CESifo WORKING PAPERS

6799
2017

December 2017

Uncertainty Across Volatility Regimes

Giovanni Angelini, Emanuele Bacchiocchi, Giovanni Caggiano, Luca Fanelli

CESifo

Impressum:

CESifo Working Papers
ISSN 2364-1428 (electronic version)
Publisher and distributor: Munich Society for the Promotion of Economic Research - CESifo GmbH
The international platform of Ludwigs-Maximilians University's Center for Economic Studies and the ifo Institute
Poschingerstr. 5, 81679 Munich, Germany
Telephone +49 (0)89 2180-2740, Telefax +49 (0)89 2180-17845, email office@cesifo.de
Editors: Clemens Fuest, Oliver Falck, Jasmin Gröschl
www.cesifo-group.org/wp

An electronic version of the paper may be downloaded
· from the SSRN website: www.SSRN.com
· from the RePEc website: www.RePEc.org
· from the CESifo website: www.CESifo-group.org/wp

CESifo *Working Paper No. 6799*
Category 6: Fiscal Policy, Macroeconomics and Growth

Uncertainty Across Volatility Regimes

Abstract

We propose a new non-recursive identification scheme for uncertainty shocks, which exploits breaks in the unconditional volatility of macroeconomic variables. Such identification approach allows us to simultaneously address two major questions in the empirical literature on uncertainty: (i) Does the relationship between uncertainty and economic activity change across macroeconomic regimes? (ii) Is uncertainty a major cause or effect (or both) of decline in economic activity? Empirical results based on a small-scale VAR with US monthly data for the period 1960-2015 suggest that (i) the effects of uncertainty shocks are regime-dependent, and (ii) uncertainty is an exogenous source of decline of economic activity, rather than an endogenous response to it.

JEL-Codes: C320, C510, E440, G010.

Keywords: heteroscedasticity, identification, non-recursive SVAR, uncertainty shocks, volatility regime.

Giovanni Angelini
University of Bologna
Bologna / Italy
giovanni.angelini3@unibo.it

Emanuele Bacchiocchi
University of Milan
Milan / Italy
emanuele.bacchiocchi@unimi.it

Giovanni Caggiano
Monash University
Australia - 3145 Caulfield East VIC
giovanni.caggiano@monash.edu

Luca Fanelli
University of Bologna
Bologna / Italy
luca.fanelli@unibo.it

November 2017
We thank Efrem Castelnuovo, Giovanni Pellegrino and Chiara Scotti for useful comments and suggestions. Paper presented at the 'Padova Macro Talks', June 2017.

1 Introduction

Since the aftermath of the recent Global Financial Crisis (GFC), there has been revamped attention on the role played by uncertainty as a driver of the business cycle. Two main stylized facts have emerged from the literature: first, heightened uncertainty triggers a contraction in real activity; second, uncertainty tends to be higher during economic recessions. The first stylized fact is consistent with the theoretical literature that shows why uncertainty can have negative macroeconomic effects. The prevailing view is that uncertainty is recessionary in presence of real options effects (e.g. Bloom, 2009) or financial frictions (e.g. Christiano, Motto and Rostagno, 2014), and its effects can be amplified in extreme conditions like high financial stress (e.g. Alfaro *et al.*,, 2016; Arellano et al, 2012; Gilchrist *et al.*, 2014) or the Zero Lower Bound (Basu and Bundick, 2017). However, uncertainty appears also to endogenously increase during recessions, as lower economic growth induces greater dispersion at the micro level and higher aggregate volatility. This second stylized fact is consistent with the theoretical literature on 'endogenous uncertainty', which contends that uncertainty is rather a consequence, not a cause, of declining economic activity, as in e.g. Van Nieuwerburgh and Veldkamp (2006), Bachmann and Moscarini (2012), Fajgelbaum *et al.* (2014), Gourio (2014), Navarro (2014) and Plante *et al.* (2017). We refer to Ludvigson *et al.* (2017a) for an excellent review.

Whether causality runs from uncertainty to real activity, or from real activity to uncertainty, or in both directions, and whether these relationships assume greater importance under different macroeconomic conditions are issues which can be investigated empirically within a Structural VAR (SVAR) framework. The first issue requires moving away from recursive identification schemes, which are by construction ill suited to shed light on the reverse causality issue. To the best of our knowledge, this issue has been explicitly analyzed only in Ludvigson *et al.* (2017a). The second issue requires moving away from linear SVARs, which would not allow to uncover possibly regime-dependent effects of uncertainty shocks. This concern has been addressed in the recent literature, and evidence that uncertainty shocks have regime-dependent effects has been provided by, among others, Alessandri and Mumtaz (2014), and Caggiano *et al.* (2014, 2017a).

This paper contributes to the empirical literature on uncertainty by proposing a methodology that allows to examine both issues simultaneously within a SVAR framework via a non-recursive identification approach, which exploits breaks in the (unconditional) volatility of post-WW2 US macroeconomic variables. As discussed in Magnusson and Mavroeidis (2014), structural breaks induced by policy shifts and/or the occurrence of financial crises, provide exogenous identifying information which can be fruitfully used for inference. Our identification strategy extends the standard 'identification-through-heteroskedasticity' approach, popularized in the empirical macroeconomic literature by Rigobon (2003), Rigobon and Sack (2004) and Lanne and Lütkepohl (2008), to the case where the structural parameters of the VAR, and hence the associated impulse response functions (IRFs), may vary with the volatility of the shocks, as in Bacchiocchi and Fanelli (2015) and Bacchiocchi *et al.* (2017). This allows us to address the causality issue, since in our setup causal ordering is not necessary to identify the shocks: uncertainty shocks are allowed to hit real activity on impact and, at the same time, real activity shocks are allowed to trigger uncertainty contemporaneously. Our framework also allows to estimate regime-dependent effects of uncertainty shocks, where regimes are endogenously identified by the estimated volatility breaks. To the best of our knowledge, this is a novelty in the empirical literature on the effects of uncertainty shocks, which allows to jointly address two issues that so far have been either ignored or treated in isolation.

We estimate, as in Ludvigson *et al.* (2017a), a small-scale SVAR with three variables: a measure of real activity, Y_t; an index of macroeconomic uncertainty, U_{Mt}; and an index of financial uncertainty, U_{Ft}. Real activity is proxied by either industrial production or employment, and the indices of macroeconomic and financial uncertainty are taken from Jurado *et al.* (2015) and Ludvigson *et al.* (2017a), respectively.[1] Data are monthly, and span the 1960-2015 sample. As highlighted by Ludvigson *et al.* (2017a), the joint use of measures of macroeconomic and financial uncertainty is crucial to identify the transmission channels of uncertainty shocks and to disentangle the causes and consequences of macroeconomic and financial uncertainty. Shocks are identified using a non-recursive approach, which exploits the differences in the average level of volatility displayed by macroeconomic variables on different sub-samples in the period 1960-2015. Volatility breaks are selected in accordance with the paths shown by the recursive and rolling-windows estimates of the VAR covariance matrix. These paths are consistent with two main breaks which can be associated with two important episodes of the US history: one is the onset of the Great Moderation, and the other is the GFC of 2007-2008. This leads to the identification of three broad volatility regimes in the data, which correspond to three well-known macroeconomic regimes: the Great Inflation period (1960M8-1984M3), the Great Moderation period (1984M4-2007M12) and the 'Great Recession+Slow Recovery' period (2008M1-2015M4).[2]

Our main findings can be summarized as follows. First, macroeconomic and financial uncertainty shocks trigger a decline of US real economic activity in all volatility regimes. Second, the magnitude and the persistence of the effects of uncertainty shocks on economic activity vary

[1] Other measures of macro uncertainty available in the literature have been proposed by Rossi *et al.* (2016) and Scotti (2016). We use the measure proposed by Jurado *et al.* (2015) to be consistent with the VAR specification in Ludvigson *et al.* (2017a), see below.

[2] Given the strong and well established association between the (average) volatility of most macroeconomic variables and specific macroeconomic regimes of U.S. economic history (e.g. McConnel and Perez-Quiros, 2000), throughout the paper we use the terms 'volatility regime' and 'macroeconomic regime' interchangeably.

substantially across the three volatility regimes, with the largest impact found in the Great Recession + Slow Recovery period. Third, our impulse responses differ substantially with those coming from a linear model with standard recursive identification scheme which ignores changes in volatility. Fourth, both macroeconomic and financial uncertainty can be better described as exogenous drivers of real activity, rather than as endogenous responses to it: we find evidence that uncertainty shocks have a contemporaneous and significant impact on real activity and the effect is robust to several robustness checks, but the opposite is not supported by the empirical evidence. This finding holds true in all three macroeconomic regimes, including the Great Recession+Slow Recovery and is robust to several perturbations of the baseline model.

From an empirical viewpoint, these findings relate our paper to different strands of the literature. We relate to contributions that have looked at time-dependent effects of uncertainty shocks, such as Beetsma and Giuliodori (2012), Choi (2013), Bontempi *et al.* (2016), Mumtaz and Theodoridis (2017) and Caggiano *et al.* (2017b). The main message of these contributions is that uncertainty shocks are more powerful if the economy is in extreme conditions, such as an economic recession and high financial strain. In line with them, we also find that uncertainty shocks have possibly time-varying effects which are related to different macroeconomic volatility regimes. All these contributions, however, either identify and estimate recursive SVARs separately on different sub-samples, or estimate time-varying recursive SVARs which cannot account for the reverse causality issue. Our approach, which exploits the heteroskedasticity of the data, allows us to identify a single non-recursive SVAR with structural breaks in both the error covariance matrix and in the structural parameters. Breaks in the structural parameters allow us to estimate regime-dependent effects of uncertainty shocks, as in the related literature. Breaks in the covariance matrix allows us to identify non-recursively uncertainty and real activity shocks, so that, unlike the above mentioned contributions, causality can run from uncertainty to real activity and viceversa. Moreover, the finding that uncertainty shocks have had larger effects in the aftermath of the GFC are in line with Basu and Bundick (2017) and Caggiano et al (2017a), who highlight the role played by the stance of monetary policy in magnifying the effects of uncertainty shocks. Differently from their papers, we do not investigate the causes of why real activity reacts more in the GFC, but we confirm their findings with a more general identification approach that, crucially in a period of high economic and financial turmoil, does not require a recursive structure.

Our result on causality that runs from uncertainty to real activity is strictly related to Ludvigson *et al.* (2017a). While we find that both macroeconomic and financial uncertainty are not contemporaneously caused by real activity shocks, they report that only financial uncertainty can be considered exogenous. The discrepancy between our result and that in Ludvigson *et* *al.* (2017a) can be explained by the different methodologies employed to identify the shocks. Ludvigson *et al.* (2017a) implement a novel approach (see also Ludvigson *et al.*, 2017b)) which combines external instruments with set-identification methods, in which financial and macroeconomic uncertainty shocks are treated asymmetrically, in the sense that one instrument is assumed to be correlated with both shocks and the other instrument is assumed to be correlated only with financial uncertainty shocks. We point-identify our non-recursive SVAR and obtain economic meaningfull IRFs by following the insight that changes in the distribution of the data induced by policy regime shifts and/or financial crises provide, once combined with economic information, additional exogenous variation that can be usefully exploited to identify the shocks non-recursively and for inference.

On the methodological side, our paper is closely related to works that have identified uncertainty shocks using non-recursive schemes. Recent examples are methods based on the combination of external instruments with other type of restrictions (Ludvigson *et al.* 2017; Piffer and Podstawski, 2017), methods based on the penalty function approach (Caldara *et al.* 2016) and methods based on sign restrictions (e.g. Furlanetto *et al.* 2017). None of these contributions, however, has examined the joint issue of causality and regime-dependence. Moreover, in our setup, the additional information necessary to point-identify the non-recursive SVAR stems from the changes in volatility of the data with some advantages. On the one hand, the researcher is exempted from any consideration about the validity and relevance of external instruments (Stock and Watson 2012, 2016; Mertens and Ravn, 2013; Olea *et al.* 2015). On the other hand, the inferential issues which arise in signed restricted SVARs are automatically circumvented (Moon *et al.* 2013; Giacomini and Kitagawa, 2015) because in our framework the inference on the SVAR coefficients and the IRFs is standard under a set of regularity conditions.

The paper is organized as follows. Section 2 introduces the identification problem and presents our non-recursive identification approach. Section 3 discusses the data and the empirical results obtained from the estimated SVAR. Section 4 modifies the baseline structural specification to account for some robustness checks. Section 5 provides some concluding remarks. Additional technical details and empirical results and robustness checks are confined in a Technical Supplement associated with the paper.[3]

2 Identifying uncertainty shocks through volatility regimes

In this Section, we outline our econometric methodology to deal with both regime-dependence and the joint identification of uncertainty and real activity shocks. Subsection 2.1 discusses

[3] Available online at http://www.rimini.unibo.it/fanelli/TS_Uncertainty36.pdf

the nature of the problem we face and possible solutions, while Subsection 2.2 presents our 'identification-through-volatility' approach.

2.1 Reverse causality, regime-dependence, and the identification problem

Consider the following SVAR:

$$X_t = c + A_1 X_{t-1} + ... + A_p X_{t-p} + Be_t = \Pi W_t + Be_t \quad , \quad e_t \sim \mathrm{WN}(0_{n\times 1},\, I_n)\ ,\ \ t = 1, ..., T \quad (1)$$

where T is the sample length, p is the system lag order, X_t is the $n \times 1$ vector of endogenous variables, c is a $n\times 1$ constant, A_i, $i = 1, ..., p$ are $n\times n$ matrices of parameters, $\Pi := (A_1, ..., A_p, c)$, $W_t := (X'_{t-1}, ...X'_{t-p}, 1)'$, B is a $n \times n$ non-singular matrix containing what we call 'structural parameters', and e_t is the vector of mean zero, unit variance and uncorrelated structural shocks. Let

$$X_t = \mu + \Psi(L)Be_t \quad (2)$$

be the associated structural moving average representation, where $\Psi(L){:=}I_n + \Psi_1 L + \Psi_2 L^2 + ...$ is a polynomial in the lag operator L of infinite order, Ψ_h, $h = 1, 2, ...$ is the $n \times n$ matrix of coefficients associated with the h-th lag of $\Psi(L)$, and $\mu{:=}\Psi(1)c$. In eq. (2), $\Psi(L) = A(L)^{-1}$, where $A(L){:=}I_n - A_1 L - ... - A_p L^p$, and it is assumed that the solutions to $\det(A(z)) = 0$ are such that $|z| > 1$. Let

$$\eta_t = Be_t \quad (3)$$

be the $n \times 1$ vector of reduced form innovations, with (unconditional) covariance matrix $\Sigma_\eta = BB'$.

Suppose we are interested in the dynamic effects of the structural shocks in e_t. Let A be the VAR companion matrix, $X^c_t{:=}(X'_t, X'_{t-1}, ..., X'_{t-p+1})'$ the state vector associated with the VAR companion form and $R{:=}(I_n, 0_{n\times n}, ..., 0_{n\times n})$ a selection matrix such that $X_t{=}RX^c_t$, $RR' = I_n$. As is known, the dynamic response of X_{t+h} to shock e_{jt} to the variable X_{jt} is summarized by the (population) IRF:

$$IRF_j(h) := \Psi_h b_j = R\,(A)^h\, R' b_j \quad , \quad h = 0, 1, 2, ..., \quad j = 1, ..., n \quad (4)$$

where b_j is the j-th column of B, i.e. $B{:=}(b_{\bullet j} : b_j : b_{j\bullet})$, and $b_{\bullet j}$ and $b_{j\bullet}$ are the sub-matrices that contain the columns that precede (if any) and follow (if any) the column b_j, respectively. Absent further restrictions on the coefficients, the IRF in eq. (4) requires that b_j is identified in the sense that it can not be expressed as linear combination of the columns in $b_{\bullet j}$ and/or in $b_{j\bullet}$. For $h = 0$, the IRF in eq. (4) is such that $\Psi_0 = I_n$, hence up to possible normalizations of the shocks, the element b_{ij} of the B matrix in eq. (3) captures the instantaneous (on-impact) effect of the j-th structural shock on the i-th variable of the system.

Consider now our specific case, where $n = 3$. Let Y_t denote a (scalar) measure of real activity, and let U_{Mt} and U_{Ft} be two (scalar) measures of macro and financial uncertainty, respectively, so that $X_t := (U_{Mt}, Y_t, U_{Ft})'$. In the absence of further restrictions, the structural relationship in eq. (3) is given by the following system of equations

$$\underbrace{\begin{pmatrix} \eta_{Mt} \\ \eta_{Yt} \\ \eta_{Ft} \end{pmatrix}}_{\eta_t} = \underbrace{\begin{pmatrix} b_{MM} & b_{MY} & b_{MF} \\ b_{YM} & b_{YY} & b_{YF} \\ b_{FU} & b_{FY} & b_{FF} \end{pmatrix}}_{B} \underbrace{\begin{pmatrix} e_{Mt} \\ e_{Yt} \\ e_{Ft} \end{pmatrix}}_{e_t} \tag{5}$$

where we conventionally call e_{Mt} 'macroeconomic uncertainty shock', e_{Ft} 'financial uncertainty shock' and e_{Yt} 'real economic activity shock'. As is known, at least three restrictions are needed in eq. (5) to identify the shocks.[4] The covariance matrix $\Sigma_\eta = BB'$ provides $n(n+1)/2 = 6$ symmetry restrictions to identify the 9 elements of B, leaving 3 element unidentified. A common solution to this problem is to specify B as a triangular matrix, which provides the 3 zero (identifying) restrictions. The empirical literature on the identification of uncertainty shocks largely relies on the use of recursive SVARs because the interest typically lies on the effect of uncertainty shocks on Y_t, while it is presumed that U_{Mt} (U_{Ft}) responds to shocks to Y_t only with lags. If one imposes an upper (lower) triangular structure on B, it is not possible to identify simultaneously the parameters of interest b_{YM}, b_{YF}, b_{MY} and b_{FY}, meaning that 'reverse causality' cannot be addressed.[5]

The reverse causality issue and the related identification problem can be addressed by using external (valid) instruments that permit to increase the number of useful moment conditions other than $\Sigma_\eta = BB'$, without further restricting B; see e.g. Stock and Watson (2012, 2016), Mertens and Ravn (2013) and Olea *et al.* (2015). Ludvigson *et al.* (2017a) discuss the peril of such an approach in the uncertainty framework, and improve upon this methodology by arguing that if U_{Mt} and U_{Ft} are potentially endogenous (i.e. they may respond endogenously to e_{Yt}),

[4]It is worth remarking that regardless of the type of identifying restrictions we impose on B, we do not have enough information in this stylized small-scale model to claim that e_{Yt} is a demand or supply shock. In general, e_{Yt} could be a combination of technology, monetary policy, preferences and government expenditures. For this reason, and in line with Ludvigson *et al.* (2017a), we refer to e_{Yt} as 'real activity shock'. Likewise, we do not have enough information to disentangle whether uncertainty shocks originate from economic policies and/or technology.

[5]Also imposing e.g. a 'conventional' non-recursive structure on B of the type

$$B := \begin{pmatrix} b_{MM} & 0 & b_{MF} \\ b_{YM} & b_{YY} & 0 \\ 0 & b_{FY} & b_{FF} \end{pmatrix}$$

which places 3 zero restrictions which identify (locally) the SVAR (Rubio-Ramirez *et al.* 2010), would not be fully consistent with our objective of analyzing reverse causality. Other rotations of the zeros in the matrix B are in principle possible, but do not generally solve the problem.

then it is difficult to find credible observable exogenous external instruments for the uncertainty shocks. Based on this intuition, and starting from the returns of a stock market index as initial external instrument, they construct 'synthetic' proxies of valid instruments within a set-identification approach. The class of set-identified SVARs consistent with the synthetic proxies is narrowed down by considering two types of shock-based restrictions, 'event constraints', which require that the identified shocks be consistent with economic reasoning in a small number of extraordinary events (think e.g. to the 1987 stock market crash) and 'component correlation constraints', which are placed on the correlation between the identified financial uncertainty shocks and real economic activity shocks.

While synthetic external instruments and set-identification methods address the reverse causality problem, they do not help dealing with the issue of possibly regime-dependent effects of uncertainty shocks. In order to jointly address both issues, one needs to combine a non-recursive structure for B with the case where the structural parameters in B may change across macroeconomic regimes, generating regime-dependent IRFs. We solve the problem by exploiting the heteroskedasticity displayed by the reduced form errors η_t across different macroeconomic regimes that characterize US business cycle. More specifically, we relax (and check empirically the validity of) both the assumption of time-invariant VAR error covariance matrix Σ_η, and the assumption of time-invariant structural parameters in B. Our identification methodology is based on the existence of different volatility regimes in the post-WW2 US business cycle, i.e. different values that the unconditional error covariance matrix Σ_η takes across sub-samples. Associated with the changes in Σ_η, changes in the structural parameters B may be also allowed. Suppose, as an example, that there are two volatility regimes in the data captured by the error covariance matrices $\Sigma_{\eta,1}$ and $\Sigma_{\eta,2}$, respectively. Based on Rigobon (2003) and Rigobon and Sacks (2004), Lanne and Lütkepohl (2008) have shown that the 'additional' moment conditions needed to identify a 'full' (but time-invariant) matrix B can be obtained from the fact that the condition $\Sigma_{\eta,1} \neq \Sigma_{\eta,2}$ implies the simultaneous factorization $\Sigma_{\eta,1} = BB'$, $\Sigma_{\eta,2} = BVB'$, where V is a diagonal matrix with positive distinct elements on the diagonal. With this approach, however, the matrix of structural parameters B is kept fixed across volatility regimes and the SVAR produces regime-invariant IRFs. Bacchiocchi and Fanelli (2015) and Bacchiocchi *et al.* (2017) have extended this approach to the case where the parameters in the matrix B are allowed (but not forced) to change across volatility regimes, so that regime-dependent IRFs arise.[6] In this framework, the condition $\Sigma_{\eta,1} \neq \Sigma_{\eta,2}$ is modelled by the specification $\Sigma_{\eta,1} = BB'$, $\Sigma_{\eta,2} = (B+Q)(B+Q)'$, where Q is a matrix whose non-zero elements capture the changes, if any, that occur in the structural parameters across the two volatility regimes. Under suitable

[6] We refer to Lütkepohl (2013) and Lütkepohl and Netšunajev (2017) for a review of this literature.

linear restrictions on B and Q, the SVAR can be (point-)identified such that the relationships $\eta_t = Be_t$ (first volatility regime) and $\eta_t = (B+Q)e_t$ (second volatility regime) are not subject to the limits of causal ordering.

2.2 Identification strategy

Consider the SVAR for $X_t{:=}(U_{Mt}, Y_t, U_{Ft})'$ defined in eq. (1) and the structure of the unconditional covariance matrix Σ_η:

$$\Sigma_\eta = E(\eta_t\eta_t'){:=}\begin{pmatrix} \sigma_M^2 & \sigma_{M,Y} & \sigma_{M,F} \\ & \sigma_Y^2 & \sigma_{Y,F} \\ & & \sigma_F^2 \end{pmatrix}, \tag{6}$$

where, $\sigma_{M,Y} = E(\eta_{Mt}\eta_{Yt})$, $\sigma_{M,F} = E(\eta_{Mt}\eta_{Ft})$ and $\sigma_{Y,F} = E(\eta_{Yt}\eta_{Ft})$. For ease of exposition, assume that there are two structural changes in the unconditional error covariance matrix, which correspond to the existence of three distinct volatility regimes.[7] If $t{=}T_{B_1}$ and $t{=}T_{B_2}$ denote the dates of the two structural breaks, with $1 < T_{B_1} < T_{B_2} < T$, then the reduced form VAR in eq. (1) can be generalized to:

$$X_t = \Pi(t)W_t + \eta_t \quad , \quad \Sigma_\eta(t){:=}E(\eta_t\eta_t') \quad , \quad t = 1, ..., T \tag{7}$$

where $W_t := (X_{t-1}', ..., X_{t-p}', 1)'$ contains lagged regressors and a constant, $\Pi(t)$ is the matrix of associated slope (autoregressive) coefficients given by

$$\Pi(t){:=}\Pi_1 \times \mathbb{1}\left(t \le T_{B_1}\right) + \Pi_2 \times \mathbb{1}\left(T_{B_1} < t \le T_{B_2}\right) + \Pi_3 \times \mathbb{1}\left(t > T_{B_2}\right) \tag{8}$$

and, finally, the error covariance matrix $\Sigma_\eta(t)$ is given by

$$\Sigma_\eta(t){:=}\Sigma_{\eta,1} \times \mathbb{1}\left(t \le T_{B_1}\right) + \Sigma_{\eta,2} \times \mathbb{1}\left(T_{B_1} < t \le T_{B_2}\right) + \Sigma_{\eta,3} \times \mathbb{1}\left(t > T_{B_2}\right) \tag{9}$$

where $\mathbb{1}(\cdot)$ is the indicator function. Key to our identification approach is that $\Sigma_{\eta,1} \neq \Sigma_{\eta,2} \neq \Sigma_{\eta,3}$. Important for our analysis, notice that the specification in eq.s (7)-(9) covers the case in which also the slope (autoregressive) parameters vary across volatility regimes ($\Pi_1 \neq \Pi_2 \neq \Pi_3$).[8]

[7] This is the case we will deal with in our empirical section. Our analysis, however, can be easily generalized to the case in which there are m structural breaks in the unconditional error covariance matrix, corresponding to $m+1$ volatility regimes in the data.

