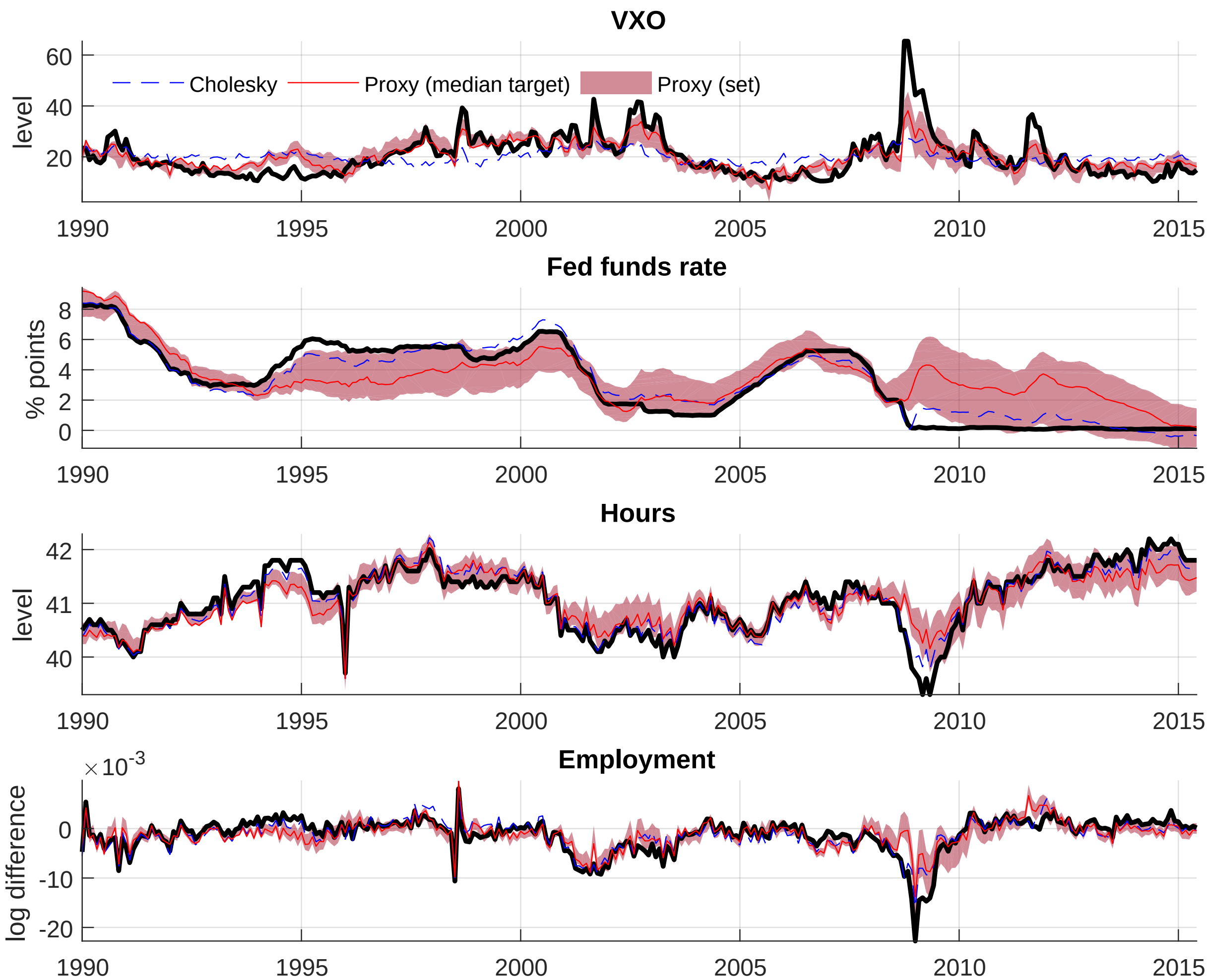
When comparing the above results with the results from the recursive approach, we find that under the recursive identification the uncertainty shock explains close to the full variance of the forecast error of the VXO and only a minor part of the variance of forecast error of the policy rate. By contrary, 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 the recursive identification resembles more the decomposition that the proxy SVAR associates with the news shock than with the uncertainty shock.

### *5.5 Historical Decomposition*

Last, we investigate the cumulative role played by the estimated uncertainty and news shocks in driving the variables of the model.

Figure 5 shows the historical decomposition of selected variables with respect to the impact of the uncertainty shock. Both identification approaches interpret 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 under both identification approaches uncertainty

**Figure 5:** Historical decomposition for uncertainty shocks




Notes: We report the data as it enters the model (solid black line) and the data after subtracting, at each time $t$, the cumulative effect of the uncertainty shocks between 1962M8 and time $t$. To make the figure clearer, we report here the decomposition for the subperiod 1990M1-2015M6. The full analysis is available in Figure H7 to Figure H10 in the appendix.

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.

Figure H7 to Figure H10 in the appendix report historical decompositions for a larger set of variables and the full sample for both uncertainty and news shocks. Compared to uncertainty shocks, news shocks have been less important in driving the business cycle during the time period analysed.

## 6 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. 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 using 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-moment changes related to news shocks, we study uncertainty shocks in a unified framework that identifies uncertainty shocks and news shocks jointly.

We find that the uncertainty shock identified within the proposed proxy SVAR generates 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. For the variables capturing real activity and the monetary policy rate, the impulse response dynamics related to the recursively identified uncertainty shock resemble more those to the news shock in the proxy SVAR, displaying hump-shaped responses of real activity and a negligible reaction of 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 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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