[8] The number of VAR lags might change across volatility regimes, i.e. the number of columns of Π_1, Π_2 and Π_3 might be different. In this and in the other sections we work, without any loss of generality, under the maintained hypothesis that the VAR lag length is the same across regimes.

We assume that the system described by eq.s (7)-(9) is subject to a set of regularity assumptions (Assumptions 1-3 in the Technical Supplement) which allow standard inference. Given the existence of three volatility regimes, the SVAR is defined by the structural specification:

$$\begin{array}{ll} \eta_t = Be_t & 1 \leq t \leq T_{B_1} \\ \eta_t = (B + Q_2)\, e_t & T_{B_1} < t \leq T_{B_2} \\ \eta_t = (B + Q_2 + Q_3)\, e_t & T_{B_2} < t \leq T \end{array} \tag{10}$$

where B, Q_2 and Q_3 are 3×3 matrices containing structural parameters and e_t:=$(e_{Mt}, e_{Yt}, e_{Ft})'$ is the vector of structural shocks such that $E(e_t)$=$0_{3\times1}$ and with normalized covariance matrix $E(e_t e_t')$:=I_3.[9] As before, we call e_{Mt} 'macroeconomic uncertainty shock', e_{Ft} 'financial uncertainty shock' and e_{Yt} 'shock to real activity'. In eq. (10), B is the non-singular matrix that governs the structural contemporaneous relationships (on-impact responses) between the variables and the shocks in the first volatility regime. The matrix Q_2 captures the changes in the structural parameters, if any, from the first to the second volatility regime, hence the non-singular matrix $(B + Q_2)$ captures the structural contemporaneous relationship (on-impact responses) between the variables and the shocks in the second volatility regime. The matrix Q_3 captures the change in the structural parameters, if any, from the second to the third volatility regime, hence the non-singular matrix $(B + Q_2 + Q_3)$ captures the structural relationship (on-impact responses) between the variables and the shocks in the third volatility regime. Eq. (10) leads to the system of second-order moment conditions

$$\Sigma_{\eta,1} = BB' \tag{11}$$

$$\Sigma_{\eta,2} = (B + Q_2)\,(B + Q_2)' \tag{12}$$

$$\Sigma_{\eta,3} = (B + Q_2 + Q_3)\,(B + Q_2 + Q_3)' \tag{13}$$

which link the reduced form to the structural parameters. System (11)-(13) represents the platform upon which the SVAR with breaks in volatility can be identified.

In order to point-identify the SVAR, it is necessary to add to system (11)-(13) a proper set of linear restrictions on B, Q_2 and Q_3, such that a rank condition is meet (Bacchiocchi and Fanelli (2015); see also Technical Supplement). These restrictions come from economic theory. The so-obtained matrices B, Q_2 and Q_3 depend uniquely on the structural parameters which

[9] An alternative and equivalent parametrization of the SVAR in eq. (10) is discussed in the Technical Supplement and is based on the assumptions that the structural shocks have a diagonal matrix covariance matrix, $E(e_t e_t')$:=Σ_e:=$diag(\sigma^2_{eM}, \sigma^2_{eY}, \sigma^2_{eF})$, and that these variances may change across volatility regimes. The IRFs presented and discussed in eq. (14) below can be 'scaled' accordingly. To keep exposition as simple as possible, throughout the paper we refer, without loss of generality, to the parametrization of the SVAR in eq. (10), except where explicitly indicated.

we collect in the vector θ, hence we use the notation $B = B(\theta)$, $Q_2 = Q_2(\theta)$ and $Q_3 = Q_3(\theta)$.[10] The appealing feature of the structural specification in eq. (10) is that the matrices $B(\theta)$, $(B(\theta) + Q_2(\theta))$ and $(B(\theta) + Q_2(\theta) + Q_3(\theta))$ need not be triangular, so that reverse causality issues can be taken into account.

Moreover, the SVAR in eq.s (7)-(10) generates regime-dependent IRFs, which allows us to address also the issue of possibly regime-dependent effects of uncertainty shocks. To see this point, let A_i, $i = 1, 2, 3$ be the reduced form companion matrices associated with the SVAR in eq.s (7)-(10). The dynamic response of X_{t+h} to a one-standard deviation shock in variable j at time t is then summarized by the (population) IRFs:

$$IRF_j(h) := \begin{cases} R'(A_1)^h R\tilde{b}_j & t \leq T_{B_1} \\ R'(A_2)^h R(\tilde{b}_j + \tilde{q}_{2j}) & T_{B_1} < t \leq T_{B_2} \\ R'(A_3)^h R(\tilde{b}_j + \tilde{q}_{2j} + \tilde{q}_{3j}) & t > T_{B_2} \end{cases} \qquad \begin{array}{c} h = 0, 1, ..., h_{\max} \\ j = M, Y, F \end{array} \tag{14}$$

where R is the selection matrix introduced in Section 2, $\tilde{b}_j$ is the j-th column of the matrix $\tilde{B}$, $\tilde{b}_j + \tilde{q}_{2j}$ is the j-th column of the matrix $\tilde{B} + \tilde{Q}_2$, $\tilde{b}_j + \tilde{q}_{2j} + \tilde{q}_{3j}$ is the j-th column of the matrix $\tilde{B} + \tilde{Q}_2 + \tilde{Q}_3$, respectively, and $h_{\max}$ is the largest horizon considered. Even in the special case in which the slope (autoregressive) coefficients do not vary across volatility regimes, i.e. when $A_1 = A_2 = A_3$ (meaning that $\Pi_1 = \Pi_2 = \Pi_3$ in eq. (8)), the IRFs in eq. (14) change across volatility regimes because of the changes in the on-impact response coefficients.

3 Empirical results

In this section, we apply the SVAR for $X_t := (U_{Mt}, Y_t, U_{Ft})'$ presented in eq. (1) to address our two main research questions: (i) Does the response of Y_t to shocks to (U_{Mt}, U_{Ft}) vary across macroeconomic regimes? (ii) Are U_{Mt} and U_{Ft} exogenous sources of fluctuations in Y_t, or do U_{Mt} and U_{Ft} also respond endogenously to shocks in Y_t? In Section 3.1 we present the data and in Section 3.2 we test for structural breaks in the unconditional volatility of the variables and present evidence on the VAR informational sufficiency. In Section 3.3 we specify and discuss the baseline non-recursive SVAR and in Section 3.4 we analyze the resultant IRFs.

3.1 Data

Our VAR includes three variables; $U_{Mt}(f), U_{Ft}(f)$ and Y_t, where Y_t is a measure of real economic activity, $U_{Mt}(f)$ is a measure of f-period-ahead macroeconomic uncertainty and $U_{Ft}(f)$ is a measure of f-period-ahead financial uncertainty, where $f = 1$ (one-month) or $f = 12$ (one-year).

[10] The quasi-maximum likelihood (QML) estimation of θ is discussed in detail in Bacchiocchi and Fanelli (2015).

Our measure of real economic activity is the growth rate of the log of real industrial production, denoted Δip_t. The real industrial production index is taken from the FRED database. The measure of financial uncertainty is taken from Ludvigson *et al.* (2017a), while the index of macroeconomic uncertainty is taken from Jurado *et al.* (2015).[11] The data are monthly and cover the period 1960M8-2015M4 for a total of $T = 653$ observations. The use of these two proxies of uncertainty, which are plotted in Figure 1 for $f = 1$ (one-month uncertainty), is motivated by two facts. First, as discussed in Jurado *et al.* (2015), other widely used measures of uncertainty based on option-based volatility indexes such as VIX or VXO are comparatively less defensible because they contain a large component attributable to changes in the variance risk premium that are unrelated to common notions of uncertainty. Second, and more important for our analysis, they allow us to disentangle macro and financial uncertainty using two proxies that have been constructed using the same econometric methodology and that differ only in terms of their informational content.

3.2 Volatility breaks and informational sufficiency

Two crucial features of our VAR are that the identification approach requires breaks in the unconditional volatility of the data, and that a small-scale VAR like ours is not affected by non-fundamentalness, which implicitly amounts to claim that it does not omit important variables. Our major hypothesis is that the relationship between uncertainty and real activity vary across the main macroeconomic regimes of post-WW2 US business cycle because of changes in the unconditional variance of Y_t . To provide evidence in favour of volatility breaks, we proceed in two steps. First, we provide suggestive evidence of time variation by looking at recursive and rolling windows estimates of the residual variances and covariances in our baseline VAR. Second, we formally test for the existence of two structural breaks using Chow-type tests, with possible break dates identified in the previous step. Next, we deal with potential non-fundamentalness of our VAR by testing for its 'informational sufficiency' using the procedure by Forni and Gambetti (2014). We do so in light of the small dimension of $X_t{:=}(U_{Mt}, Y_t, U_{Ft})'$ because non-fundamentalness is best seen as an informational deficiency problem. Not rejecting the informational sufficiency of $X_t{:=}(U_{Mt}, Y_t, U_{Ft})'$ ensures that we can correctly estimate the effects of uncertainty shocks through IRFs.

We start by estimating our baseline VAR for $X_t{:=}(U_{Mt}, Y_t, U_{Ft})'$ with four lags ($p = 4$) both recursively and over 10- and 15-years rolling-windows. The estimates of the six elements of the unconditional VAR error covariance matrix Σ_η are plotted in Figure 2. The graphs on the diagonal report the estimated variances while the off-diagonal terms report the estimated

[11] The Technical Supplement also discusses at length how the two proxies of uncertainty have been constructed.

covariances for the recursive (blue line), the 10-years (red line) and the 15-years (yellow line) rolling windows VARs. The graph in the position (2,2) reports the unconditional variance of the residuals of the second equation of our VAR, the one associated with Y_t, i.e. σ_Y^2 in Σ_η in eq. (6). The graph clearly shows that the average volatility level is time-varying, being higher during the seventies and eighties, declining from the mid-eighties until the end of 2007, and then increasing again after the financial crisis of 2007–08 before stabilizing. All the remaining graphs in Figure 2 broadly confirm the presence of three volatility regimes. As expected, the two main changes of volatility occur in correspondence of the beginning of the Great Moderation and Great Recession periods, respectively. The two dashed vertical lines correspond to the possible break dates, i.e. T_{B_1} = 1984M3 and T_{B_2} =2007M12. These two break dates would partition the whole sample period 1960M8-2015M4 into three different sub-samples: the Great Inflation period (1960M8-1984M3, $T = 280$), the Great Moderation period (1984M4-2007M12, $T = 285$), and the Great Recession+Slow Recovery period (2008M1-2015M4, $T = 88$).[12] It is worth noting, however, that while the unconditional variance associated with the proxy of macroeconomic uncertainty roughly follows the same volatility pattern as the unconditional volatility of Y_t (position (1,1) in Figure 2), the unconditional variance associated with the proxy of financial uncertainty increases until the beginning of nineties probably because of the process of financial innovation which characterizes US financial markets (position (3,3) in Figure 2). Interestingly, these differences in volatility patterns provide identification information in our approach.

The evidence reported in Figure 2 is consistent with the information conveyed in Table 1. The second column of Table 1 summarizes the OLS-based estimates of the VAR covariance matrix Σ_η on the whole sample, i.e. under the null hypothesis that there are no volatility regimes in the data ($H_0' : \Sigma_{\eta,1} = \Sigma_{\eta,2} = \Sigma_{\eta,3}$), and then separately on the three volatility sub-periods.[13] As already shown in Figure 2, these results confirm that unconditional variances and covariances have changed over time. Table 1 also summarizes some diagnostic statistics associated with the estimated models, which suggest that VAR residuals tend to be not Gaussian but not serially

[12] As concerns the third volatility regime, according to the U.S. National Bureau of Economic Research the Great Recession began in December 2007 and ended in June 2009, thus extending over 19 months. Thus, we treat T_{B_2} =2007M12 as the date in which the Great Moderation ends. Considering three distinct volatility regimes does not necessarily rule out the possibility that the VAR for X_t:=$(U_{Mt}, Y_t, U_{Ft})'$ might display unconditional (or possibly conditional) heteroskedastic disturbances within regimes, other than across them. This is clearly seen from the graphs in Figure 2 but, as discussed below, does not represent a major obstacle to the implementation of our identification approach.

[13] The OLS estimates in Table 1 can be interpreted as QML estimates generated by maximizing Gaussian densities within each of the considered samples, see e.g. Bai (2000) and Qu and Perron (2007).

correlated within regimes.[14] The non-normality of VAR disturbances is detected, as expected, on the overall sample period but also within macroeconomic regimes and is fully consistent with the analysis in e.g. Cúrdia *et al.* (2014). We remark that the possible presence of within-regimes heteroskedasticity (conditional or unconditional), while affecting the full efficiency of our estimates, does not represent a major obstacle to the identification strategy presented below.

To verify formally the hypothesis that there are two main structural breaks in the VAR error covariance matrix at the dates T_{B_1} =1984M3 and T_{B_2} = 2007M12, we compute a set of Chow-type tests. We first test whether the joint null hypothesis of absence of structural breaks in all VAR coefficients:

$$H_0 : \begin{pmatrix} \Pi_1 \\ \Sigma_{\eta,1} \end{pmatrix} = \begin{pmatrix} \Pi_2 \\ \Sigma_{\eta,2} \end{pmatrix} = \begin{pmatrix} \Pi_3 \\ \Sigma_{\eta,3} \end{pmatrix} = \begin{pmatrix} \Pi \\ \Sigma_{\eta} \end{pmatrix} \tag{15}$$

is rejected and, conditional on the rejection of H_0, we test the null hypothesis of absence of volatility regimes

$$H_0' : \Sigma_{\eta,1} = \Sigma_{\eta,2} = \Sigma_{\eta,3} \tag{16}$$

under the maintained restriction: $\Pi_1 = \Pi_2 = \Pi_3 = \Pi$ on slope coefficients. Results are summarized in the bottom panel of Table 1 which reports the quasi-LR tests for the hypotheses H_0 and H_0', respectively. Both H_0 and H_0' are strongly rejected by the data. This result is consistent with Aastveit *et al.* (2017) who, using a wide range of econometric techniques, provide substantial evidence against the stability of common VARs in the period since the Great Recession.

Other than documenting the existence of three broad volatility regimes in the data, Table 1 provides some rough evidence about the changing nature of the relationships between our proxies of uncertainty, U_{Mt} and U_{Ft}, and real economic activity, Y_t. This can be partly seen from the correlations obtained from the estimated VAR residuals in the third column. The negative correlation between the Y_t-residuals and the U_{Mt}-residuals increases systematically in the move from the Great Moderation to the Great Recession+Slow Recovery, while the correlation between the Y_t-residuals and the U_{Ft}-residuals is negative only on the Great Recession+Slow Recovery period. Although it is not possible to infer any causality direction from the correlations in Table 1, the data clearly point towards changing relationships.

Finally, we check the 'informational sufficiency' of our small-scale VAR using the testing procedure of Forni and Gambetti (2014). For each macroeconomic regime, we consider an

[14] Albeit the multivariate test for residuals autocorrelation associated the VAR estimated on the Great Recession+Slow Recovery period reported in Table 1 leads to reject the null hypothesis of absence of correlation, the corresponding uni-equational tests computed on the single VAR equations do not reject the null. Results are available upon request to the authors.

augmented VAR system (a FAVAR) comprising X_t plus a vector of factors, included in the vector V_t, extracted from the McCracken and Ng's (2015) large set of macroeconomic and financial variables. We then test whether V_t Granger-causes X_t. Detailed results are reported in the Technical Supplement and show that the null of absence of Granger-causality from V_t to X_t is supported in all three volatility regimes. This is evidence against the presence of nonfundamental shocks induced by lack of informational sufficiency, and suggests that the risk of incorrectly recovering the shocks from our non-recursive SVAR is under control.

3.3 The structural model

In this section we discuss the specification of the matrices of structural parameters $B = B(\theta)$, $Q_2 = Q_2(\theta)$ and $Q_3 = Q_3(\theta)$ in eq. (10). Recall that the vector of shocks is $e_t{:=}(e_{Mt}, e_{Yt}, e_{Ft})'$, and we call conventionally e_{Mt} 'macroeconomic uncertainty shock', e_{Ft} 'financial uncertainty shock' and e_{Yt} 'shock to real activity', see the discussion in Section 2.

The three volatility regimes we have identified in the previous section provide us with 18 moment conditions. Since we have 27 parameters to estimate, we need to place at least 9 parameter restrictions to achieve identification. We do so by imposing a triangular structure in the first subsample only, which guarantees non-triangular structures (in particular, 'full' matrices) in the second and third subsamples. This means that in the Great Inflation period causality runs from macro uncertainty to real activity and financial uncertainty, but not the reverse.[15] Such restrictions allow us to keep the number of identifying constraints to place on $Q_2 = Q_2(\theta)$ and $Q_3 = Q_3(\theta)$ in the two remaining regimes at a minimum, so to tackle jointly the issues of time-variation and reverse causality. It is important to notice that the triangular structure imposed in the first subsample means that we give financial factors the 'passive' role of merely amplifying the shocks before the eighties, and bring the role of financial markets back to center-stage of business cycle when we consider periods after the mid-eighties. This is in line with Ng and Wright (2013), who stress how the role played by financial factors in driving business cycle fluctuations has become relevant only from the 1980s onwards.[16]

[15] Results are robust to the inversion of macroeconomic and financial uncertainty in the VAR, see Section 4.

[16] Our choice is also supported by institutional facts, in particular the changes in the norms regulating financial markets which occurred in the early 1980s, like the Depository Institutions Deregulation and Monetary Control Act in 1980, particularly the termination of regulation Q, and the Garn-St. Germain Act of 1982, which granted easier access to financial liquidity to households and firms only from the mid-eighties onwards.

Based on these considerations, the non-recursive SVAR in eq. (10) is based on the matrices:

Great Inflation:

$$\tilde{B}:=\begin{pmatrix} b_{MM} & 0 & 0 \\ b_{YM} & b_{YY} & 0 \\ b_{FM} & b_{FY} & b_{FF} \end{pmatrix}$$

Great Moderation:

$$\tilde{B}+\tilde{Q}_2:=\begin{pmatrix} b_{MM} & q_{2,MY} & q_{2,MF} \\ b_{YM}+q_{2,YM} & b_{YY}+q_{2,YY} & q_{2,YF} \\ b_{FM} & b_{FY}+q_{2,FY} & b_{FF} \end{pmatrix} \tag{17}$$

Great Recession + Slow Recovery:

$$\tilde{B}+\tilde{Q}_2+\tilde{Q}_3:=\begin{pmatrix} b_{MM} & q_{2,MY}+q_{3,MY} & q_{2,MF}+q_{3,MF} \\ b_{YM}+q_{2,YM}+q_{3,YM} & b_{YY}+q_{2,YY}+q_{3,YY} & q_{2,YF}+q_{3,YF} \\ b_{FM} & b_{FY}+q_{2,FY}+q_{3,FY} & b_{FF} \end{pmatrix},$$

hence the vector of structural parameters θ contains 18 non-zero coefficients $b_{i,j}s$, $q_{2,ij}$ and $q_{3,ij}$, $i,j=M,Y,F$ (dim(θ)=18). The symbol '$\sim$' remarks that $\tilde{B}=B(\theta)$, $\tilde{B}+\tilde{Q}_2=B(\theta)+Q_2(\theta)$ and $\tilde{B}+\tilde{Q}_2+\tilde{Q}_3=B(\theta)+Q_2(\theta)+Q_3(\theta)$ respect the necessary and sufficient rank condition for identification. The non-recursive structures of the matrices $\tilde{B}+\tilde{Q}_2$ (Great Moderation) and $\tilde{B}+\tilde{Q}_2+\tilde{Q}_3$ (Great Recession+Slow Recovery) in eq. (17) stresses that we are 'agnostic' about causality links from the onset of the Great Moderation and let the data determine whether macroeconomic and financial uncertainty also respond endogenously to negative economic fluctuations. Observe that the estimation of two separate SVARs, one based on $\eta_t=(\tilde{B}+\tilde{Q}_2)e_t$ on the Great Moderation period and the other based on $\eta_t=(\tilde{B}+\tilde{Q}_2+\tilde{Q}_3)e_t$ on the Great Recession+Slow Recovery period, respectively, would not be possible with 'standard' recursive schemes.

Eq. (17) gives rise to the following system

$$\Sigma_{\eta,1} = \tilde{B}\tilde{B}' \tag{18}$$

$$\Sigma_{\eta,2} = (\tilde{B}+\tilde{Q}_2)(\tilde{B}+\tilde{Q}_2)' \tag{19}$$

$$\Sigma_{\eta,3} = (\tilde{B}+\tilde{Q}_2+\tilde{Q}_3)(\tilde{B}+\tilde{Q}_2+\tilde{Q}_3)' \tag{20}$$

which maps 18 structural parameters contained in $\tilde{B}$, $\tilde{B}+\tilde{Q}_2$ and $\tilde{B}+\tilde{Q}_2+\tilde{Q}_3$ (dim(θ)=18) to 18 second-order moment conditions provided by $\Sigma_{\eta,1}$, $\Sigma_{\eta,2}$ and $\Sigma_{\eta,3}$.

3.4 The dynamic effects of uncertainty shocks

The non-recursive SVAR specified in eq. (17) is estimated on the period 1960M8-2015M4 imposing the two break dates $T_{B_1}=$ 1984M3 and $T_{B_2}=$2007M12 which define the three volatility regimes analyzed in Section 3.2. The quasi-maximum likelihood (QML) estimates of the structural parameters θ that enter the matrices $\tilde{B}$, $\tilde{B}+\tilde{Q}_2$ and $\tilde{B}+\tilde{Q}_2+\tilde{Q}_3$ are reported for $f=1$ (one-month uncertainty) in the upper panel of Table 2, along with analytic and bootstrap standard errors.[17] The estimated $\hat{\theta}$ corresponds to the on-impact responses featured by our IRFs.

A plot of the estimated structural shocks $\hat{e}_{jt}$, $t=1,...,T$, $j=M,Y,F$, where $\hat{e}_t=\hat{B}_i^{-1}\hat{\eta}_t$, $i=1,2,3$, $\hat{B}_1=\tilde{B}$, $\hat{B}_2=\tilde{B}+\tilde{Q}_2$, $\hat{B}_3=\tilde{B}+\tilde{Q}_2+\tilde{Q}_3$, is reported in Figure 3. The graph interestingly shows that the identified macro and financial uncertainty shocks are substantially different. Prominent macro uncertainty shocks are those corresponding to the two oil price shocks of the 1970s and the fiscal battles in the 2010s, while the stock market crash in 1987 and the Asian crisis in the late 1990s are examples of two major financial uncertainty shocks which did not cause any increase in macroeconomic uncertainty. The GFC in 2007-2009 is an example of a shock that has increased both macro and financial uncertainty.

The IRFs are computed as in eq. (14) by replacing A_1, A_2 and A_3 and $\tilde{B}$, $\tilde{B}+\tilde{Q}_2$ and $\tilde{B}+\tilde{Q}_2+\tilde{Q}_3$ with their QML estimates, and are plotted in Figures 4-7 over an horizon of $h_{\max}$ =60 periods (5 years). Figure 4 compares the IRFs obtained on the three volatility regimes for $f=1$ (one-month uncertainty) on the same graph. Figures 5-7 plot the IRFs separately for each regime, disentangling the case $f=1$ (one-month uncertainty) from the case $f=12$ (one-year uncertainty). All plots show responses to one standard deviation changes in e_{jt}, $j=M,Y,F$ in the direction that leads to an increase in its own variable X_{it}, $i=M,Y,F$, where $X_{Mt}=U_{Mt}$, $X_{Yt}=Y_t$ and $X_{Ft}=U_{Ft}$, respectively. This normalization allows us to directly compare the responses of real economic activity in the three volatility regimes.

In Figure 4 (which can be fully appreciated in color), the blue IRFs refer to the Great Inflation period, the red IRFs to the Great Moderation period and the yellow IRFs to the Great Recession+Slow Recovery period. The first row reports the response to each shock of macroeconomic uncertainty, the second row reports the response of industrial production, and the third row reports the response of financial uncertainty. Confidence bands have not been reported to ease reading.[18] In order to compare results with simple benchmarks, Figure 4 also plots the IRFs generated by two recursive Cholesky-based SVARs estimated on the whole sample 1960M8-2015M4, i.e. under the hypothesis of constant parameters (which has been sharply rejected by

[17] Bootstrap standard errors are computed using Kilian's (1998) bootstrap-after-bootstrap method, keeping the break dates T_{B_1} = 1984M3 and T_{B_2} =2007M12 fixed and resampling (non-parametrically) separately within each volatility regime.

[18] Recall that the reduced form analysis in Section 3.2 shows that there are significant differences between all VAR coefficients (autoregressive parameters and covariance matrices) across the three volatility regimes. Accordingly, the three IRFs in each graph of Figure 4 read as transformations of parameters which are different in their population values.

the data in Section 3.2). One recursive SVAR is based on the ordering $X_t^R{:=}(U_{Mt}, Y_t, U_{Ft})'$ (dashed black IRFs), and the other is based on the ordering $X_t^{R'}{:=}(U_{Ft}, Y_t, U_{Mt})'$ (dotted black IRFs). We consider these two orderings in order to be as neutral as possible on the relative importance of the two sources of uncertainty.

The graphs in Figure 4 suggest four main comments. First, there is evidence of substantial time variation in the impulse responses: the estimated IRFs differ quantitatively and qualitatively across the three volatility regimes. Although uncertainty shocks curb industrial production growth in all three macroeconomic regimes, the persistence of the shocks and the number of periods after which the negative peak is reached vary across regimes. Second, the effects of macroeconomic uncertainty shocks on all variables are larger and more persistent in the Great Recession+Slow Recovery period.[19] In particular, macroeconomic uncertainty seems to have played a sizable role in driving persistently down economic activity during this period. Third, while real activity reacts negatively and persistently to uncertainty shocks, uncertainty reacts only mildly to real activity shocks, if anything. Fourth, there exists substantial difference between the IRFs estimated with our non-recursive SVAR and the IRFs produced with conventional Cholesky-based systems which ignore the presence of volatility regimes in the data. In particular, the constant-parameter VARs with Cholesky identification fail to capture both the magnitude and the persistence of the responses in the Great Recession+Slow recovery period.

The differences between the IRFs in the three macroeconomic regimes can further be appreciated by looking at the numbers in Tables 3a-3b, which extrapolate the significant peaks of the IRFs plotted in Figure 4 along with the number of months necessary to achieve these peaks. Table 3a refers to our non-recursive SVAR, while Table 3b refers to the two Cholesky-based systems. Table 3a indicates that within each macroeconomic regime, both the magnitude and persistence of the effects of uncertainty shocks increase with the length of the uncertainty horizon f. Moreover, the negative effects of uncertainty shocks tend to be higher on the Great Recession+Slow Recovery sample, which is the period characterized by higher financial frictions after the financial crisis of 2007-2008. Finally, the magnitude of the effect of macroeconomic uncertainty shocks is typically higher, on average, than the effect of financial uncertainty shocks. The comparison of estimates in the two Tables shows that ignoring the regime-dependence nature of the effects of uncertainty shocks leads one to underestimate their impact. Consider, as an example, the case $f = 1$: the estimated highest negative effect of macroeconomic uncertainty shocks ranges from -0.11 to -0.07 percentage points according to the Cholesky-based SVARs,

[19]The comparatively more jagged profile of the IRFs estimated on the Great Recession+Slow Recovery period (yellow lines) in Figure 4 can be explained in terms of the combined effects of the financial crisis of 2007–08 and the shorter estimation sample ($T = 88$ monthly observations as opposed to $T = 280$ observations on the Great Inflation and $T = 280$ observations on the Great Moderation).

and is achieved either on-impact or 3 months after the shock; with the non-recursive SVAR, the effect is instead equal to -0.178 percentage points and is achieved 5 months after the shock on the Great Recession+Slow recovery period.

Overall, combined with the reduced form evidence in Section 3.2, Figure 4 and Table 3 provide a positive answer to our first research question: the short-run relationship between uncertainty and real economic activity changes qualitatively and quantitatively across macroeconomic regimes. A researcher who ignores the regime-dependent nature of uncertainty shocks is likely to estimate compounded effects, which hide the different dynamics displayed in the data.

We now examine in more detail the specific features of each macroeconomic regime by looking at Figures 5-7, which report the estimated IRFs with associated 90% bootstrap confidence bands (shaded areas) separately for the three volatility regimes. The we focus on the reverse causality issue.

Great Inflation. Figure 5 plots the dynamic responses of the variables in $X_t{:=}(U_{Mt}, Y_t, U_{Ft})'$ to each structural shock during the Great Inflation period (1960M8-1984M3) considering both $f = 1$ (one-month uncertainty, blue line) and $f = 12$ (one-year uncertainty, red line). The graphs show that, in line with the specification in eq. (17), positive shocks to macroeconomic uncertainty lead to a decline in industrial production growth, which is statistically significant for a large number of months. IRFs are shorter-lived and less persistent in the case $f = 1$. For $f = 1$, the largest effect is on impact and is equal to -0.101 percentage points, while for $f = 12$ the negative significant peak is obtained 8 months after the shock and is equal to -0.067 percentage points.

Positive shocks to financial uncertainty have lagged (recall that there is no instantaneous impact according to eq. (17)) and slightly less persistent negative effects on industrial production growth relative to the case of macroeconomic uncertainty shocks. The effect of financial uncertainty shocks lasts for roughly 12 months after the shock, reaches its maximum significant negative effect 3 months after the shocks and is equal to -0.121 ($f = 1$) and -0.101 ($f = 12$) percentage points, respectively.

Notably, regardless of whether one considers macroeconomic or financial uncertainty shocks, industrial production growth does not overshoot its trend after recovering, suggesting that the decline in industrial production might be permanent.[20] Conversely, for both $f = 1$ and $f = 12$,

[20] This phenomenon is further scrutinized in the Technical Supplement where we report the associated cumulated long-run multipliers, which quantify the final effect of uncertainty shocks on the level of industrial production once all dynamic adjustments are taken into account. The analysis confirms the existence of a significant long run negative impact.

macroeconomic and financial uncertainty do not respond significantly to shocks to real economic activity, suggesting that there might be no reverse causality on the Great Inflation period.

Overall, for the Great Inflation period, the IRFs in Figure 5 corroborate the hypothesis that both macroeconomic and financial uncertainty shocks trigger recessionary effects. They also support the view that uncertainty is a driver, rather than a consequence, of business cycle fluctuations.

Great Moderation. Figure 6 plots the dynamic responses of the variables in $X_t{:=}(U_{Mt}, Y_t, U_{Ft})'$ to each structural shock on the Great Moderation period (1984M4-2007M12). In this case, we have a fully non-recursive structural framework, as the matrix $\tilde{B} + \tilde{Q}_2$ in eq. (17) is full and does not exclude short-run instantaneous causality from macroeconomic and financial uncertainty shocks to real economic activity and, simultaneously, from real economic activity shocks to macroeconomic and financial uncertainty.

The graphs show that positive shocks to macroeconomic uncertainty lead to a decline in industrial production growth with a slowdown which remains statistically significant for about 12 months after the shock for $f = 1$, and for about 30 months after the shocks for $f = 12$. The peak effect of macroeconomic uncertainty shocks is on-impact and is equal to -0.085 percentage points for $f = 1$, while it occurs after 2 months and is -0.069 percentage points for $f = 12$, which are similar in magnitude to what observed in the Great Inflation period.

Positive shocks to financial uncertainty lead to a sharp decline in industrial production growth but the effect is short-lived. Indeed, for both $f = 1$ and $f = 12$, the highest significant negative effect is on-impact and is equal to -0.194 and -0.173 percentage points, respectively. Also in this case, both macroeconomic and financial uncertainty shocks seem to lead to a permanent drop in industrial growth because the dynamics of Y_t does not overshoot its trend significantly after recovering.

As concerns the reverse causality issue, the estimated IRFs suggest that while macroeconomic uncertainty does not respond significantly to real economic activity shocks in the short-run, the response of one-month ($f = 1$) financial uncertainty is significant for about 20 months after the shock. This result is in line with the positive response of financial uncertainty to industrial production shocks found by Ludvigson *et al.* (2017a) on the entire 1960-2015 period, although the IRFs are less persistent in their case. Also Bekaert *et al.* (2013) find a positive response of their measure of financial uncertainty to positive shocks to industrial production growth: they consider the sample 1990M1-2007M7 which is compatible with our Great Moderation period, but their IRFs are not statistically significant.[21] The procyclical significant responses of U_{Ft}

[21] Popescu and Smets (2010) show that real industrial production shocks in Germany have significant, yet non-monotonic, effects on perceived uncertainty. In their case, both uncertainty and risk premia initially fall in

to real economic shocks in the system X_t:=$(U_{Mt}, Y_t, U_{Ft})'$ during the Great Moderation are not permanent because the associated long-run impact multipliers, reported in the Technical Supplement, are not statistically significant. Moreover, as it will be seen in Section 4, the dynamic causality link from real economic activity shocks to one-month financial uncertainty does not prove to be robust to a crucial control for financial frictions.

Overall, the IRFs in Figure 6 confirm that both macroeconomic and financial uncertainty curb real economic activity during the Great Recession period with slightly larger effects for financial uncertainty shocks compared to what estimated on the Great Inflation period.

Great Recession+Slow Recovery. Figure 7 plots the dynamic responses of the variables in X_t:=$(U_{Mt}, Y_t, U_{Ft})'$ to each structural shock on the Great Inflation+Slow Recovery period (2008M1-2015M4). Also in this case, the non-recursive structure of the matrix $\tilde{B} + \tilde{Q}_2 + \tilde{Q}_3$ in eq. (17) is full and features reverse causality.

In this case, positive shocks to macroeconomic uncertainty lead to a decline in industrial production growth with a slowdown which remains statistically significant for about 10 months for both $f = 1$ and $f = 12$. Regardless of the length of the uncertainty horizon, the highest negative impact of macroeconomic uncertainty shocks is reached 5 months after the shock and is equal to -0.178 ($f = 1$) and -0.174 ($f = 12$) percentage points, respectively. Compared to the previous subsamples, the response of industrial production is less persistent but the magnitude is remarkably larger.

Positive shocks to financial uncertainty produce comparatively more jagged responses of industrial production growth. The highest negative significant peak is obtained 3 months after the shock and is equal to -0.183 ($f = 1$) percentage points and -0.123 ($f = 12$) percentage points, respectively.

As before, both macroeconomic and financial uncertainty shocks do not seem to generate overshooting phenomena in industrial production growth. We do not detect reverse causality in this regime.

Overall, the IRFs in Figure 7 show that the real effects of uncertainty shocks have become larger during the Great Recession+Slow Recovery period. We notice that this is in line with several contributions in the literature, which highlight how uncertainty shocks have had larger effects during the Great Recession. This can be due to large financial frictions, as in Alfaro *et al.* (2016), Caggiano *et al.* (2017b), and Gilchrist *et al.* (2014), or to the presence of the Zero Lower Bound, as in Caggiano *et al.* (2017a) and Basu and Bundik (2017).

Reverse causality: discussion. The IRFs plotted in Figures 5-7 deliver also an answer

response to positive output shocks, but eventually increase.

to our second research question, i.e. whether uncertainty is an exogenous source of economic fluctuations or an endogenous response to it, or both. Overall, the estimated dynamic causality relationships provide clear evidence that uncertainty shocks trigger a persistent reaction in real activity, while evidence that uncertainty reacts to real activity shocks is scant.

These findings on reverse causality allow us to make contact with Ludvigson *et al.* (2017a), the paper in the literature that is the closest to ours in this respect. In line with their results, we find that financial uncertainty is an important driver of the business cycle, and it is not a reaction to it. However, we find remarkable differences compared to their analysis when we look at the behavior of macroeconomic uncertainty. While they report that macroeconomic uncertainty shocks have positive effects on real activity and that it could be characterized as an endogenous response to business cycle fluctuations, we find that macroeconomic uncertainty is as important as financial uncertainty in triggering a downturn in real activity, and that it is exogenous to the business cycle. As discussed in Section 2.1, Ludvigson *et al.* (2017a) base their conclusions from a novel methodology which combines the external instruments approach with the mechanics of set-identification, see also Ludvigson *et al.* (2017b). The endogeneity of macroeconomic uncertainty they document might reflect the 'asymmetric' characterization of financial and macroecomomic uncertainty shocks implicit in their approach (i.e. the fact that both of their two synthetic instruments are correlated with financial uncertainty while only one of them is correlated with macroeconomic uncertainty), and the effects of the constraints they impose on the unobservable shocks. Instead, our approach point-identifies the non-recursive SVAR by treating macroeconomic and financial uncertainty symmetrically, and allowing for regime-dependence in the SVAR parameters, which unveils important time-variation in the dynamic responses to uncertainty shocks. Strictly speaking, the two approaches are not directly comparable: in our case, sampling uncertainty is evaluated using frequentist confidence intervals; on the other hand, as argued in Ludvigson *et al.* (2017b), in set-identified models the evaluation of sampling uncertainty from a frequentist perspective is challenging and is specific to the imposition of the particular identifying restictions.

4 Robustness checks

In this section, we check the robustness of our findings to a number of perturbations of the baseline structural model. These refer to: the inclusion of a measure of financial stress in the system to control for first-moment financial shocks; the ordering of the variables in the first volatility regime; the use of a measure of macroeconomic uncertainty 'purged' from its financial component as in Ludvigson *et al.* (2017a); the use of the growth rate of employment as a measure of real economic activity. Here we sketch a summary of these checks which are analyzed in details in the Technical Supplement.

The role of financial frictions. Our baseline empirical analysis considers macroeconomic and financial uncertainty jointly but ignores financial frictions, which have been analyzed in several recent contributions, see e.g. Bachmann *et al.* (2013), Christiano *et al.* (2014), Gilchrist *et al.* (2014), Alessandri and Mumatz (2014) and Alfaro *et al.* (2016); see also Caldara *et al.* (2016), Caggiano *et al.* (2017b) and Furlanetto *et al.* (2017). We check whether the omission of measures of financial frictions drive our main results by estimating our non-recursive SVAR for two different vectors of endogenous variables: $X_t^* := (U_{Ft}, Y_t, CS_t)'$ and $X_t^{*\circ} := (U_{Mt}, Y_t, CS_t)'$, respectively, where CS_t is the spread between yields on Baa- and Aaa-rated long-term industrial corporate bonds (source FRED database). In both models we assume, in line with the specification in eq. (17), that the uncertainty measure is exogenous on the Great Inflation period, while it can also respond contemporaneously to other shocks on the Great Moderation and Great Recession+Slow Recovery regimes. Results are reported in Figures TS.1-TS.3 of the Technical Supplement. The baseline findings in Figures 5-7 on the contractionary effect of uncertainty shocks tend to be confirmed: industrial production reacts negatively to both macro and financial uncertainty, and it does so by more in the Great Recession+Slow Recovery period. As far the reverse causality issue is concerned, controlling for first-moment financial shocks reinforces the baseline result of exogenous uncertainty: in none of the three macroeconomic regimes real economic activity shocks trigger significant responses to financial uncertainty. In particular, Figure TS.2 shows that also in the Great Moderation period, financial uncertainty U_{Ft} does no longer respond significantly to real economic activity shocks.

Different ordering of macroeconomic and financial uncertainty in the first volatility regime. The main advantage of our identification approach over a number of alternative methods is that it allows full contemporaneous reactions of all variables to all shocks. This holds true, looking at the specification in eq. (17), in all identified volatility regimes except the first one, i.e. the Great Inflation period, where we take a specific stance on causality, which we assume running from macroeconomic to financial uncertainty. In principle, this restriction might drive, at least partly, our findings on time variation and reverse causality in the Great Inflation period and, more generally, in all identified volatility regimes. To check whether our baseline findings, i.e. real activity reacts more to macroeconomic uncertainty shocks in the Great Recession+Slow Recovery period and causality runs from uncertainty to real activity, are driven by this restriction, we re-estimate the structural model by including financial uncertainty first and macroeconomic uncertainty last. Estimated IRFs, reported in Figures TS.4-TS.6 of the Technical Supplement, point out that there are not appreciable differences relative to the baseline case in Figures 5-7.

'Purged' measure of macroeconomic uncertainty. The proxy of macroeconomic uncertainty used in our baseline model, taken from Jurado *et al.* (2015), is constructed using a dataset that contains both macroeconomic and financial indicators. In principle, this measure might have substantial overlap with the financial uncertainty index by Ludvigson *et al.* (2017a) and might be capturing not pure macroeconomic uncertainty but a mixture of macro and financial uncertainty. To overcome this problem, we proceed as in Ludvigson *et al.* (2017a) and adopt a measure of macroeconomic uncertainty which is extracted from a smaller dataset including only real activity indicator ('real uncertainty'). We label this sub-index U_{Mt}^{p}. Estimated IRFs, reported in Figures TS.7-TS.9 of the Technical Supplement, tend to confirm substantially the overall picture in Figures 5-7 produced for the baseline case.

Employment as real activity indicator. Our main findings show that real activity, proxied by the growth rate of industrial production, reacts significantly to both macro and financial uncertainty shocks and that these effects are remarkably larger in the Great Recession+Slow Recovery period. To check whether this finding is not confined to the specific measure of real activity we have adopted, we use as an alternative to industrial production the growth rate of employment. IRFs are reported in Figures TS.10-TS.12 of the Technical Supplement and confirm qualitatively the baseline scenario in Figures 5-7.

Overall, the robustness checks reported in this section show that our two main findings hold true after changing the baseline specification in different directions, i.e. (i) the effects of uncertainty shocks are time varying and depend on the macroeconomic regime, and (ii) uncertainty, both macroeconomic and financial, is better characterized as an exogenous driver of the business cycle rather than an endogenous response to it.

5 Concluding remarks

There has recently been a remarkable attention on the role played by time-varying uncertainty in driving business cycle fluctuations. In spite of the expanding theoretical and empirical literature on this topic, two main issues remain controversial: whether the real effects of uncertainty shocks have changed over time, and whether time-variation in uncertainty should be considered as an exogenous driver of the business cycle or, rather, an endogenous response to it.

This paper addresses both issues empirically and simultaneously by resorting to an 'identification-through-volatility' approach, which is novel in the literature on uncertainty. Unlike other existing identification approaches, our framework allows us to jointly estimate regime-dependent effects of uncertainty shocks and is general enough to account for reverse causality, i.e. to allow for a contemporaneous response of both real activity to uncertainty shocks and of uncertainty to real activity shocks. We apply this identification approach to a small-scale non-recursive SVAR estimated on US post-WW2 data.

Our results suggest that there are important differences in the impact and propagation mechanisms of uncertainty shocks across the three main macroeconomic regimes that characterize US business cycle, and that uncertainty, both macro and financial, is better approximated as an exogenous source of economic decline rather than an endogenous response to it. We find that uncertainty shocks, both macroeconomic and financial, have always had a contractionary impact on real activity, but that these effects have become larger since the GFC.

Overall, our findings support theoretical and empirical research that highlights how uncertainty shocks might have time-varying effects which depend on different macroeconomic conditions like, e.g. the level of financial frictions (Alfaro *et al.*, 2016; Gilchrist *et al.*, 2014, Alessandri and Mumtaz, 2014), the stance of the business cycle (Cacciatore and Ravenna, 2016; Caggiano *et al.*, 2014), or the stance of monetary policy (Basu and Bundick, 2017, Caggiano *et al.*, 2017a). They also supports the theoretical models where uncertainty is an exogenous driver of economic fluctuations, as in e.g. Bloom (2009) and Basu and Bundick (2017). In this respect, our analysis is partially consistent with the evidence reported in Ludvigson *et al.* (2017a) who also investigate the exogeneity/endogeneity of financial and macroeconomic uncertainty empirically. While we find that both macroeconomic and financial uncertainty are exogenous in all macroeconomic regimes, Ludvigson *et al.* (2017a) report that macroeconomic uncertainty responds endogenously to negative economic shocks. This discrepancy can be ascribed to the different methods used to identify the uncertainty shocks. The two methods are not directly comparable in terms of sample variability that can be associated with the estimated dynamic causality effects, but the advantage of our non-recursive SVAR specification is that it combines economic reasoning with the "truly exogenous" identification information provided by the changes in the distribution of the data which reflect the changes in the impact and propagation of uncertainty shocks across macroeconomic regimes.

References

Aastveit, K.A., Carriero, A., Clark, T.D. and Marcellino, M. (2017), Have standard VARs remained stable since the crisis?, *Journal of Applied Econometrics* 32, 931-951.

Alessandri, P. and Mumtaz, H. (2014), Financial regimes and uncertainty shocks, BCAM *Working Paper* No. 1404.

Alfaro, I.N., Bloom, N. and Lin, X. (2016), The finance-uncertainty multiplier, *Working Paper*, Stanford University and Ohio State University.

Bacchiocchi, E. and Fanelli, L. (2015), Identification in Structural Vector Autoregressive models with structural changes, with an application to U.S. monetary policy, *Oxford Bulletin of Economics and Statistics* 77, 761-779.

Bacchiocchi, E., Castelnuovo, E. and Fanelli, L. (2017), Give me a break ! Identification and estimation of the macroeconomic effects of monetary policy shocks in the U.S., *Macroeconomic Dynamics*, forthcoming.

Bachmann, R. and Moscarini, G. (2012), Busyness cycles and endogenous uncertainty, *Unpublished Manuscript*, Aachen University.

Bachmann, R., Elstner, S. and Sims, E. R. (2013), Uncertainty and economic activity: Evidence from business survey data, *American Economic Journal: Macroeconomics* 5, 217-249.

Bai, J. (2000), Vector Autoregressive models with structural changes in regression coefficients and in variance-covariance matrices, *Annals of Economics and Finance* 1, 303-339.

Basu, S. and Bundik, B. (2017), Uncertainty shocks in a model of effective demand, *Econometrica*, forthcoming.

Beetsma, R. and Giuliodori, M. (2012), The changing macroeconomic response to stock market volatility shocks, *Journal of Macroeconomics* 34, 281-293.

Bekaert, G., Hoereva,M. and Lo Duca, M. (2013), Risk, uncertainty and monetary policy, *Journal of Monetary Economics* 60, 771-786.

Bloom, N. (2009), The impact of uncertainty shocks, *Econometrica* 77, 623-685.

Bontempi, M.E., Golinelli, R. and Squadrani, M. (2016), A new index of uncertainty based on internet searches: A friend or foe of other indicators? *Working Paper* DSE No. 1062, University of Bologna.

Cacciatore, M. and Ravenna, F. (2016), Uncertainty, Wages, and the Business Cycle, *Unpublished Manuscript.*

Caggiano, G., Castelnuovo, E. and Groshenny, N. (2014), Uncertainty shocks and employment dynamics in U.S. recessions, *Journal of Monetary Economics* 67, 78-92.

Caggiano, G., Castelnuovo, E. and Pellegrino, G. (2017a), Estimating the Real Effects of Uncertainty Shocks at the Zero Lower Bound, *European Economic Review* 100, 257-272.

Caggiano, G., Castelnuovo, E., Delrio, S. and Robinson, T. (2017b), Time-dependent finance-uncertainty multipliers, *Working Paper*.

Caldara, D., Fuentes-Albero, C., Gilchrist, S. and Zakrajšek, E. (2016), The macroeconomic impact of financial and uncertainty shocks, *European Economic Review* 88, 185-207.

Choi, S. (2013), Are the effects of Bloom's uncertainty shocks robust, *Economic Letters* 119, 216-220.

Christriano, J.C., Motto, R. and Rostagno, M. (2014), Risk shocks, *American Economic Review* 104, 27–65.

Cúrdia, V., Del Negro, M. and Greenwald, D.L. (2014); Rare shocks, great recession, *Journal of Applied Econometrics* 29, 1031-1052.

Fajgelbaum, P., Taschereau-Dumouchel, M., and Schaal, E. (2014), Uncertainty traps, *NBER Working Paper* No. 19973.

Forni, M. and Gambetti, L. (2014), Sufficient information in structural VARs, *Journal of Monetary Economics* 66, 124-136.

Furlanetto, F., Ravazzolo, F. and Sarferaz, S. (2017), Identification of financial factors in economic fluctuations, *The Economic Journal*, forthcoming.

Giacomini, R. and Kitagawa, T. (2015), Robust inference about partially identified SVARs, *Unpublished Manuscript*.

Gilchrist, S., Sim, J. and Zakrajsek, E. (2014), Uncertainty, financial frictions and investment dynamics, *NBER Working Paper* No. 20038.

Gourio, F. (2014), Financial distress and endogenous uncertainty, Working Paper, Federal Reserve Bank of Chicago.

Jurado, K., Ludvigson, S.C. and Ng, S. (2015), Measuring uncertainty, *American Economic Review* 105(3), 1177-1216.

Kilian, L. (1998), Small-sample confidence intervals for impulse response functions, *Review of Economics and Statistics* 80, 218-230.

Lanne, M. and Lütkepohl, H. (2008), Identifying monetary policy shocks via changes in volatility, *Journal of Money, Credit and Banking* 40, 1131-1149.

Ludvigson, S.C., Ma, S. and Ng, S. (2017a), Uncertainty and business cycles: exogenous impulse or endogenous response? *Working Paper,* version January 4, 2017.

Ludvigson, S.C., Ma, S. and Ng, S. (2017b), Shock restricted Structural Vector-Autoregressions, *Working Paper,* version March 1, 2017.

Lütkepohl, H. (2013), Vector Autoregressive Models, in N. Hashimzade and M.A. Thornton (Eds.), *Handbook of Research Methods and Applications in Empirical Macroeconomics*, Cheltenham: Edward Elgar, 139-164.

Lütkepohl, H., and Netšunajev, A. (2017), Structural vector autoregressions with heteroskedasticity: A review of different volatility models, *Econometrics and Statistics* 1, 2-18.

Magnusson, L. M. and Mavroeidis, S. (2014), Identification using stability restrictions, *Econometrica* 82, 1799-1851.

McConnell, M.M. and Perez-Quiros, G. (2000). Output fluctuations in the United States: what has changed since the early 1980's?, *American Economic Review* 90, 1464-1476.

McCracken, M.W. and Ng, S. (2015), FRED-MD: A monthly database for macroeconomic research, *Journal of Business and Economic Statistics* 34, 574-589.

Mertens, K. and Ravn, M.O. (2013), The dynamic effects of personal and corporate income tax changes in the United States, *American Economic Review* 103, 1212-1247.

Moon, H., Schorfheide, F. and Granziera, E. (2013), Inference for VARs identified with sign restrictions, *Unpublished Manuscript.*

Mumatz, H. and Theodoridis, K. (2017), The changing transmission of uncertainty shocks in the US: An empirical analysis, *Journal of Business and Economic Statistics*, forthcoming.

Navarro, G. (2014), Financial crises and endogenous volatility, *Working Paper*, New York University.

Ng, S. and Wright, J.H. (2013), Facts and challenges from the Great Recession for forecasting and macroeconomic modeling, *Journal of Economic Literature* 51, 1120-1154.

Olea, J.L.M., Stock, J.H. and Watson, M.D. (2015), Inference in Structural VARs with external instruments, *Unpublished Manuscript*, Harvard University.

Popescu, A. and Smets, F. R. (2010), Uncertainty, risk-taking, and the business cycle in Germany, *CESifo Economic Studies* 56, 596-626.

Piffer, M. and M. Podstawski (2017), Identifying uncertainty shocks using the price of gold, *The Economic Journal* 121, forthcoming.

Plante, M., Richter, A.W. and Throckmorton, N.A. (2017), The Zero Lower bound and endogenous uncertainty, *The Economic Journal*, forthcoming.

Qu, Z. and Perron, P. (2007), Estimating and testing structural changes in multivariate regressions, *Econometrica* 75, 459-502.

Rigobon, R. (2003), Identification through heteroskedasticity, *Review of Economics and Statistics* 85, 777-792.

Rigobon, R. and Sack B. (2003), Measuring the reaction of monetary policy to the stock market, *Quarterly Journal of Economics* 118, 639-669.

Rossi, B., Sekhposyan, T. and Soupre, M. (2016), Understanding the sources of macroeconomic uncertainty, *Unpublished Manuscript.*

Rubio-Ramírez, J.F., Waggoner, D.F. and Zha, T. (2010), Structural Vector Autoregressions: Theory of identification and algorithms for inference, *Review of Economic Studies* 77, 665-696.

Scotti, C. (2016), Surprise and uncertainty indexes: Real-Time aggregation of real-activity macro Surprises, *Journal of Monetary Economics* 82, 1-19.

Stock, J.H. and Watson, M. (2012), Disentangling the channels of the 2007-2009 recession, *NBER Working Paper* No. 18094.

Stock, J.H. and Watson, M. (2016), Dynamic factor models, factor-augmented autoregressions, and structural vector autoregressions in macroeconomics, Chap. 8 in *Handbook of Macroeconomics*, vol. 2. John B. Taylor and Harald Uhlig (eds.), 415-526, Elsevier.

Van Nieuwerburgh, S. and Veldkamp, L. (2006), Learning asymmetries in real business cycles, *Journal of Monetary Economics* 53, 753-772.

TABLE 1. Estimated reduced form VAR covariance and correlation matrices and Chow-type tests for structural breaks.

Overall period: 1960M8-2015M4 (T=653)

log-Likelihood = 2871.6

$N_{DH} = 645.281[0.000]$

$AR_5 = 19.216[0.997]$

$$\hat{\Sigma}_\eta = \begin{pmatrix} 1.05e\text{-}04^* & -0.011^* & 6.94e\text{-}05^* \\ & 0.433^* & 6.80e\text{-}04 \\ & & 7.39e\text{-}04^* \end{pmatrix}, \quad \hat{\rho}_\eta = \begin{pmatrix} 1 & -0.167^* & 0.249^* \\ & 1 & 0.038 \\ & & 1 \end{pmatrix}$$

GI: 1960M8-1984M3 (T=280)

log-Likelihood = 1170.5

$N_{DH} = 111.242[0.000]$

$AR_5 = 35.521[0.843]$

$$\hat{\Sigma}_{\eta,1} = \begin{pmatrix} 1.25e\text{-}04^* & -0.001^* & -3.49e\text{-}05^* \\ & 0.587^* & 0.002 \\ & & 6.72e\text{-}04^* \end{pmatrix}, \quad \hat{\rho}_{\eta,1} = \begin{pmatrix} 1 & -0.157^* & 0.120^* \\ & 1 & 0.086 \\ & & 1 \end{pmatrix}$$

GM: 1984M4-2007M12 (T=285)

log-Likelihood = 1399.9

$N_{DH} = 317.978[0.000]$

$AR_5 = 51.729[0.228]$

$$\hat{\Sigma}_{\eta,2} = \begin{pmatrix} 7.18\text{-}05^* & -5.58e\text{-}04^* & 7.62e\text{-}05^* \\ & 0.221^* & 4.24e\text{-}04 \\ & & 7.84e\text{-}05^* \end{pmatrix}, \quad \hat{\rho}_{\eta,2} = \begin{pmatrix} 1 & -0.140^* & 0.321^* \\ & 1 & 0.032 \\ & & 1 \end{pmatrix}$$

GR+SR: 2008M1-2015M4 (T=88)

log-Likelihood = 428.1

$N_{DH} = 108.785[0.000]$

$AR_5 = 79.523[0.001]$

$$\hat{\Sigma}_{\eta,3} = \begin{pmatrix} 8.51e\text{-}05^* & -0.001^* & 7.90e\text{-}05^* \\ & 0.378^* & -0.001 \\ & & 4.62e\text{-}04^* \end{pmatrix}, \quad \hat{\rho}_{\eta,3} = \begin{pmatrix} 1 & -0.214^* & 0.398^* \\ & 1 & -0.089 \\ & & 1 \end{pmatrix}$$

H_0 : quasi-$LR_T = 253.99[0.000]$ (no breaks in all VAR coefficients)

H_0' : quasi-$LR_T = 96.061[0.000]$ (no breaks in the VAR covariance matrix)

Notes: Results are based on a VAR for $X_t := (U_{Mt}, Y_t, U_{Ft})'$ (with four lags) with $Y_t = \Delta ip_t$ (industrial production growth). Top panel: estimates on the whole sample. Second, third and fourth panels: estimates on partial samples. Bottom panel: Quasi-LR_T in the bottom panel are the Chow-type quasi-LR tests for the null H_0 in eq. (15) and the null H_0' in eq. (16). Asterisks (*) denote statistical significance at the 10% confidence level. N_{DH} is the Doornik-Hansen multivariate test for Gaussian disturbances. AR_5 is an LM-type test for the absence of residual autocorrelation against the alternative of autocorrelated VAR disturbance up to 5 lags. P-values in brackets. 'GI'=Great Inflation, 'GM'=Great Moderation and 'GR+SR'=Great Recession + Slow Recovery.

TABLE 2. Estimated structural parameters.

SVAR for $X_t := (U_{Mt}, Y_t, U_{Ft})'$

GI: 1960M8-1984M3

$$\hat{B} := \begin{pmatrix} \underset{\substack{(0.0003)\\(0.0004)^*}}{0.0097} & 0 & 0 \\ \underset{\substack{(0.0393)\\(0.0509)^*}}{-0.1012} & \underset{\substack{(0.0320)\\(0.0379)^*}}{0.7570} & 0 \\ \underset{\substack{(0.0012)\\(0.0012)^*}}{0.0037} & \underset{\substack{(0.0015)\\(0.0015)^*}}{0.0028} & \underset{\substack{(0.0009)\\(0.0014)^*}}{0.0247} \end{pmatrix},$$

GM: 1984M4-2007M12

$$\hat{B}+\hat{Q}_2 := \begin{pmatrix} \underset{\substack{(0.0003)\\(0.0004)^*}}{0.0097} & \underset{\substack{(0.0010)\\(0.0005)^*}}{0.0008} & \underset{\substack{(0.0007)\\(0.0005)^*}}{0.0016} \\ \underset{\substack{(0.0616)\\(0.0460)^*}}{-0.0850} & \underset{\substack{(0.0305)\\(0.0512)^*}}{0.4220} & \underset{\substack{(0.0541)\\(0.0979)^*}}{-0.1940} \\ \underset{\substack{(0.0012)\\(0.0012)^*}}{0.0037} & \underset{\substack{(0.0031)\\(0.0073)^*}}{0.0129} & \underset{\substack{(0.0009)\\(0.0014)^*}}{0.0247} \end{pmatrix},$$

GR+SR: 2008M1-2015M4

$$\hat{B}+\hat{Q}_2+\hat{Q}_3 := \begin{pmatrix} \underset{\substack{(0.0003)\\(0.0004)^*}}{0.0097} & \underset{\substack{(0.0027)\\(0.0029)^*}}{0.0000} & \underset{\substack{(0.0012)\\(0.0016)^*}}{0.0031} \\ \underset{\substack{(0.1854)\\(0.1465)^*}}{-0.1379} & \underset{\substack{(0.0605)\\(0.1012)^*}}{0.6006} & \underset{\substack{(0.1513)\\(0.1585)^*}}{-0.048} \\ \underset{\substack{(0.0012)\\(0.0012)^*}}{0.0037} & \underset{\substack{(0.0053)\\(0.0071)^*}}{0.0000} & \underset{\substack{(0.0009)\\(0.0014)^*}}{0.0247} \end{pmatrix}$$

Notes: Estimated structural parameters based on the non-recursive SVAR for $X_t := (U_{Mt}, Y_t, U_{Ft})'$, $Y_t = \Delta ip_t$ (industrial production growth), specified in eq. (17). Hessian-based standard errors in parenthesis; bootstrap standard errors are denoted with asterisks '*', see footnote 17 for details; 'GI'=Great Inflation; 'GM'=Great Moderation; 'GR+SR'=Great Recession + Slow Recovery.

TABLE 3a. IRFs estimated from the non-recursive SVAR, negative peaks (percentage points).

	GI: 1960M8-1984M3		GM: 1984M4-2007M12		GR+SR: 2008M1-2015M4	
	$f=1$	$f=12$	$f=1$	$f=12$	$f=1$	$f=12$
			SVAR for $X_t := (U_{Mt}, Y_t, U_{Mt})'$			
$e_{Mt} \to Y_t$	$-0.101(0)$	$-0.067(8)$	$-0.085(0)$	$-0.069(2)$	$-0.178(5)$	$-0.174(5)$
$e_{Ft} \to Y_t$	$-0.121(3)$	$-0.101(3)$	$-0.194(0)$	$-0.173(0)$	$-0.183(3)$	$-0.123(3)$

Notes: Highest negative (significant) responses of $Y_t = \Delta ip_t$ (industrial production growth) to one standard deviation change in macroeconomic (e_{Mt}) and financial (e_{Ft}) uncertainty shocks at the one-month ($f=1$) and one-year ($f=12$) uncertainty horizons, obtained from the non-recursive SVAR for $X_t := (U_{Mt}, Y_t, U_{Ft})'$ specified in eq. (17). In parenthesis the number of months after the shock at which the highest negative peak is reached.

TABLE 3b. IRFs estimated from Cholesky-based SVARs, negative peaks (percentage points).

	SVAR for $X_t^R := (U_{Mt}, Y_t, U_{Ft})'$		SVAR for $X_t^{R'} := (U_{Ft}, Y_t, U_{Mt})'$	
	$f=1$	$f=12$	$f=1$	$f=12$
$e_{Mt} \to Y_t$	$-0.110(0)$	$-0.085(4)$	$-0.073(3)$	$-0.054(4)$
$e_{Ft} \to Y_t$	$-0.071(3)$	$-0.065(3)$	$-0.091(3)$	$-0.067(3)$

Notes: Highest negative (significant) responses of $Y_t = \Delta ip_t$ (industrial production growth) to one standard deviation change in macroeconomic (e_{Mt}) and financial (e_{Ft}) uncertainty shocks at the one-month ($f=1$) and one-year ($f=12$) uncertainty horizons, obtained from two Cholesky SVARs for $X_t^R := (U_{Mt}, Y_t, U_{Ft})'$ and $X_t^{R'} := (U_{Ft}, Y_t, U_{Mt})'$, respectively, on the whole sample: 1960M8-2015M4. In parenthesis the number of months after the shock at which the highest negative peak is reached.

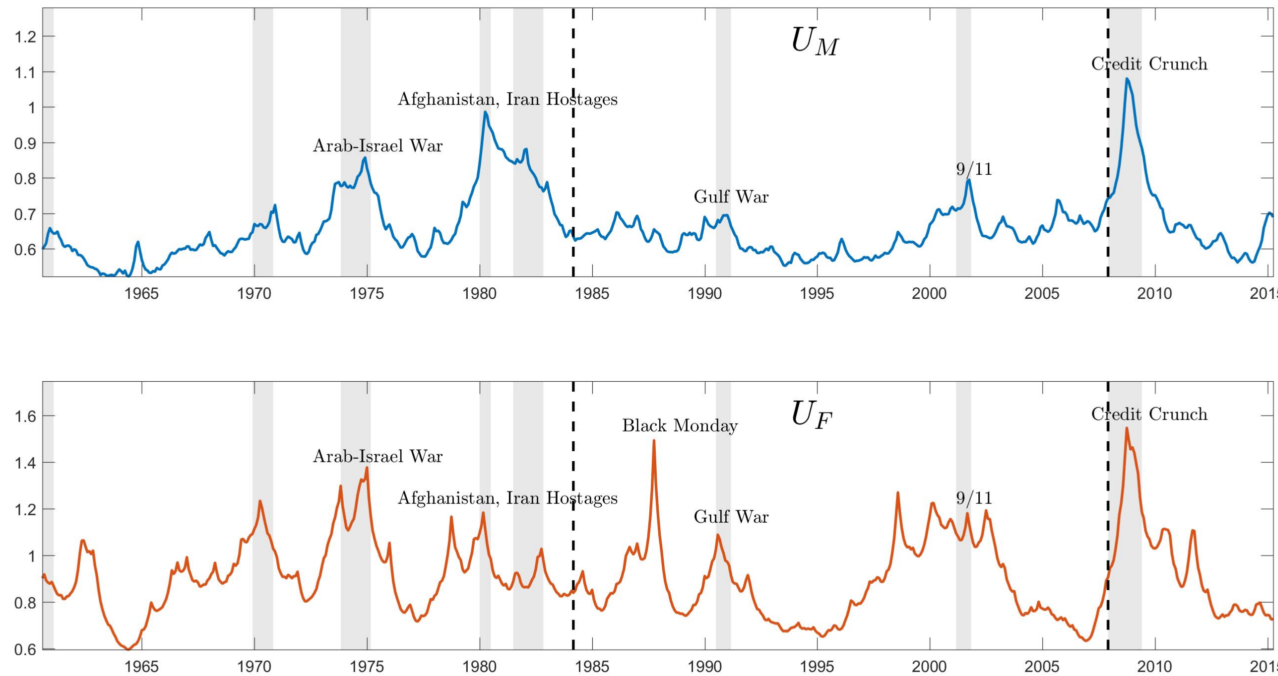

Figure 1: Measures of one-month ($f = 1$) macroeconomic uncertainty U_{Mt} (top-panel) and financial uncertainty U_{Ft} (bottom-panel). U_{Mt} is taken from Jurado *et al.* (2015); U_{Ft} is taken from Ludvigson *et al.* (2017). Dashed black lines denote the two break dates T_{B_1}=1984M3 and T_{B_2}=2007M12 which separate the three volatility regimes used to identify the shocks. The shaded areas correspond to the NBER recession dates. Overall sample: 1960M8-2015M4.

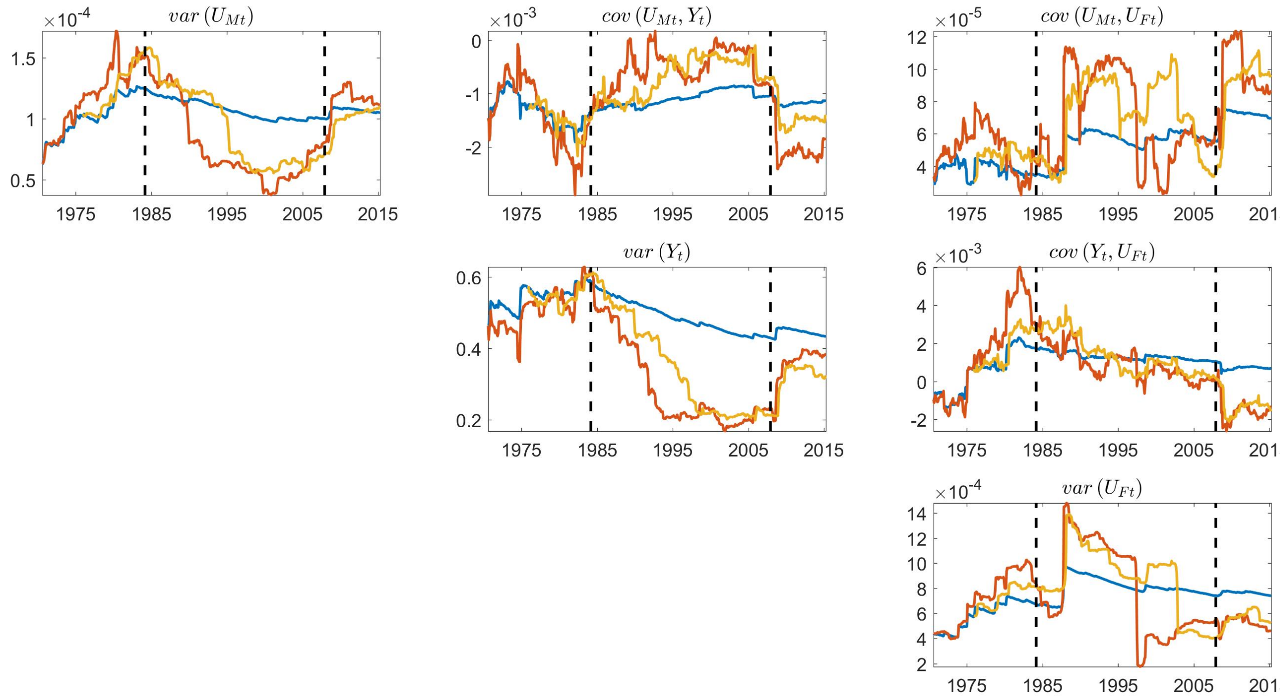

Figure 2: Recursive (blue line), 10-years (red line) and 15-years (yellow line) rolling windows estimates of the error covariance matrix of the VAR for $X_t := (U_{Mt}, Y_t, U_{Ft})'$, $Y_t = \Delta ip_t$ (industrial production growth). Dashed black lines denote the two break dates T_{B_1}=1984M3 and T_{B_2}=2007M12 which separate the three volatility regimes used to identify the shocks. Overall sample: 1960M8-2015M4.

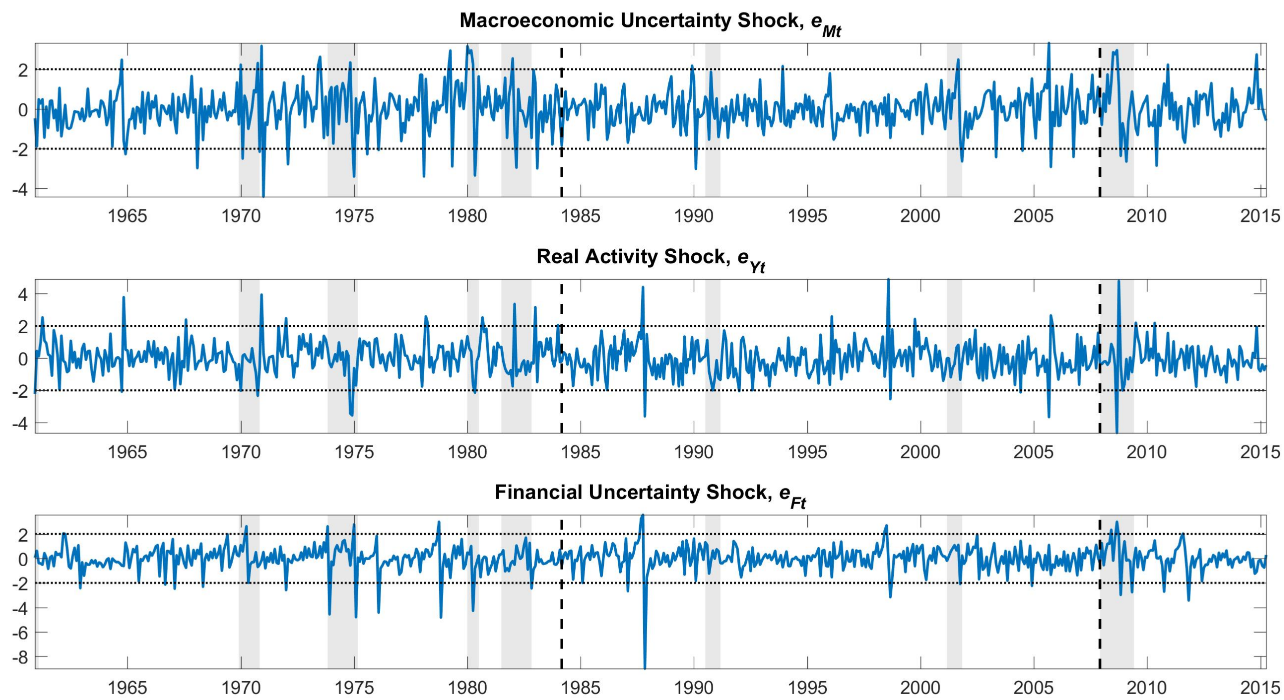

Figure 3: Estimated structural shocks $\hat{e}_{jt}$, $j = M, Y, F$ where $\hat{e}_t = \hat{B}_i^{-1}\eta_t$, $i = 1, 2, 3$, $\hat{B}_1 = \hat{B}$, $\hat{B}_2 = (\hat{B}+\hat{Q}_2)$ and $\hat{B}_3 = (\hat{B}+\hat{Q}_2+\hat{Q}_3)$ from the non-recursive SVAR for $X_t := (U_{Mt}, Y_t, U_{Ft})'$, $Y_t = \Delta ip_t$ (industrial production growth), specified in eq. (17). The first panel plots the estimated macroeconomic uncertainty shock $\hat{e}_{Mt}$, the second panel the estimated real activity shock $\hat{e}_{Yt}$ and the last panel the estimated financial uncertainty shock $\hat{e}_{Ft}$. Vertical dashed black lines are the two break dates T_{B_1}=1984M3 and T_{B_2}=2007M12. Horizontal dotted black lines correspond to 2 standard deviations above/below the unconditional mean of each series. The shaded areas correspond to the NBER recession dates. Overall sample: 1960M8-2015M4.

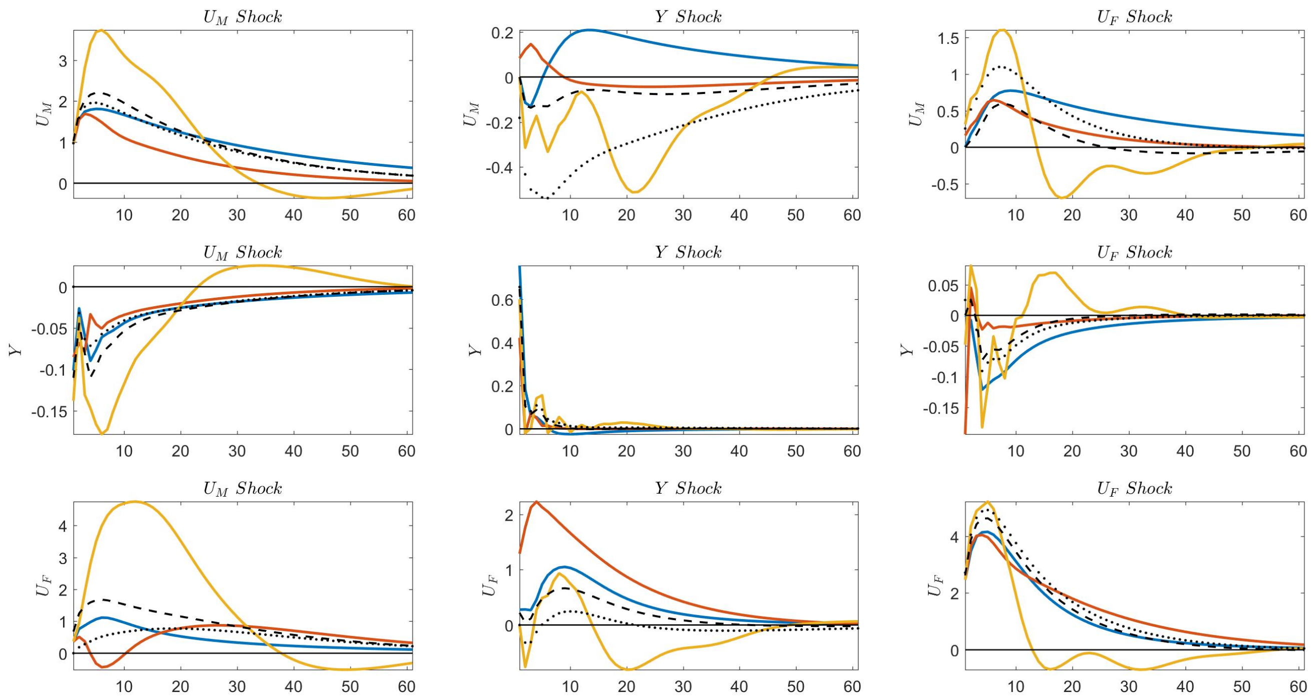

Figure 4: IRFs obtained from the beseline non-recursive SVAR for $X_t := (U_{Mt}, Y_t, U_{Ft})'$, $Y_t = \Delta ip_t$ (industrial production growth) specified in eq. (17). U_{Mt} and U_{Ft} refer to the one-month ($f = 1$) uncertainty horizon. The blue line refers to the first volatility regime (Great Inflation, 1960M8-1984M3); the red line refers to the second volatility regime (Great Moderation, 1984M4-2007M12); the yellow line refers to the third volatility regime (Great Recession + Slow Recovery, 2008M1-2015M4). Dashed and dotted black lines plot the IRFs obtained with two Cholesky-based SVARs with $X_t^R := (U_{Mt}, Y_t, U_{Ft})'$ and $X_t^{R'} := (U_{Ft}, Y_t, U_{Mt})'$ respectively on the whole sample 1960M8-1984M3. Responses are measured with respect to one standard deviation changes in structural shocks.

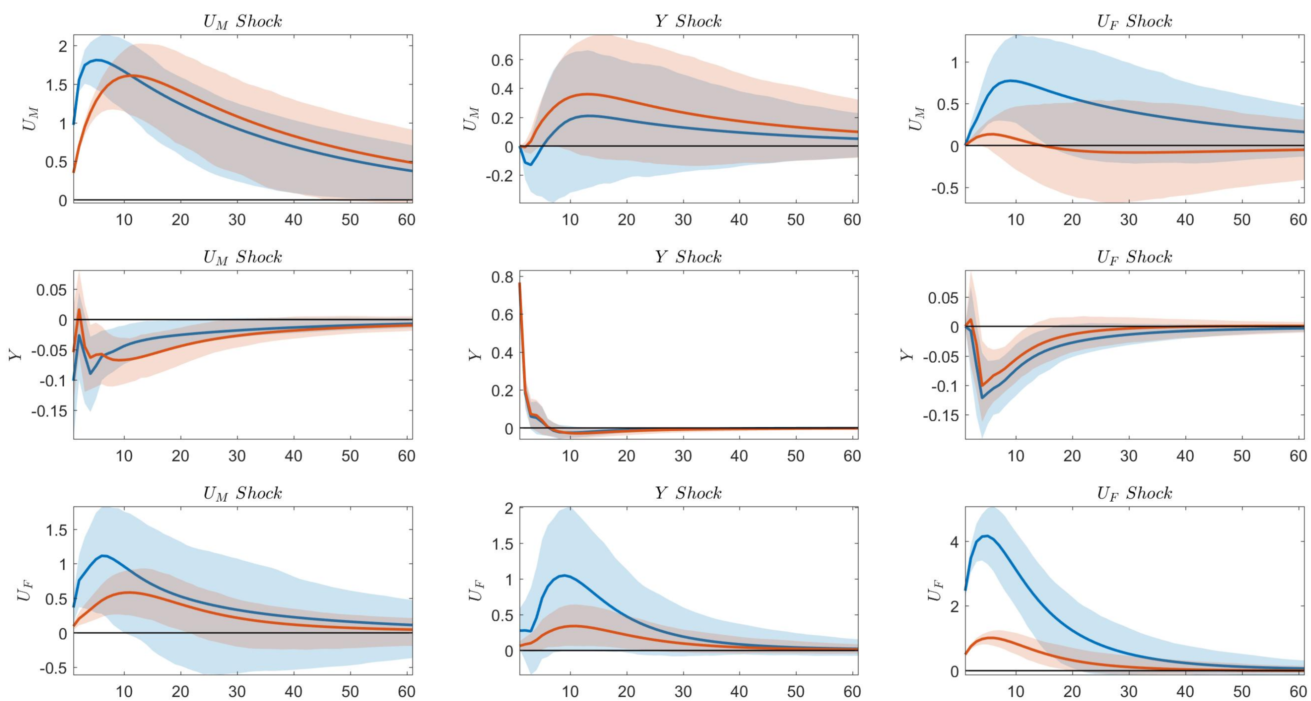

Figure 5: IRFs obtained in the first volatility regime (Great Inflation, 1960M8-1984M3) from the baseline non-recursive SVAR for $X_t := (U_{Mt}, Y_t, U_{Ft})'$, $Y_t = \Delta ip_t$ (industrial production growth) specified in eq. (17). The blue lines refer to the one-month ($f = 1$) uncertainty horizon and blue shaded areas denote the associated 90% bootstrap confidence bands; the red lines refer to the one-year ($f = 12$) uncertainty horizon and red shaded areas denote the associated 90% bootstrap confidence bands; bootstrap confidence bands are computed using Kilian's (1998) method. Responses are measured with respect to one standard deviation changes in structural shocks.

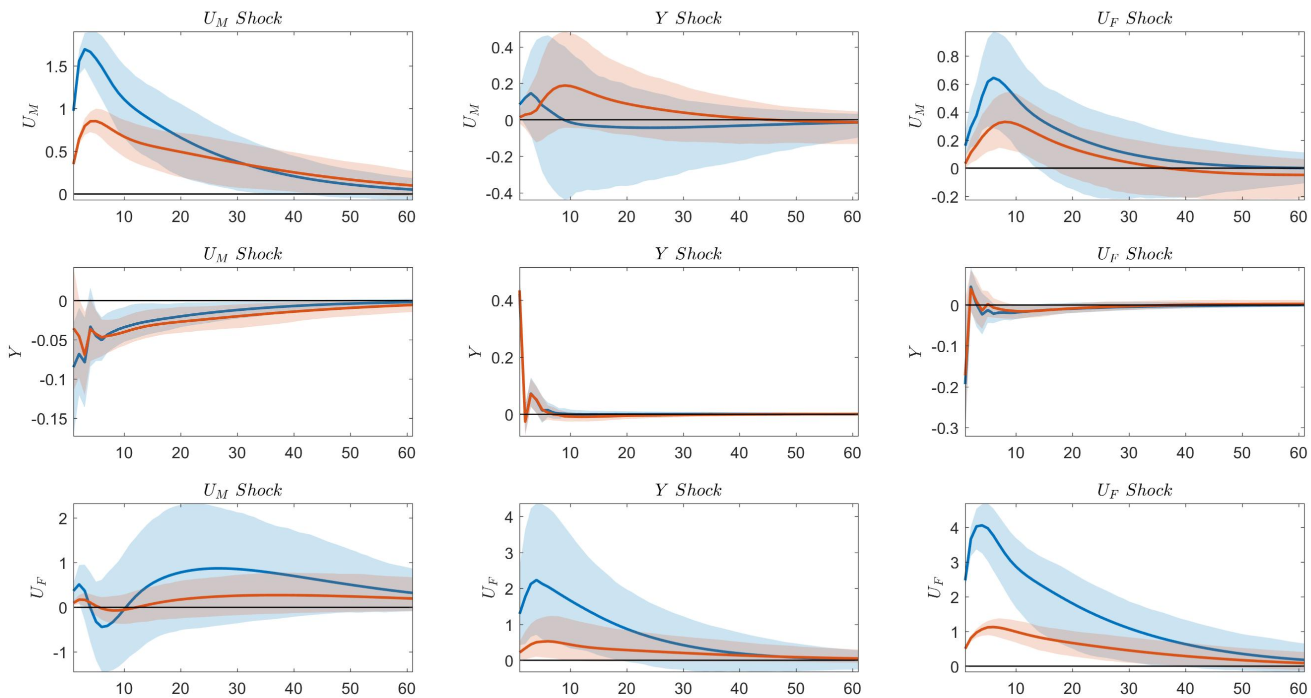

Figure 6: IRFs obtained in the second volatility regime (Great Moderation, 1984M4-2007M12) from the baseline non-recursive SVAR for $X_t := (U_{Mt}, Y_t, U_{Ft})'$, $Y_t = \Delta ip_t$ (industrial production growth) specified in eq. (17). The blue lines refer to the one-month ($f = 1$) uncertainty horizon and blue shaded areas denote the associated 90% bootstrap confidence bands; the red lines refer to the one-year ($f = 12$) uncertainty horizon and red shaded areas denote the associated 90% bootstrap confidence bands; bootstrap confidence bands are computed using Kilian's (1998) method. Responses are measured with respect to one standard deviation changes in structural shocks.

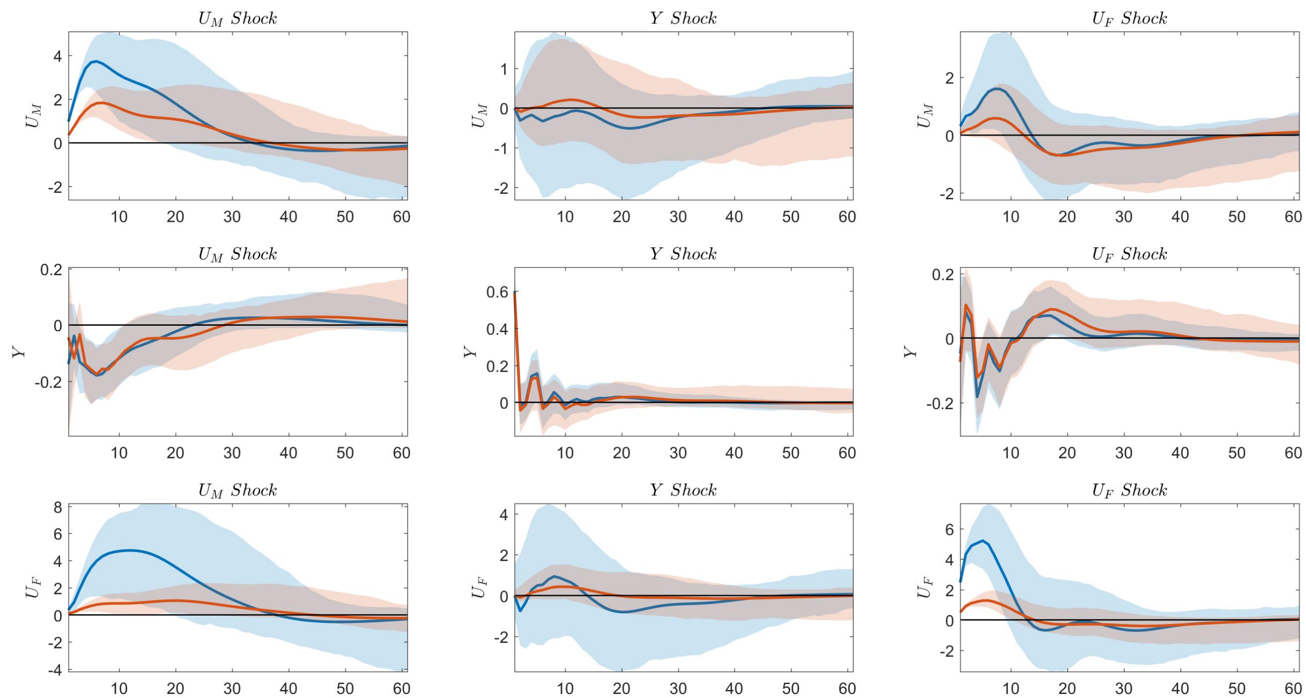

Figure 7: IRFs obtained in the third volatility regime (Great Recession + Slow recovery, 2008M1-2015M4) from the baseline non-recursive SVAR for $X_t := (U_{Mt}, Y_t, U_{Ft})'$, $Y_t = \Delta ip_t$ (industrial production growth) specified in eq. (17). The blue lines refer to the one-month ($f = 1$) uncertainty horizon and blue shaded areas denote the associated 90% bootstrap confidence bands; the red lines refer to the one-year ($f = 12$) uncertainty horizon and red shaded areas denote the associated 90% bootstrap confidence bands; bootstrap confidence bands are computed using Kilian's (1998) method. Responses are measured with respect to one standard deviation changes in structural shocks.

Technical Supplement to

Uncertainty Across Volatility Regimes

Giovanni Angelini
University of Bologna

Emanuele Bacchiocchi
University of Milan

Giovanni Caggiano
Monash University and University of Padova

Luca Fanelli
University of Bologna

November 2017

TS.1 Introduction

This Technical Supplement develops/expands a number of topics only partly discussed in the paper and provides additional empirical results.

Section TS.2 formalizes the assumptions and regularity conditions which permit standard asymptotic inference in the reduced form VAR with breaks in the covariance matrix, which is at the basis of our non-recursive SVAR specification and identification approach. Section TS.3 presents an alternative but equivalent parametrization of the non-recursive SVAR, and discusses the necessary and sufficient rank conditions for (point-)identification. Section TS.4 presents an alternative estimation approach to the quasi-maximum likelihood (QML) method used in the paper, which re-interprets the estimation of the non-recursive SVAR as a classic minimum distance (CMD) problem. Section TS.5 summarizes how the proxies of uncertainty U_{Mt} and U_{Ft} used in the paper and taken from Jurado *et al.* (2015) and Ludvigson *et al.* (2017), respectively, have been constructed. Section TS.6 investigates whether the VAR systems based on $X_t{:=}(U_{Mt}, Y_t, U_{Ft})'$ and $X_t^*{:=}(U_{Ft}, Y_t, CS_t)'$, where CS_t is a measure of credit spreads, are 'informational sufficient' in the sense of Forni and Gambetti (2014). Section TS.7 investigates whether the IRFs reported in the paper also support significant long-run effects as measured by cumulated long-run multipliers. Finally, Section TS.8 provides the graphs and detailed comments for three robustness checks which are only briefly mentioned in the paper.

TS.2 Model assumptions

In this section we formalize the set of assumptions behind the QML estimation of our non-recursive SVAR with breaks in the error covariance matrix. For simplicity, we focus on the case of $m = 2$ breaks and $m + 1 = 3$ volatility regimes in the data, which is the situation we face in the empirical section of the paper.

Our reference model is the SVAR discussed in Section 3 of the paper. The reduced form belongs to the class of 'VAR models with structural changes in regression coefficients and in covariance matrices' considered in Bai (2000), the only difference being that throughout the paper we treat, without limiting the scopes of our analysis, the two volatility change points (break dates) T_{B_1} and T_{B_2} as known. Our identification and estimation approach, however, can also be applied by relaxing the assumption that T_{B_1} and T_{B_2} are known because it is in principle possible to infer these dates directly from the data along the lines suggested by e.g. Qu and Perron (2007) (see also references therein); see instead Podstawski and Velinov (2016) for a possible generalization of our approach to the case of Markov-Switching SVARs.

Let $\mathcal{F}_t{:=}\sigma(X_t, X_{t-1}, ..., X_1)$ be the sigma-field generated by the sequence $X_t, X_{t-1}, ..., X_1$ and let $\|\cdot\|$ be the Euclidean norm. Let $(\Pi_i^0, \Sigma_{\eta,i}^0)$ be the true values of the VAR parameters $(\Pi_i, \Sigma_{\eta,i})$, $i = 1, 2, 3$ in eq.s (7)-(9) of the paper. $T_{B_i}^0 = [T\tau_i^0]$, $0 < \tau_i^0 < 1$, $i = 1, 2$ are the true break dates.

Assumption 1 *The sequence* $\{\eta_t, \mathcal{F}_t\}$ *is a MDS* ($E(\eta_t \mid \mathcal{F}_{t-1}) = 0_{n\times 1}$) *which, in addition, satisfies the condition* $\sup_t E(\|\eta_t\|^{4+\delta}) < \infty$.

Assumption 2 $\Sigma_{\eta,i}^0 \neq \Sigma_{\eta,i+1}^0$, $i = 1, 2, 3$. *In addition, each entry in* $\Sigma_{\eta,i}^0$ *is different from the corresponding entry in* $\Sigma_{\eta,i+1}^0$. *Each true regime parameter* $(\Pi_i^0, \Sigma_{\eta,i}^0)$ *corresponds to that of a stationary process so that unit roots and explosive roots are ruled out.*

Assumption 3 $T_{B_i}^0 = [T\tau_i^0]$, *where* τ_i^0 *is the true fraction of the sample,* $i = 1, 2$, *are known.*

Assumption 1 is a relatively standard regularity condition which models the VAR disturbances as MDS (conditional on past information) and requires the existence of up to fourth moments. The first part of Assumption 2 requires that the differences of unconditional covariance matrices across regimes involve all elements of the covariance matrix. Actually, for the purposes of inference on the reduced form parameters, Assumption 2 could be relaxed by simply requiring that there exists an entry in $\Sigma_{\eta,i}^0$ which is different from the corresponding entry in $\Sigma_{\eta,i+1}^0$. We impose the stronger condition that all elements of the covariance matrices differ across volatility regimes to guarantee the identifiability of the non-recursive SVAR.

More precisely, Assumption 2 posits that the covariance matrices $\Sigma^0_{\eta,1}$, $\Sigma^0_{\eta,2}$ and $\Sigma^0_{\eta,3}$ provide enough information to identify shocks in a non-recursive framework. We refer to Magnusson and Mavroeidis (2014) for a thorough discussion of the inferential issues, including weak identification issues, that may arise when possible instabilities in the moments and certain heterogeneity in the data generating process is assumed. The second part of Assumption 2 establishes that each volatility regime is characterized by 'asymptotically stable' VAR processes. Assumption 3 posits that the break dates are known to the econometrician but, as already observed, could be relaxed.

Under Assumptions 1-3, the inference on the parameters $(\Pi_i, \Sigma_{\eta,i})$, $i = 1, 2, 3$ in the SVAR is standard, see e.g. Bai (2000) and Qu and Perron (2007). Therefore, also the inference on the IRFs stemming from the associated SVAR is of standard type.

TS.3 Identification analysis

In this Section we discuss the necessary order conditions and the necessary and sufficient rank conditions for (local) identification of the structural parameters θ which define the matrices $B, (B + Q_2)$ and $(B + Q_2 + Q_3)$ of the non-recursive SVAR specified in Section 3 of the paper. Also in this case, we focus on the case of $m = 2$ breaks and $m + 1 = 3$ volatility regimes, which is the situation we face in the empirical section of the paper. The three volatility regimes are associated with the covariance matrices $\Sigma_{\eta,1}$, $\Sigma_{\eta,2}$ and $\Sigma_{\eta,3}$, respectively.

Before discussing identification, it is worth mentioning an alternative but equivalent parametrization of the non-recursive SVAR with changes in volatility regimes presented in Section 2 of the paper. In Section 2 of the paper, the structural shocks have been specified by normalizing their variance to the unit matrix, i.e. $E(e_t e_t') = I_n$, and the matrices of structural parameters $B, (B + Q_2)$ and $(B + Q_2 + Q_3)$ does not incorporate particular 'normalization' restrictions. Actually, it is possible to consider an equivalent specification of our SVAR based on $E(e_t e_t'){:=}\Sigma_e{:=}diag(\sigma^2_{eM}, \sigma^2_{eY}, \sigma^2_{eF})$, where $\sigma^2_{eM}, \sigma^2_{eY}, \sigma^2_{eF}$ are the variances of the three structural shocks. With this parametrization, eq. (10) in the paper must be adapted to allow for changes in Σ_e across volatility regimes and, at the same time, the matrices $B, (B + Q_2)$ and $(B + Q_2 + Q_3)$ must be properly normalized. Let $\Sigma_{e,1}$, $\Sigma_{e,2}$ and $\Sigma_{e,3}$ be the three covariance matrices of the structural shocks in the three volatility regimes, where we denote with $e_{i,t}$ the structural shocks in the i-th volatility regime, where $E(e_{i,t}) = 0_{3\times 1}$ and $E(e_{i,t} e_{i,t}') = \Sigma_{e,i}$, $i = 1, 2, 3$. Eq. (10) in the paper changes in the form

$$
\begin{aligned}
\eta_t &= B^* \Sigma_{e,1}^{1/2} e_{1t}^* && 1 \leq t \leq T_{B_1} \\
\eta_t &= (B+Q_2)^* \, \Sigma_{e,2}^{1/2} e_{2t}^* && T_{B_1} < t \leq T_{B_2} \\
\eta_t &= (B+Q_2+Q_3)^* \, \Sigma_{e,3}^{1/2} e_{3t}^* && T_{B_2} < t \leq T
\end{aligned}
$$

where $B^*, (B+Q_2)^*$ and $(B+Q_2+Q_3)^*$ are the analogs of the matrices $B, (B+Q_2)$ and $(B+Q_2+Q_3)$ in eq. (10), but with diagonal elements normalized to '1' and $e_{it}^* := \Sigma_{e,i}^{-1/2} e_{i,t}$, $i = 1, 2, 3$. Thus, the moment conditions in eq.s (11)-(13) of the paper become

$$
\begin{aligned}
\Sigma_{\eta,1} &= B^* \Sigma_{e,1} B^{*\prime} \\
\Sigma_{\eta,2} &= (B+Q_2)^* \, \Sigma_{e,2} \, (B+Q_2)^{*\prime} \\
\Sigma_{\eta,3} &= (B+Q_2+Q_3)^* \, \Sigma_{e,3} \, (B+Q_2+Q_3)^{*\prime}
\end{aligned}
$$

and a possible parametrization for $\Sigma_{e,1}$, $\Sigma_{e,2}$ and $\Sigma_{e,3}$ can be given as follows: $\Sigma_{e,1} := diag(\sigma_{eM,1}^2, \sigma_{eY,1}^2, \sigma_{eF,1}^2)$, $\Sigma_{e,2} = \Sigma_{e,1} + diag(\varrho_{1,2}, \varrho_{2,2}, \varrho_{3,2})$ and $\Sigma_{e,3} = \Sigma_{e,2} + diag(\varrho_{1,3}, \varrho_{2,3}, \varrho_{3,3})$, where the non-zero parameters ϱs capture the changes, if any, in the variance of the structural shocks across volatility regimes.[1] In this case, the vector of structural parameters include the non-zero off-diagonal elements of $B^*, (B+Q_2)^*$ and $(B+Q_2+Q_3)^*$ and the variances $\sigma_{eM,1}^2, \sigma_{eY,1}^2, \sigma_{eF,1}^2$ and the non-zero ϱs. Once we account for these adjustments, the necessary order conditions and the necessary and sufficient rank conditions for identification are exactly the same we discuss below for the baseline parametrization used in the paper. Moreover, once the system has been identified, and defined s_j to be the j-th column of the identify matrix, the dynamic response of X_{t+h} to a shock in variable j at time t of size $e_{j,t} = \delta_j$ is in this case summarized by the (population) IRFs:

$$
IRF_j(h) := \begin{cases}
R'(A_1)^h R B^* \frac{1}{\sigma_{ej,1}^2} \Sigma_{e,1} s_j \delta_j & t \leq T_{B_1} \\
R'(A_2)^h R \left(\tilde{B} + \tilde{Q}_2\right)^* \frac{1}{\sigma_{ej,2}^2} \Sigma_{e,2} s_j \delta_j & T_{B_1} < t \leq T_{B_2} \\
R'(A_3)^h R (\tilde{B} + \tilde{Q}_2 + \tilde{Q}_3) \frac{1}{\sigma_{ej,3}^2} \Sigma_{e,3} s_j \delta_j & t > T_{B_2}
\end{cases}
\quad \begin{array}{c} h = 0, 1, ..., h_{\max} \\ j = M, Y, F \end{array}
\tag{TS.1}
$$

which, apart from the scaling, mimic the ones in eq. (14) of the paper. Hence, R is a selection matrix, $\tilde{B}^*$, $\left(\tilde{B} + \tilde{Q}_2\right)^*$ and $\left(\tilde{B} + \tilde{Q}_2 + \tilde{Q}_3\right)^*$ are the identified counterparts of $B^*, (B+Q_2)^*$ and $(B+Q_2+Q_3)^*$, and $h_{\max}$ is the largest horizon considered.

Now we turn to the identification conditions of the non-recursive SVAR based on the system

[1] Bacchiocchi (2017) proposes a different parametization that allows both changes in the structural parameters and in the variances of the shocks across different volatility regimes, without normalizing the diagonal elements to '1'.

of second-order moment conditions in eq.s (11)-(13) of the paper, here reported for convenience:

$$\Sigma_{\eta,1} = BB' \tag{TS.2}$$

$$\Sigma_{\eta,2} = (B + Q_2)(B + Q_2)' \tag{TS.3}$$

$$\Sigma_{\eta,3} = (B + Q_2 + Q_3)(B + Q_2 + Q_3)'. \tag{TS.4}$$

Here $B = B(\theta)$, $Q_2 = Q_2(\theta)$ and $Q_3 = Q_3(\theta)$ are matrices that depend on the vector of structural parameters θ which contains the non-zero elements contained in the matrices $B, (B + Q_2)$ and $(B + Q_2 + Q_3)$. Eq.s (TS.2)-(TS.4) link the reduced form to the structural parameters. Let $r = \frac{3}{2}n(n+1)$ be number of free elements contained in the matrices $\Sigma_{\eta,1}$, $\Sigma_{\eta,2}$ and $\Sigma_{\eta,3}$. Under Assumption 2, system (TS.2)-(TS.4) provides $r = \frac{3}{2}n(n+1)$ identifying restrictions on B, Q_2 and Q_3 induced by symmetry. The total number of elements in B, Q_2 and Q_3 is $3n^2$, hence it is necessary to impose at least $3n^2 - r$ additional constraints to achieve identification. The $3n^2 - r$ constraints needed to identify the SVAR are provided by economic reasoning, which means that our identification approach combines both data properties (i.e. the heteroskedasticity provided by the data) and theoretical considerations reflected in the specification of the structure of the matrices B, $(B + Q_2)$ and $(B + Q_2 + Q_3)$.

Defined the vector $\psi{:=}(vec(B)', vec(Q_2)', vec(Q_3)')'$, the set of theory-based linear identifying restrictions on B, Q_2 and Q_3 can be represented compactly in explicit form by:

$$\tilde{\psi} = G\theta + d \tag{TS.5}$$

where G is a known $3n^2 \times \dim(\theta)$ selection matrix of full-column rank, $d{:=}(d'_B, d'_{Q_2}, d'_{Q_3})'$ is a $3n^2 \times 1$ vector containing known elements and $\tilde{\psi} := (vec(\tilde{B})', vec(\tilde{Q}_2)', vec(\tilde{Q}_3)')'$, where we denote with $\tilde{B} = B(\theta)$, $\tilde{Q}_2 = Q_2(\theta)$ and $\tilde{Q}_3 = Q_3(\theta)$ the identified counterparts of B, Q_2 and Q_3. Other than accounting for (possibly) non-homogeneous restrictions,[2] eq. (TS.5) allows for cross-regime constraints, i.e. simultaneous restrictions which involve the elements of the matrices B, Q_2 and Q_3 like, for example, $b_{12} + q_{2,12} = 0$ or $b_{12} + q_{2,12} + q_{2,12} = 1$, where b_{12}, $q_{2,12}$ and $q_{3,12}$ are the (1,2) elements of B, Q_2 and Q_3, respectively.

The moment conditions in eq.s (TS.2)-(TS.4) along with the constraints in eq. (TS.5) can be conveniently summarized in the expression

$$\sigma^+ = g(\theta) \tag{TS.6}$$

where $\sigma^+{:=}(vech(\Sigma_{\eta,1})', vech(\Sigma_{\eta,2})', vech(\Sigma_{\eta,3})')'$ is $r \times 1$, and $g(\cdot)$ is a nonlinear (differentiable) vector function, see Bacchiocchi and Fanelli (2015) for details. The necessary and sufficient rank

[2]This means that the vector d can be non-zero.

condition for identification is that the Jacobian matrix $J(\theta) := \frac{\partial g(\theta)}{\partial \theta'}$ be regular and of full-column rank, $\dim(\theta)$, when evaluated in a neighborhood of the true parameter value θ_0.

The necessary order condition is $\dim(\theta) \leq r$. The Jacobian $J(\theta)$ can be derived analytically or evaluated numerically. If the rank condition for identification is satisfied, the SVAR in eq.s (7)-(13) of the paper generates regime-dependent IRFs.

TS.4 Alternative estimation approach

In this Section we sketch an alternative estimation approach to QML for our baseline non-recursive SVAR. The alternative estimation method reads as classical minimum-distance (CMD) approach.

The idea is that the relationship in eq. (TS.6), written here as

$$\sigma^{+} - g(\theta) = 0_{r\times 1} \tag{TS.7}$$

can be interpreted as a measure of distance between the reduced form parameters (error variances and covariances) in σ^{+} and the structural parameters θ. Moreover, under Assumptions 1-3 we can estimate σ^{+} consistently so that eq. (TS.7) forms the basis for the CMD estimation of θ.

Our starting point is the condition

$$T^{1/2}(\hat{\sigma}_T^{+} - \sigma_0^{+}) \xrightarrow{d} N(0_{r\times 1}, V_{\sigma^{+}})$$

which holds under Assumptions 1-3 of Section TS.2. Here $\hat{\sigma}_T^{+}{:=}(vech(\hat{\Sigma}_{\eta,1})', vech(\hat{\Sigma}_{\eta,2})', vech(\hat{\Sigma}_{\eta,3})')$ is a consistent (say, OLS) estimate of σ^{+}, σ_0^{+} is the true value of σ^{+}, the symbol '$\xrightarrow{d}$' denotes converge in distribution as $T \to \infty$, and $V_{\sigma^{+}}$ is a block-diagonal asymptotic covariance matrix with form

$$V_{\sigma^{+}}{:=}\begin{pmatrix} V_{\sigma_1^{+}} & & \\ & V_{\sigma_2^{+}} & \\ & & V_{\sigma_3^{+}} \end{pmatrix}, \quad V_{\sigma_i^{+}}{:=}2D_3^{+}(\Sigma_{\eta,i} \otimes \Sigma_{\eta,i})(D_3^{+})', \; i = 1,2,3 \tag{TS.8}$$

where $D_3^{+}{:=}(D_3'D_3)^{-1}D_3'$ is the Moore-Penrose inverse of the duplication matrix D_3 (Magnus and Neudecker, 2007); empty spaces denote zeros. Notice that $V_{\sigma^{+}}$ can be estimated consistently by $\hat{V}_{\sigma^{+}}$ by simply replacing $\Sigma_{\eta,i}$ with their consistent estimates $\hat{\Sigma}_{\eta,i} := \frac{1}{T_i}\sum_{t=1}^{T_i}(X_t - \hat{\Pi}_i W_t)(X_t - \hat{\Pi}_i W_t)'$, $i = 1,2,3$ in eq. (TS.8).

We have all the ingredients to define the CMD estimation problem:

$$\min_{\theta} \; \left(\hat{\sigma}_T^{+} - g(\theta)\right)' \left(\hat{V}_{\sigma^{+}}\right)^{-1} \left(\hat{\sigma}_T^{+} - g(\theta)\right) \tag{TS.9}$$

which provides a CMD estimate $\hat{\theta}_T$ of the structural parameters. When $r >$dim(θ), a test of overidentification restrictions implied by the SVAR specification is immediately available after estimation, because under the null hypothesis $\sigma_0^+ = g(\theta_0)$ it holds:

$$T\left(\hat{\sigma}_T^+ - g(\hat{\theta}_T)\right)'\left(\hat{V}_{\sigma^+}\right)^{-1}\left(\hat{\sigma}_T^+ - g(\hat{\theta}_T)\right) \xrightarrow{d} \chi^2(r - \dim(\theta)). \qquad \text{(TS.10)}$$

TS.5 Measures of uncertainty

In this section we briefly review how the two proxies of uncertainty used in the paper have been built.

Following Jurado *et al.* (2015) and Ludvigson *et al.* (2017), the time series that proxy the uncertainty indexes $U_{it}(f)$, $i = M, F$, where f denotes the uncertainty horizon ($f = 1$ one-month uncertainty and $f = 12$ one-year uncertainty in the paper), are estimated as the average of the time-varying volatility, as produced by stochastic volatility models, of the forecast error of each series in a large panel of macroeconomic ($U_{Mt}(f)$) and financial variables ($U_{Ft}(f)$), conditional on information available.

To keep presentation as simple as possible, consider the quantity:

$$U_{it}(f) := \lim_{N_i \to \infty} \frac{1}{N_i} \sum_{j=1}^{N_i} U_{jt}^i(f) \quad , \quad i = M, F \qquad \text{(TS.11)}$$

where N_i is the number of time series in category $i = M, F$ for which individual indices of the type

$$U_{jt}^i(f) := \left(E\left[\left(e_{jt+f}^i\right)^2 \mid \mathcal{I}_t\right]\right)^{1/2} \quad , \quad i = M, F \qquad \text{(TS.12)}$$

are computed. In eq. (TS.12), $e_{j,t+f}^i := v_{j,t+f}^i - E(v_{j,t+f}^i \mid \mathcal{I}_t)$; $v_{j,t+f}^i$ is the individual time series at time $t + f$ that belongs to the category $i = M, F$; $\mathcal{I}_t$ is the information set available at time t; $E(v_{j,t+f}^i \mid \mathcal{I}_t)$ is the conditional forecast of $v_{j,t+f}^i$ based on information $\mathcal{I}_t$; $e_{j,t+f}^i$ is the associated conditional forecast error. Eq. (TS.12) defines the uncertainty associated with the jth variable in the category $i = M, F$ as the square root of the conditional volatility generated by the (unpredictable) forecast error associated with that variable. Eq. (TS.11) aggregates all the individual uncertainties in the category $i = M, F$. In particular, $N_M = 134$ 'monthly macroeconomic time series' covering the sample 1960M7-2015M4 are used for $U_{Mt}(f)$ and $N_F = 147$ 'monthly financial indicators' are used for $U_{Ft}(f)$;see Ludvigson *et al.* (2017) and references therein for details.

We now focus on how the individual measures of uncertainty that enter eq. (TS.12) are estimated in practice. Jurado *et al.* (2015) use factor augmented autoregressive models to estimate the conditional forecasts $E(v^i_{j,t+f} \mid \mathcal{I}_t)$ and the decomposition $e^i_{j,t+f} = \gamma^i_{j,t+f}\varepsilon^i_{j,t+f}$, where $\varepsilon^i_{j,t+f}$ is iidN(0,1) and $\gamma^i_{j,t+f}$ is driven by stochastic volatility models of the form

$$\log\left(\gamma^i_{j,t+f}\right)^2 = \alpha^i_j + \delta^i_j \log\left(\gamma^i_{j,t+f-1}\right)^2 + \tau^i_j \xi_{j.t+f} \ , \ \ \xi_{j,t+f} \sim iidN(0,1) \ , \quad i = M, F$$

where the parameters $(\alpha^i_j,\ \delta^i_j,\ \tau^i_j)$ are subject to standard regularity conditions. Given the estimates of $(\alpha^i_j,\ \delta^i_j,\ \tau^i_j)$ for the jth variable in the category $i = M, F$, one gets the dynamics of $U^i_{jt}(f)$ in eq. (TS.12) and from these the measures of uncertainty in eq. (TS.11) are obtained by aggregation.

TS.6 Information sufficiency and omitted variables analysis

In this section we analyze the 'informational sufficiency' of the VARs used in the paper to analyze the relationships between uncertainty and real economic activity. We also investigate the properties of the structural shocks estimated from our baseline structural specification with respect to some historical events. To do this, we divide the section into two parts. In the first part, we analyze the information sufficiency of the reduced form VARs for $X_t{:=}(U_{Mt}, Y_t, U_{Ft})'$, $X^*_t{:=}(U_{Ft}, Y_t, CS_t)'$, and $X^{*\circ}_t{:=}(U_{Ft}, Y_t, CS_t)'$. In the second part, we describe some properties of the estimated structural shocks $\hat{e}_t$ obtained from the non-recursive SVAR (see eq. (17) and Table 2 of the paper) for $X_t{:=}(U_{Mt}, Y_t, U_{Ft})'$, $X^*_t{:=}(U_{Ft}, Y_t, CS_t)'$, and $X^{*\circ}_t{:=}(U_{Ft}, Y_t, CS_t)'$.

Informational sufficiency and omitted information

Given our small-scale system, a natural concern is whether the VAR for $X_t := (U_{Mt}, Y_t, U_{Ft})'$ satisfies the necessary and sufficient conditions which permit to correctly recover the structural shocks of interest. To do so, we follow Forni and Gambetti (2014) and test the 'informational sufficiency' of the specified VAR. Indeed, in light of the small dimension of X_t, not rejecting the informational sufficiency of $X_t{:=}(U_{Mt}, Y_t, U_{Ft})'$ allows us to rule out problems of nonfundamentalness, so that we can correctly estimate the effects of uncertainty shocks through IRFs. In practice, we estimate a FAVAR model for the vector $W_t{:=}(X'_t, V'_t)'$ where $V_t{:=}(v_1, v_{2t}, v_{3t}, v_{4t})'$ contains orthogonal factors extracted from a large set of macroeconomic and financial variables which jointly account for almost 90% of the entire variability, see McCracken and Ng (2015), and then run simple Granger-causality tests of V_t on X_t. This allows to check whether there exists a substantial discrepancy between the econometrician's information set and the agent's information set which, if present, would compromise the recovering of the shocks. We estimate the FAVAR for W_t on the Great Inflation, Great Moderation and Great Recession+Slow recovery periods, respectively and on each macroeconomic regime test whether V_t Granger-causes X_t.

The upper panel of Table TS.1 reports bootstrapped p-values[3] associated with the test for the null of absence of Granger-causality, equation-wise and at the system level. It can be noticed that the null hypothesis is not generally rejected at the 5% level of significance.

The mid and lower panels of Table TS.1 repeat the same exercise for the two alternative VAR specifications based on $X_t^* := (U_{Ft}, Y_t, CS_t)'$ and $X_t^{*\circ} := (U_{Mt}, Y_t, CS_t)'$, respectively, CS_t being a measure of financial frictions proxied with the spread between yields on Baa- and Aaa-rated long-term industrial corporate bonds (source FRED). As for the baseline specification, also in this case there are no rejections of the null hypotheses.

The results reported in Table TS.1 refer to a FAVAR model with four lags for the dependent variables and eight lags for the factors. The results, however, are robust to more parsimonious specifications with respect to the number of factors included in the analysis.[4]

In addition to informational sufficiency, a further simple check can be directly based on the structural shocks $\hat{e}_{jt}$, $j = M, Y, F$ estimated from the baseline non-recursive SVAR for X_t:=$(U_{Mt}, Y_t, U_{Ft})'$ (see eq. (17) and Table 2 of the paper). The shocks are obtained through $\hat{e}_t = \hat{B}_i^{-1}\hat{\eta}_t$, $i = 1, 2, 3$, where $\hat{B}_1 = \hat{B}, \hat{B}_2 = (\hat{B} + \hat{Q}_2)$ and $\hat{B}_3 = (\hat{B} + \hat{Q}_2 + \hat{Q}_3)$ are fixed at the QML estimates reported in Table 2 of the paper. It is natural to analyze whether $\hat{e}_t$ still contains predictable information with respect to the inflation rate (π_t) and the federal fund rate (i_t) which are variables excluded from the baseline three-equation VAR. To do so, we regress $\hat{e}_t := (\hat{e}_{Mt}, \hat{e}_{Yt}, \hat{e}_{Ft})'$ on two lags of π_t and i_t and then test whether the associated regression coefficients are jointly significant equation-wise and at the system level. The results of the tests are reported in the upper panel of Table TS.2 in the form of bootstrapped p-values. It can be noticed that we do not reject the null hypothesis of irrelevant regressors at the 5% nominal significance level. We repeat the same exercise considering the structural shocks estimated from the non-recursive SVARs for $X_t^* := (U_{Ft}, Y_t, CS_t)'$ and $X_t^{*\circ} := (U_{Mt}, Y_t, CS_t)'$, respectively, keeping the structural specification of the SVAR in eq. (17) of the paper fixed. Results are summarized in the mid and lower panels of Table TS.2 and, again, suggest that the structural shocks produced by our small-scale non-recursive SVARs are not seriously affected by the omission of the inflation rate and the federal funds rate.

As a final check, we come back on the factors $V_t := (v_1, v_{2t}, v_{3t}, v_{4t})'$ considered before in the informational sufficiency analysis. We first perform a regression of $\hat{e}_t$ on the first two lags of the first factor (i.e. v_{1t-1} and v_{1t-2}), which account for more than 55% of the total variability. Then, we repeat the analysis by regressing $\hat{e}_t$ on the first two lags of all four factors which jointly account for almost 90% of the entire variability. The non rejection of the null hypothesis that

[3]All the bootstrap exercises, in this section, refer to the 'wild bootstrap' technique. We use the wild bootstrap to control for the heteroskedasticity of the shocks within regimes in small samples.

[4]The complete set of results is available from the authors upon request.

V_t does not bear relevant information on $\hat{e}_t$ is substantially confirmed and is also valid for the two alternative SVARs containing the credit spread indicator. The complete set of results is reported in Table TS.3.

Estimated structural shocks and important historical events

Having verified the 'statistical' properties of estimated structural shocks $\hat{e}_{jt}$, $j = M, Y, F$, plotted in Figure TS.1 for the baseline specification, we analyze qualitatively whether they reproduce important historical events characterizing the US and global economy. The upper panel of Figure TS.1 plots the estimated macroeconomic uncertainty shock, $\hat{e}_{Mt}$, the mid panel plots the estimated real activity shock, $\hat{e}_{Yt}$, and the lower panel plots the estimated financial uncertainty shocks $\hat{e}_{Ft}$. The horizontal dotted black lines in the graphs correspond to 2 standard deviations above/below the unconditional mean of each series, while the shaded areas summarize NBER official recession dates. From the graphs, it clearly emerges that the estimated shocks are systematically higher in coincidence of the NBER recession dates (the shaded areas in the graphs). An interesting exception refers to the so-called Black Monday (October 19, 1987), when stock markets crashed around the world. The crash, originating from Hong Kong, almost immediately spreads to Europe, hitting also the U.S. The Dow Jones Industrial Average (DJIA) fell more than 22%. Other interesting events are the IMF Crisis in the United Kingdom in 1976 which forced the government to borrow $3.9 billion from the International Monetary Fund (IMF), generating instabilities on the US financial market too, and the reactions of US policy authorities in late 1978 that, facing with a collapse in confidence in the dollar, announced the mobilization of more than $20 billion to defend the currency's value in foreign exchange markets.

TS.7 Long-run multipliers

As is known, IRFs provide short-run (transitory) dynamic causal effects. In addition, IRFs are explicitly aimed at identifying 'structural shocks' rather than measuring causal links between time series, see e.g. Dufour and Renault (1998), Bruneau and Jondeau (1999), Yamamoto and Kurozumi (2006) and Dufour *et al.* (2006) for a thorough discussion. For instance, it can be easily shown that zero on-impact responses may become non-zero after a certain number of periods. In this section we complement the analysis based on the IRFs reported in the paper with long-run total multipliers (or long-run cumulative impulse response matrix). These multipliers capture the (cumulative) limit impact of the structural shocks on the variables, if statistically significant, by taking into account all dynamic adjustments at work in the system.[5]

[5]Interestingly, while Granger-noncausality at all horizons implies a long-run multiplier equal to zero, the converse does generally not hold, hence the condition of zero long-run effect is less stringent than the one of

In our setup, long-run multipliers are given by

$$\sum_{h=0}^{\infty} IRF_j(h) := \begin{cases} R'(I_3 - A_1)^{-1}R\tilde{b}_j & t \leq T_{B_1} \\ R'(I_3 - A_2)^{-1}R(\tilde{b}_j + \tilde{q}_{2j}) & T_{B_1} < t \leq T_{B_2} \\ R'(I - A_3)^{-1}R(\tilde{b}_j + \tilde{q}_{2j} + \tilde{q}_{3j}) & t > T_{B_2} \end{cases} \qquad \begin{matrix} h = 0, 1, ..., h_{\max} \\ j = M, Y, F \end{matrix}$$

where we have used the same notation as in the paper. The structural specification of the SVAR is that of eq. (17) of the paper. Estimates are summarized in Table TS.4 for $f = 1$ (one-month uncertainty) and $f = 12$ (one-year uncertainty), respectively. The upper panel of Table TS.4 refers to the baseline non-recursive SVAR for $X_t := (U_{Mt}, Y_t, U_{Ft})'$, while the lower panel refers to the non-recursive SVAR based on $X_t^* := (U_{Ft}, Y_t, CS_t)'$, where CS_t is proxied by considering the spread between yields on Baa- and Aaa-rated long-term industrial corporate bonds. In both cases the structural specification is summarized in eq. (17) of the paper. Each estimated long-run multiplier is associated with a bootstrap-based standard error. Recall that since we consider the long-run cumulative impulse response matrix, the estimates obtained in correspondence of '$e_{Mt} \to Y_t$', '$e_{Ft} \to Y_t$' and '$e_{CSt} \to Y_t$' capture the long-run effect of uncertainty shocks and credit shocks on the industrial production level.

The multipliers in Table TS.4 confirm that regardless of macroeconomic regimes and the length of the uncertainty horizon f, macroeconomic uncertainty shocks cause a permanent decline in real economic activity. The long-run total multiplier associated with macroeconomic uncertainty shocks is negative and strongly significant. Instead, the long-run multipliers associated with the impact of financial uncertainty shocks are not statistically significant. Overall, Table TS.4 leads one to rule out the hypothesis that a rebound takes place after uncertainty shocks curb economic activity. Indeed, the long-run (permanent) effect of these shocks is either negative and significant (macroeconomic uncertainty shocks), or not significant (financial uncertainty shocks).

Focusing instead on the reverse causality issue, the long-run multipliers in Table TS.4 show that there are no significant long-run effects of real economic activity shocks on macroeconomic and financial uncertainty.

Finally, results in the lower panel of Table TS.4 confirm what the IRFs reported in the paper already suggested about causality links between credit spreads and financial uncertainty: while credit spreads shocks do not have permanent long-run effects on financial uncertainty, financial uncertainty shocks trigger a strong deterioration of credit conditions. This result is particularly evident on the Great Recession+Slow Recovery period.

absence of Granger-causality at all forecasting horizons, see e.g. Fanelli and Paruolo (2010).

TS.8 Robustness checks

In this section we report a set of robustness checks that complement the results discussed in the paper and above. In Section TS.8.1 we analyze the role of financial frictions. In Section TS.8.2 we evaluate the robustness of results to inverting financial and macroeconomic uncertainty in our non-recursive SVAR, which implies a change in the Great Inflation period. In Section TS.8.3 we replace the original measure of macroeconomic uncertainty, U_{Mt}, with a measure of 'real uncertainty', see Ludvigson *et al.* (2017), purged from the part of uncertainty which can be ascribed to financial markets. Finally, in Section TS.8.4 we check whether results are robust to the use of a different proxy of real economic activity, i.e. employment (growth).

TS.8.1 Financial frictions

The baseline empirical analysis reported in the paper considers macroeconomic and financial uncertainty jointly but ignores financial frictions. As argued in Bachmann et al. (2013), the prolonged negative response of production to a surprise increase in uncertainty might indicate that channels other than 'wait and see' may be relatively more important in the United States. A number of recent papers have brought attention to such alternative channels. Arellano et al. (2012) build a quantitative general equilibrium model in which an increase in uncertainty, in the presence of imperfect financial markets leads firms to downsize projects to avoid default; this impact is exacerbated through an endogenous tightening of credit conditions and leads to a persistent reduction in output. Similarly, Christiano et al. (2014) develop a large-scale New Keynesian model with financial frictions in which risk shocks have persistent effects on output. The role of financial frictions as amplifiers of the effects of uncertainty shocks and cause of possible permanent decline in economic activity is also rationalized in Gilchrist et al. (2014), Alessandri and Mumatz (2014) and Alfaro et al. (2016). Caldara et al. (2016) and Caggiano et al. (2017) analyze the interaction between financial conditions and economic uncertainty and find that uncertainty shocks have an especially negative impact in situations where they trigger a tightening of financial conditions. Furlanetto et al. (2017) disentangle the role of credit and uncertainty shocks and find that shocks originating in the credit markets have larger and longer-lived effects than uncertainty shocks. A common element in these contributions is that uncertainty interacts with financial frictions to generate sizable and persistent reductions in production.

We check whether the omission of measures of financial frictions drive our main results by estimating our non-recursive SVAR for two different vectors of endogenous variables: $X_t^* := (U_{Ft}, Y_t, CS_t)'$ and $X_t^{*\circ} := (U_{Mt}, Y_t, CS_t)'$, respectively, where CS_t is the spread between yields on Baa- and Aaa-rated long-term industrial corporate bonds (source FRED).[6] The reduced form analyses of these systems, not reported here but available upon request to the authors, confirm the existence of three broad volatility regimes in the data which can be associated with the Great Inflation, Great Moderation and Great Recession+Slow Recovery, respectively. In both specifications we assume, in line with the specification in eq. (17) of the paper, that the uncertainty measure is exogenous on the Great Inflation period, while it can also respond contemporaneously to other shocks on the Great Moderation and Great Recession+Slow Recovery regimes.

Results are reported in Figures TS.1-TS3. The baseline findings on the contractionary effect of uncertainty shocks is confirmed also in the case where we control for first-moment financial shocks: industrial production reacts negatively to both macro and financial uncertainty, and it does so by more in the Great Recession+Slow Recovery period. As far the reverse causality issue is concerned, controlling for first-moment financial shocks reinforces our baseline result of exogenous uncertainty: in none of the three macroeconomic regimes real economic activity shocks trigger significant responses to financial uncertainty. In particular, Figure TS.2 shows that also in the Great Moderation period, financial uncertainty U_{Ft} does no longer respond significantly to real economic activity shocks.

TS.8.2 Macroeconomic and financial uncertainty inverted in the Great Inflation period

The identification strategy discussed in Sections 2 and 3 of the paper does not depend on the ordering of the variables. However, the specification of our non-recursive SVAR in eq. (17) implies a fully non-recursive structure for the responses on-impact of the variables to the shocks only for the second (Great Moderation) and third (Great Recession+Slow recovery) volatility regimes. In the first regime, it is imposed a recursive identification scheme which assumes that macroeconomic uncertainty is exogenous in this regime and that financial uncertainty shocks do not contemporaneously affect macroeconomic uncertainty and real economic activity. Although widely justifiable, we check whether this choice affects the main conclusions of the paper.

We replicate the same analysis presented in the paper by considering the non-recursive SVAR for $X_t := (U_{Ft}, Y_t, U_{Mt})'$, i.e. with financial and macroeconomic uncertainty inverted. This particular ordering of the variables, combined with the lower triangular structure imposed in the first regime in eq. (17), implies the exogeneity of financial uncertainty in the Great Inflation period. This constraint, however, is removed starting from the Great Moderation regime onward.

[6] Also in these cases, the reduced form analysis does not lead us to reject the hypothesis that the data are characterized by the three volatility regimes and that the reduced form systems can be considered informational sufficient in the sense of Forni and Gambetti (2014).

Figures TS.4-TS.6 plot the dynamic responses of the variables in $X_t := (U_{Mt}, Y_t, U_{Ft})'$ to each structural shock during the Great Inflation, Great Moderation and Great Recession + Slow Recovery periods, respectively, for $f = 1$ (one-month uncertainty, yellow line) and $f = 12$ (one-year uncertainty, green line).

Results point out that there are not appreciable differences relative to the baseline case neither in terms of the recessionary effect of uncertainty shocks, nor as concerns the exogeneity of the two sources of uncrtainty in all macroeconomic regimes.

TS.8.3 Real uncertainty

As noticed in Ludvigson *et al.* (2017), with e.g. $f = 1$, the proxy of uncertainty $U_{Ft}(1)$ and $U_{Mt}(1)$ (Section TS.5) display comovement but also have independent variations as the correlation between them is 'only' 0.58. Part of this correlation might be simply due, however, to the fact that $U_{Mt}(f)$ includes by construction also the uncertainty from a category of financial variables which potentially overlap with the variables used to build the index $U_{Ft}(f)$. For this reason, we proceed as in Ludvigson *et al.* (2017) and adopt a measure of macroeconomic uncertainty which is extracted from a smaller dataset including only real activity indicators ('real uncertainty', U^{p}_{Mt}). We re-estimate our non-recursive SVAR by replacing $U_{Mt}(f)$ with $U^{p}_{M,t}(f)$.

Figures TS.7-TS.9 plot the implied IRFs considering both $f = 1$ (one-month uncertainty, yellow line) and $f = 12$ (one-year uncertainty, green line) and $Y_t = \Delta ip_t$ (industrial production growth). All the results confirm the main findings of the paper. Both macroeconomic and financial uncertainty shocks induce recessionary, although regime-specific, effects on the real activity indicator. These effects are qualitatively and quantitatively comparable to those reported in the paper and obtained through the 'extended' indicator for macroeconomic uncertainty U_{Mt}. The results are very similar for both one-month $f = 1$ and one-year $f = 12$ uncertainty horizons. It turns out that, differently from Ludvigson *et al.* (2017), macroeconomic uncertainty is as important as financial uncertainty in triggering a downturn in real activity.

Moreover, apart a slightly positive reaction of the financial uncertainty indicator to a real activity shock during the Great Moderation regime, these results robustify the finding that uncertainty, both macroeconomic and financial, can be approximated as exogenous sources of decline of economic activity.

TS.8.4 Real economic activity: employment growth

In this section we reproduce the analysis presented in the paper for the baseline case $X_t := (U_{Mt}, Y_t, U_{Ft})'$ by measuring real economic activity Y_t with $Y_t = \Delta emp_t$, where emp_t is the log of the employment level (source: FRED database). The reduced form analyses of these systems, not reported here but available upon request to the authors, confirm the existence of three broad volatility regimes in the data which can be associated with the Great Inflation, Great Moderation and Great Recession+Slow Recovery, respectively. The structural specification is the same as in eq. (17) of the paper.

Figures TS.10-TS.12 plot the dynamic responses of the variables in $X_t := (U_{Mt}, Y_t, U_{Ft})'$ to each structural shock in the Great Inflation, Great Moderation and Great Recession + Slow Recovery periods, respectively. The response of employment to macroeconomic and financial uncertainty shocks is negative and regime dependent. The effects of financial uncertainty shocks, in general, are larger in magnitude than the macroeconomic uncertainty ones. Dynamic causality results suggest that macroeconomic and financial uncertainty act as exogenous sources, not endogenous responses, of decline in economic activity.

Overall, the analysis confirms qualitatively the results discussed in the paper using industrial production growth for Y_t.

References

Alessandri, P. and Mumtaz, H. (2014), Financial regimes and uncertainty shocks, BCAM *Working Paper* No. 1404.

Alfaro, I.N., Bloom, N. and Lin, X. (2016), The finance-uncertainty multiplier, *Working Paper*, Stanford University and Ohio State University.

Arellano, C., Bai, Y. and Kehoe, P. (2012), Financial markets and fluctuations in uncertainty, *Federal Reserve Bank of Minneapolis Staff Report*, March.

Bacchiocchi, E. (2017), On the identification of interdependence and contagion of financial crises, *Oxford Bulletin of Economics and Statistics* 79, 1148-1175.

Bacchiocchi, E. and Fanelli, L. (2015), Identification in Structural Vector Autoregressive models with structural changes, with an application to U.S. monetary policy, *Oxford Bulletin of Economics and Statistics* 77, 761-779.

Bai, J. (2000), Vector Autoregressive models with structural changes in regression coefficients and in variance-covariance matrices, *Annals of Economics and Finance* 1, 303-339.

Bachmann, R., Elstner, S. and Sims, E. R. (2013), Uncertainty and economic activity: Evidence from business survey data, *American Economic Journal: Macroeconomics* 5, 217-249.

Bruneau, C. and Jondeau, E. (1999), Long-run causality, with application to international links between long-term interest rates, *Oxford Bulletin of Economics and Statistics* 61, 545–568.

Caggiano, G., Castelnuovo, E., Delrio, S. and Robinson, T. (2017), Time-dependent finance-uncertainty multipliers, *Working Paper*.

Caldara, D., Fuentes-Albero, C., Gilchrist, S. and Zakrajšek, E. (2016), The macroeconomic impact of financial and uncertainty shocks, *European Economic Review* 88, 185-207.

Christriano, J.C., Motto, R. and Rostagno, M. (2014), Risk shocks, *American Economic Review* 104, 27–65.

Dufour, J.M. and Renault, E. (1998), Short tun and long run causality in time series: theory, *Econometrica*, 66, 1099-1125.

Dufour, J.M. Pelletier, D. and Renault, E. (2006), Short run and long run causality in time series: inference, *Journal of Econometrics* 132, 337-362.

Fanelli, L., and Paruolo, P. (2010), Speed of adjustment in cointegrated systems, *Journal of Econometrics* 158, 130-141

Forni, M. and Gambetti, L. (2014), Sufficient information in structural VARs, *Journal of Monetary Economics* 66, 124-136.

Furlanetto, F., Ravazzolo, F. and Sarferaz, S. (2017), Identification of financial factors in economic fluctuations, *The Economic Journal*, forthcoming.

Gilchrist, S., Sim, J. and Zakrajsek, E. (2014), Uncertainty, financial frictions and investment dynamics, *NBER Working Paper* No. 20038.

Jurado, K., Ludvigson, S.C. and Ng, S. (2015), Measuring uncertainty, *American Economic Review* 105(3), 1177-1216.

Kilian, L. (1998), Small-sample confidence intervals for impulse response functions, *Review of Economics and Statistics* 80, 218-230.

Ludvigson, S.C., Ma, S. and Ng, S. (2017), Uncertainty and business cycles: exogenous impulse or endogenous response? Working Paper.

Magnus, J.R. and Neudecker, H. (2007), *Matrix differential calculus with applications in statistics and econometrics*, John Wiley and Sons.

Magnusson, L.M. and Mavroeidis, S. (2014), Identification using stability restrictions, *Econometrica* 82, 1799-1851.

McCracken, M.W. and Ng, S. (2015), FRED-MD: A monthly database for macroeconomic research, *Journal of Business and Economic Statistics* 34, 574-589.

Podstawski, M. and Velinov, A. (2016), The state dependent impact of the bank exposure on sovereign risk, DIW Berlin, Discussion Paper 1550.

Qu, Z., and Perron, P. (2007), Estimating and testing structural changes in multivariate regressions, *Econometrica* 75, 459-502.

Yamamoto, T. and Kurozumi, E. (2006), Tests for long run Granger non-causality in cointegrated systems, *Journal of Time Series Analysis* 27, 703-723.

TABLE TS.1: Information sufficiency: Bootstrap p-values of the Granger causality tests for the first four factors in the FAVAR model.

	GI: 1960M8-1984M3	GM: 1984M4-2007M12	GR+SR: 2008M1-2015M4
	VAR for $X_t^F := (U_{Mt}, Y_t, U_{Ft}, v_1, v_2, v_3, v_4)'$		
U_{Mt}	0.20	0.06	0.99
Y_t	0.05	0.02	0.88
U_{Ft}	0.20	0.61	0.88
System	0.08	0.32	0.87
	VAR for $X_t^{*F} := (U_{Ft}, Y_t, CS_t, v_1, v_2, v_3, v_4)'$		
U_{Ft}	0.12	0.49	0.20
Y_t	0.01	0.02	0.05
CS_t	0.01	0.17	0.13
System	0.07	0.26	0.08
	VAR for $X_t^{*\circ F} := (U_{Mt}, Y_t, CS_t, v_1, v_2, v_3, v_4)'$		
U_{Mt}	0.03	0.17	0.75
Y_t	0.01	0.02	0.70
CS_t	0.01	0.30	0.32
System	0.02	0.12	0.43

Notes: Upper panel: the FAVAR model contains the variables $X_t^F := (U_{Mt}, Y_t, U_{Ft}, v_1, v_2, v_3, v_4)'$. Mid panel: the FAVAR contains the variables $X_t^{*F} := (U_{Ft}, Y_t, CS_t, v_1, v_2, v_3, v_4)'$. Lower panel: the FAVAR model contains the variables $X_t^{*\circ F} := (U_{Mt}, Y_t, CS_t, v_1, v_2, v_3, v_4)'$. In all specifications, v_{it}, $i = 1, \ldots, 4$ are the first four factors described in Section TS.6, $Y_t = \Delta ip_t$ (industrial production growth) and CS_t is a proxy of credit spread. The p-values are obtained using the 'wild' bootstrap approach. 'GI'=Great Inflation, 'GM'=Great Moderation and 'GR+SR'=Great Recession + Slow Recovery.

TABLE TS.2: Structural shocks and monetary policy stance: Bootstrap p-values of the Granger causality tests for interest rate (i_t) and inflation rate (π_t) on the estimated structural shocks.

	two lags for i_t and π_t	eight lags i_t and π_t
SVAR for $X_t := (U_{Mt}, Y_t, U_{Ft})'$		
$\hat{e}_{Mt}$	0.04	0.04
$\hat{e}_{Yt}$	0.21	0.93
$\hat{e}_{Ft}$	0.94	0.98
System	0.27	0.36
SVAR for $X_t^* := (U_{Ft}, Y_t, CS_t)'$		
$\hat{e}_{Ft}$	0.21	0.75
$\hat{e}_{Yt}$	0.21	0.58
$\hat{e}_{CSt}$	0.48	0.03
System	0.42	0.19
SVAR for $X_t^{*\circ} := (U_{Mt}, Y_t, CS_t)'$		
$\hat{e}_{Mt}$	0.05	0.19
$\hat{e}_{Yt}$	0.39	0.77
$\hat{e}_{CSt}$	0.74	0.05
System	0.38	0.27

Notes: Upper panel: the structural shocks are estimated through a SVAR for $X_t := (U_{Mt}, Y_t, U_{Ft})'$. Mid panel: the structural shocks are estimated through a SVAR for $X_t^* := (U_{Ft}, Y_t, CS_t)'$. Lower panel: the structural shocks are estimated through a SVAR form $X_t^{*\circ} := (U_{Mt}, Y_t, CS_t)'$. $Y_t = \Delta ip_t$ (industrial production growth) and CS_t is a proxy of credit spread. The p-values are obtained using the 'wild' bootstrap approach. Overall sample: 1960M8-2015M4.

TABLE TS.3: Structural shocks and factors: Bootstrap p-values of the Granger causality test for the factors $(v_1, v_2, v_3, v_4)'$ on the estimated structural shocks.

Shock	two lags for v_{1t}	two lags for $(v_1, v_2, v_3, v_4)'$	eight lags for $(v_1, v_2, v_3, v_4)'$
SVAR for $X_t := (U_{Mt}, Y_t, U_{Ft})'$			
$\hat{e}_{Mt}$	0.09	0.15	0.60
$\hat{e}_{Yt}$	0.48	0.14	0.48
$\hat{e}_{Ft}$	0.40	0.84	0.82
System	0.32	0.50	0.38
SVAR for $X_t^* := (U_{Ft}, Y_t, CS_t)'$			
$\hat{e}_{Ft}$	0.16	0.39	0.69
$\hat{e}_{Yt}$	0.02	0.02	0.43
$\hat{e}_{CSt}$	0.93	0.75	0.43
System	0.08	0.08	0.037
SVAR for $X_t^{*\circ} := (U_{Mt}, Y_t, CS_t)'$			
$\hat{e}_{Mt}$	0.12	0.08	0.60
$\hat{e}_{Yt}$	0.26	0.11	0.43
$\hat{e}_{CSt}$	0.35	0.46	0.42
System	0.07	0.06	0.57

Notes: Upper panel: the structural shocks are estimated through a SVAR for $X_t := (U_{Mt}, Y_t, U_{Ft})'$. Mid panel: the structural shocks are estimated through a SVAR for $X_t^* := (U_{Ft}, Y_t, CS_t)'$. Lower panel: the structural shocks are estimated through a SVAR form $X_t^{*\circ} := (U_{Mt}, Y_t, CS_t)'$. In all specifications, v_{it}, $i = 1, \ldots, 4$ are the first four factors described in Section TS.6. $Y_t = \Delta ip_t$ (industrial production growth) and CS_t is a proxy of credit spread. The p-values are obtained using the 'wild' bootstrap approach. Overall sample: 1960M8-2015M4.

TABLE TS.4. Long-run total multipliers.

	GI: 1960M8-1984M3		GM: 1984M4-2007M12		GR+SR: 2008M1-2015M4	
	$f = 1$	$f = 12$	$f = 1$	$f = 12$	$f = 1$	$f = 12$
			SVAR for $X_t := (U_{Mt}, Y_t, U_{Ft})'$			
$e_{Mt} \to Y_t$	−1.7257 (0.6564)	−2.2605 (0.7861)	−1.1188 (0.3801)	−1.4108 (0.4328)	−1.4640 (0.6535)	−1.3691 (0.6690)
$e_{Mt} \to U_{Ft}$	0.3019 (0.3111)	0.1685 (0.1388)	0.3762 (0.3584)	0.164 (0.1781)	0.8957 (0.4479)	0.2299 (0.1517)
$e_{Yt} \to U_{Mt}$	0.0800 (0.1394)	0.1639 (0.1640)	−0.0124 (0.0614)	0.0232 (0.0490)	−0.0919 (0.1975)	−0.0309 (0.1506)
$e_{Yt} \to U_{Ft}$	0.2001 (0.1451)	0.0795 (0.0570)	0.4100 (0.2820)	0.1386 (0.1430)	−0.0746 (0.3507)	0.008 (0.1425)
$e_{Ft} \to U_{Mt}$	0.3014 (0.2240)	−0.0409 (0.2590)	0.1044 (0.0876)	0.0255 (0.0696)	0.0317 (0.1859)	−0.0772 (0.1449)
$e_{Ft} \to Y_t$	−1.6905 (0.5985)	−0.8816 (0.6286)	−0.5103 (0.3549)	−0.2140 (0.3959)	0.1138 (0.5766)	0.4796 (0.6573)
			SVAR for $X_t^* := (U_{Ft}, Y_t, CS_t)'$			
$e_{Ft} \to Y_t$	−1.1617 (0.4609)	−1.2032 (0.4997)	0.0768 (0.3597)	−0.6527 (0.3888)	−0.7784 (0.6490)	−0.8860 (0.9849)
$e_{Ft} \to CS_t$	2.8209 (0.7482)	2.9894 (0.8366)	0.8467 (0.4988)	1.0349 (0.5046)	1.8272 (0.6168)	2.3013 (1.544)
$e_{Yt} \to U_{Ft}$	0.1285 (0.1249)	0.0363 (0.0413)	−0.4678 (0.3228)	0.1451 (0.1365)	−0.1874 (0.3404)	−0.0398 (0.1875)
$e_{Yt} \to CS_t$	−0.5685 (0.4756)	−0.4939 (0.4818)	−0.6899 (0.3890)	0.2397 (0.4517)	−0.6149 (0.5465)	−0.5714 (0.7878)
$e_{CSt} \to U_{Ft}$	−0.3297 (0.2002)	−0.0930 (0.0668)	−0.1848 (0.4316)	−0.0773 (0.1991)	−0.2619 (0.3894)	−0.1568 (0.3329)
$e_{CSt} \to Y_t$	0.2573 (0.3740)	0.2963 (0.4141)	−0.2527 (0.3933)	−0.2449 (0.3853)	−0.7506 (0.5099)	−0.6702 (0.7767)

Notes: Estimated long-run total multipliers produced by the non-recursive SVAR (see eq. 17 of the paper), for $X_t := (U_{Mt}, Y_t, U_{Ft})'$ (top panel), and $X_t^* := (U_{Ft}, Y_t, CS_t)'$ (bottom panel), at one-month ($f = 1$) and one-year ($f = 12$) uncertainty horizons, $Y_t = \Delta ip_t$ (industrial production growth) and CS_t is a proxy of credit spread. Bootstrap standard errors in parenthesis. 'GI'=Great Inflation, 'GM'=Great Moderation and 'GR+SR'=Great Recession + Slow Recovery.

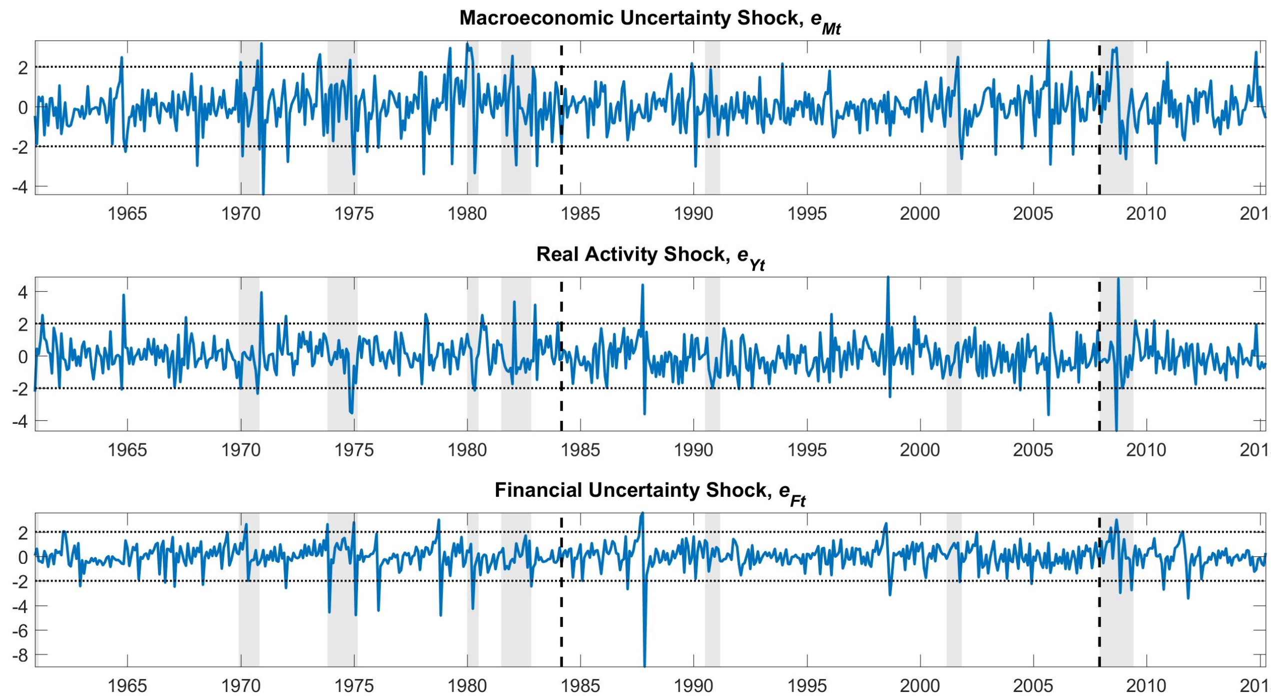

TABLE TS.4: Estimated structural shocks $\hat{e}_{jt}$, $j = M, Y, F$ where $\hat{e}_t = \hat{B}_i^{-1}\eta_t$, $i = 1, 2, 3$, $\hat{B}_1 = \hat{B}, \hat{B}_2 = (\hat{B} + \hat{Q}_2)$ and $\hat{B}_3 = (\hat{B} + \hat{Q}_2 + \hat{Q}_3)$ from the non-recursive SVAR for $X_t := (U_{Mt}, Y_t, U_{Ft})'$, $Y_t = \Delta ip_t$ (industrial production growth), specified in eq. (17) of the paper. The first panel plots the estimated macroeconomic uncertainty shock $\hat{e}_{Mt}$, the second panel the estimated real activity shock $\hat{e}_{Yt}$ and the last panel the estimated financial uncertainty shock $\hat{e}_{Ft}$. Vertical dashed black lines are the two break dates T_{B_1}=1984M3 and T_{B_2}=2007M12. Horizontal dotted black lines correspond to 2 standard deviations above/below the unconditional mean of each series. The shaded areas correspond to the NBER recession dates. Overall sample: 1960M8-2015M4.

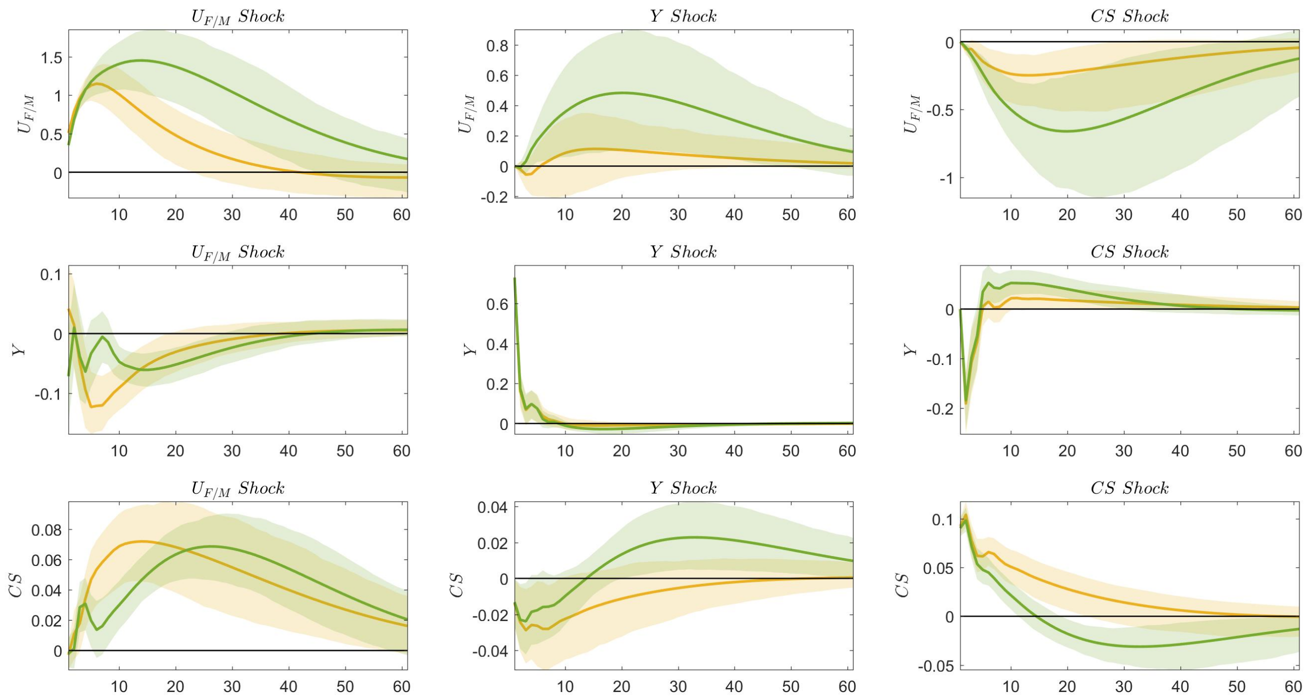

FIGURE TS.1: **Robustness check:** IRFs obtained in the first volatility regime (Great Inflation, 1960M8-1984M3) from the non-recursive SVARs for $X_t^* := (U_{Ft}, Y_t, CS_t)'$ (yellow lines) and $X_t^{*\circ} := (U_{Mt}, Y_t, CS_t)'$ (green lines), respectively, specified in eq. (17) of the paper. The uncertainty horizon is one-year ($f = 12$); $Y_t = \Delta ip_t$ (industrial production growth); CS_t is a proxy of credit spread; the yellow and the green shaded areas denote the associated 90% bootstrap confidence bands; bootstrap confidence bands are computed using Kilian's (1998) method. Responses are measured with respect to one standard deviation changes in structural shocks.

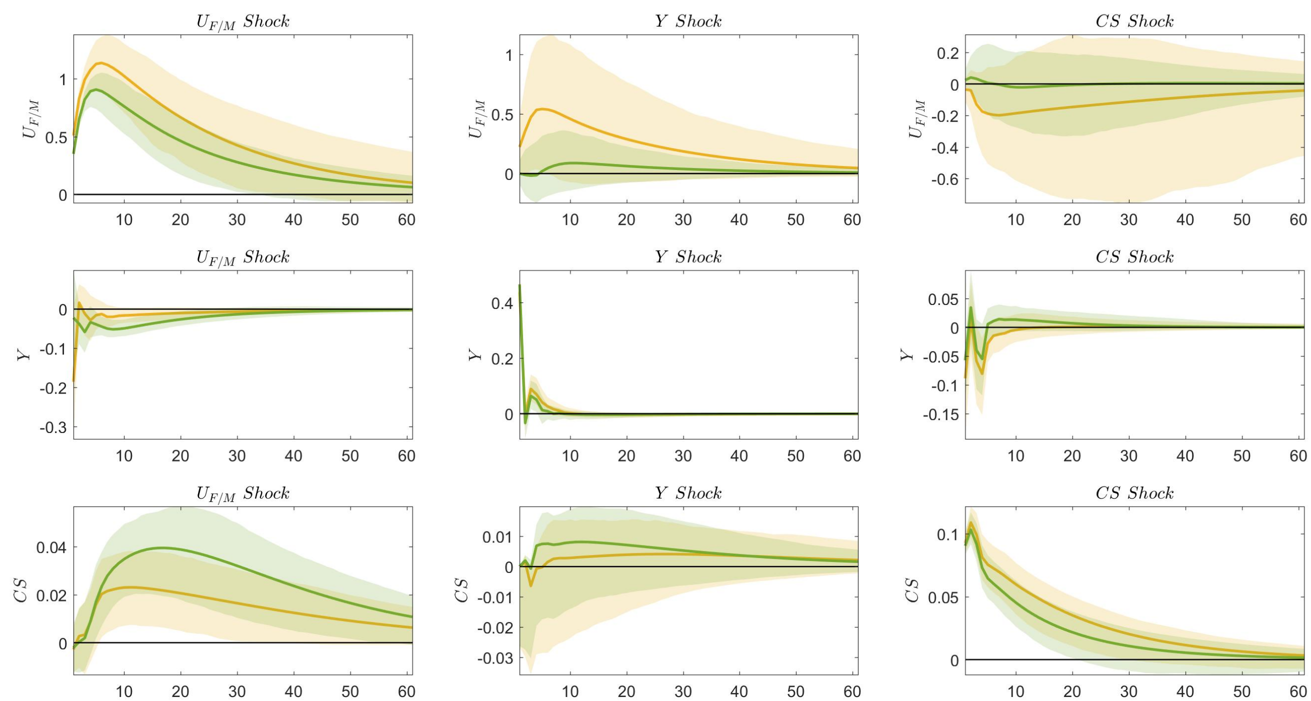

FIGURE TS.2: **Robustness check:** IRFs obtained in the second volatility regime (Great Moderation, 1984M4-2007M12) from the non-recursive SVARs for $X_t^* := (U_{Ft}, Y_t, CS_t)'$ (yellow lines) and $X_t^{*\circ} := (U_{Mt}, Y_t, CS_t)'$ (green lines), respectively, specified in eq. (17) of the paper. The uncertainty horizon is one-year ($f = 12$); $Y_t = \Delta ip_t$ (industrial production growth); CS_t is a proxy of credit spread; the yellow and the green shaded areas denote the associated 90% bootstrap confidence bands; bootstrap confidence bands are computed using Kilian's (1998) method. Responses are measured with respect to one standard deviation changes in structural shocks.

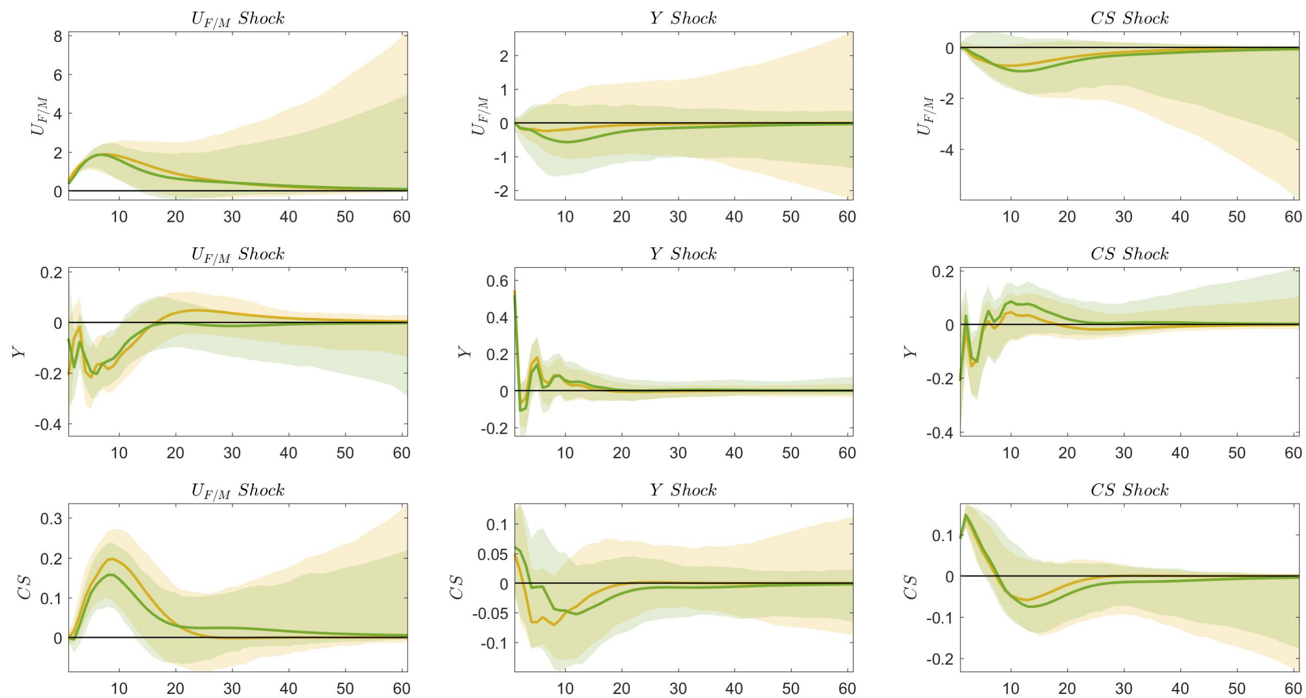

FIGURE TS.3: **Robustness check:** IRFs obtained in the third volatility regime (Great Recession + Slow recovery, 2008M1-2015M4) from the non-recursive SVARs for $X_t^* := (U_{Ft}, Y_t, CS_t)'$ (yellow lines) and $X_t^{*\circ} := (U_{Mt}, Y_t, CS_t)'$ (green lines), respectively, specified in eq. (17) of the paper. The uncertainty horizon is one-year ($f = 12$); $Y_t = \Delta ip_t$ (industrial production growth); CS_t is a proxy of credit spread; the yellow and the green shaded areas denote the associated 90% bootstrap confidence bands; bootstrap confidence bands are computed using Kilian's (1998) method. Responses are measured with respect to one standard deviation changes in structural shocks.

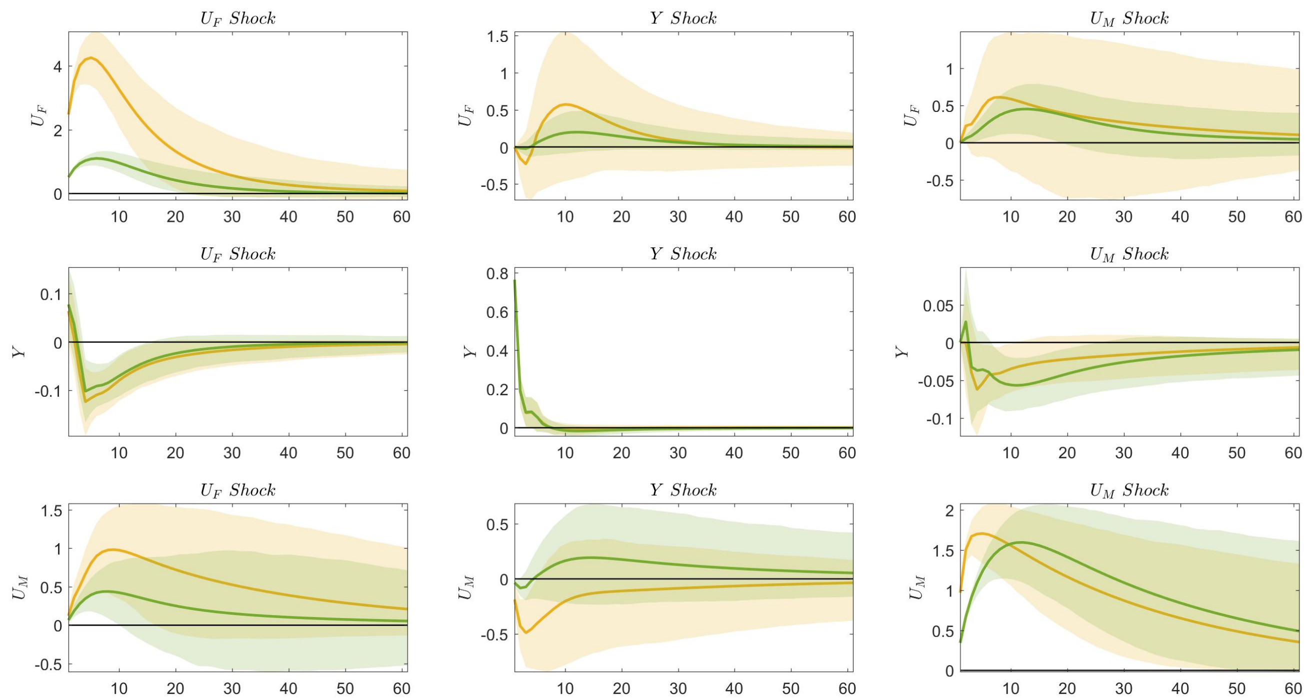

FIGURE TS.4: **Robustness check:** IRFs obtained in the first volatility regime (Great Inflation, 1960M8-1984M3) from the non-recursive SVAR for $X_t := (U_{Ft}, Y_t, U_{Mt})'$, $Y_t = \Delta ip_t$ (industrial production growth) specified in eq. (17) of the paper. The yellow lines refer to the one-month ($f = 1$) uncertainty horizon and yellow shaded areas denote the associated 90% bootstrap confidence bands; the green lines refer to the one-year ($f = 12$) uncertainty horizon and green shaded areas denote the associated 90% bootstrap confidence bands; bootstrap confidence bands are computed using Kilian's (1998) method. Responses are measured with respect to one standard deviation changes in structural shocks.

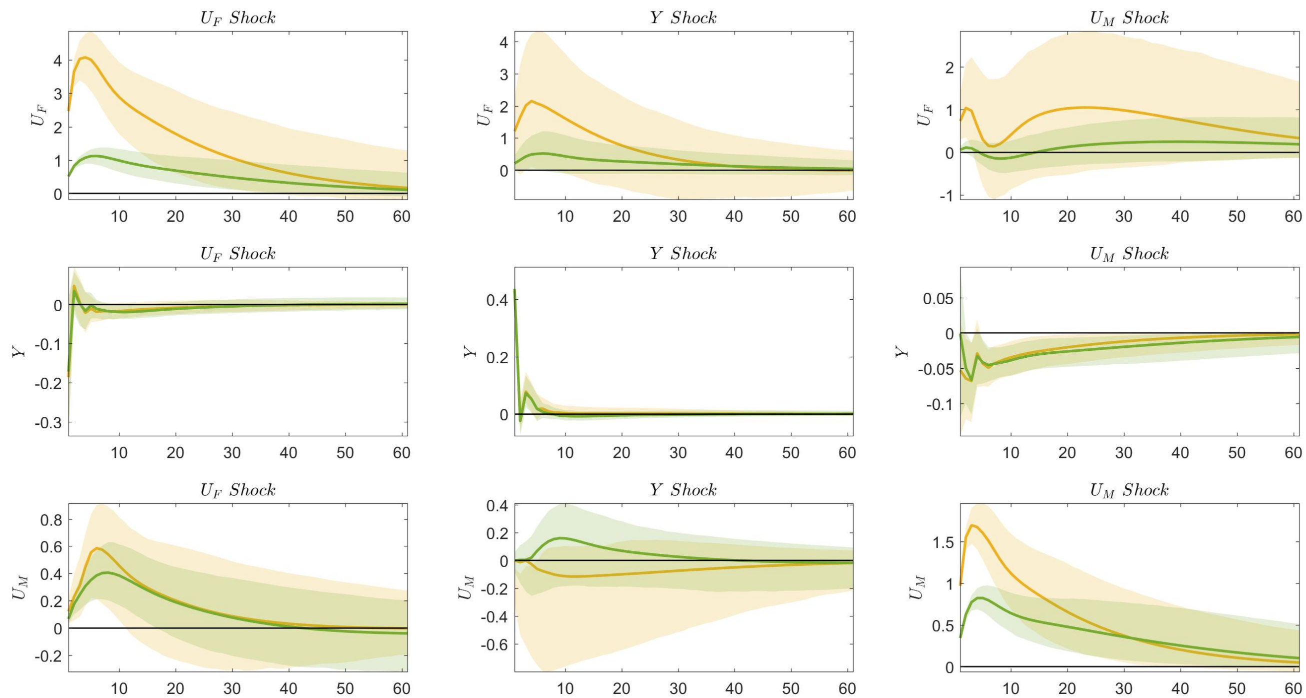

FIGURE TS.5: **Robustness check:** IRFs obtained in the second volatility regime (Great Moderation, 1984M4-2007M12) from the non-recursive SVAR for $X_t := (U_{Ft}, Y_t, U_{Mt})'$, $Y_t = \Delta ip_t$ (industrial production growth) specified in eq. (17) of the paper. The yellow lines refer to the one-month ($f = 1$) uncertainty horizon and yellow shaded areas denote the associated 90% bootstrap confidence bands; the green lines refer to the one-year ($f = 12$) uncertainty horizon and green shaded areas denote the associated 90% bootstrap confidence bands; bootstrap confidence bands are computed using Kilian's (1998) method. Responses are measured with respect to one standard deviation changes in structural shocks.

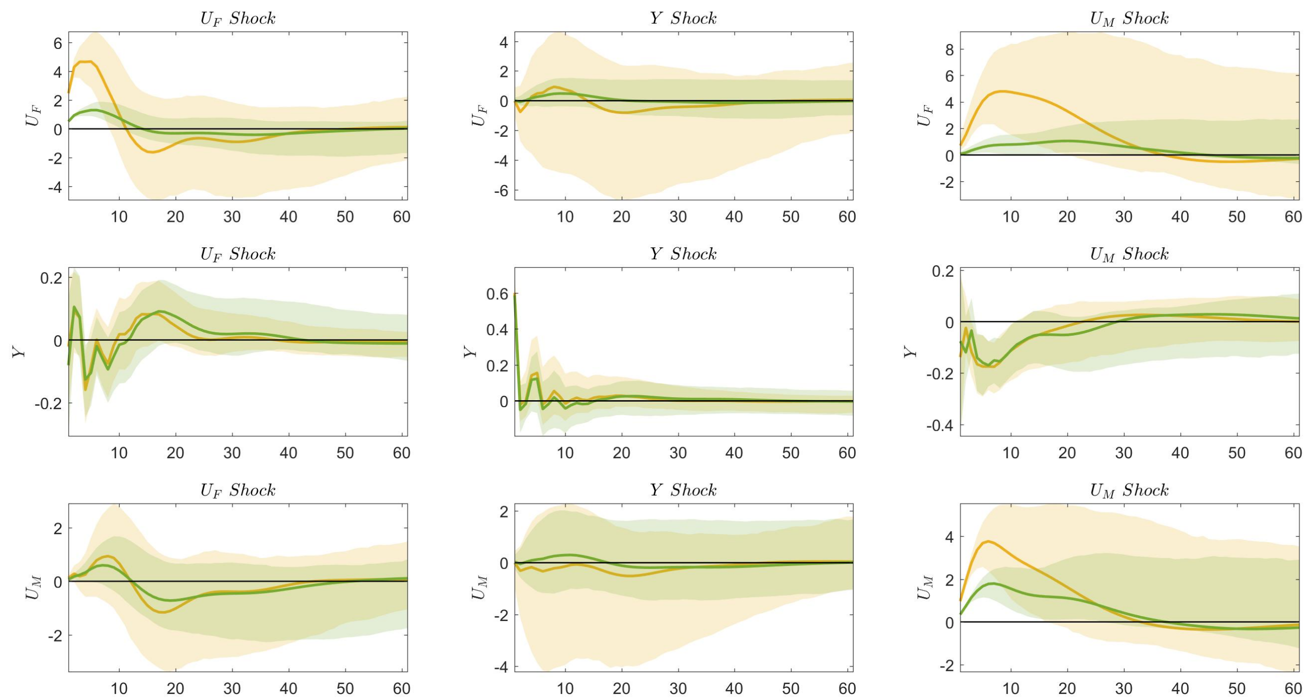

FIGURE TS.6: **Robustness check:** IRFs obtained in the third volatility regime (Great Recession + Slow Recovery, 2008M1-2015M4) from the non-recursive SVAR for $X_t := (U_{Ft}, Y_t, U_{Mt})'$, $Y_t = \Delta ip_t$ (industrial production growth) specified in eq. (17) of the paper. The yellow lines refer to the one-month ($f = 1$) uncertainty horizon and yellow shaded areas denote the associated 90% bootstrap confidence bands; the green lines refer to the one-year ($f = 12$) uncertainty horizon and green shaded areas denote the associated 90% bootstrap confidence bands; bootstrap confidence bands are computed using Kilian's (1998) method. Responses are measured with respect to one standard deviation changes in structural shocks.

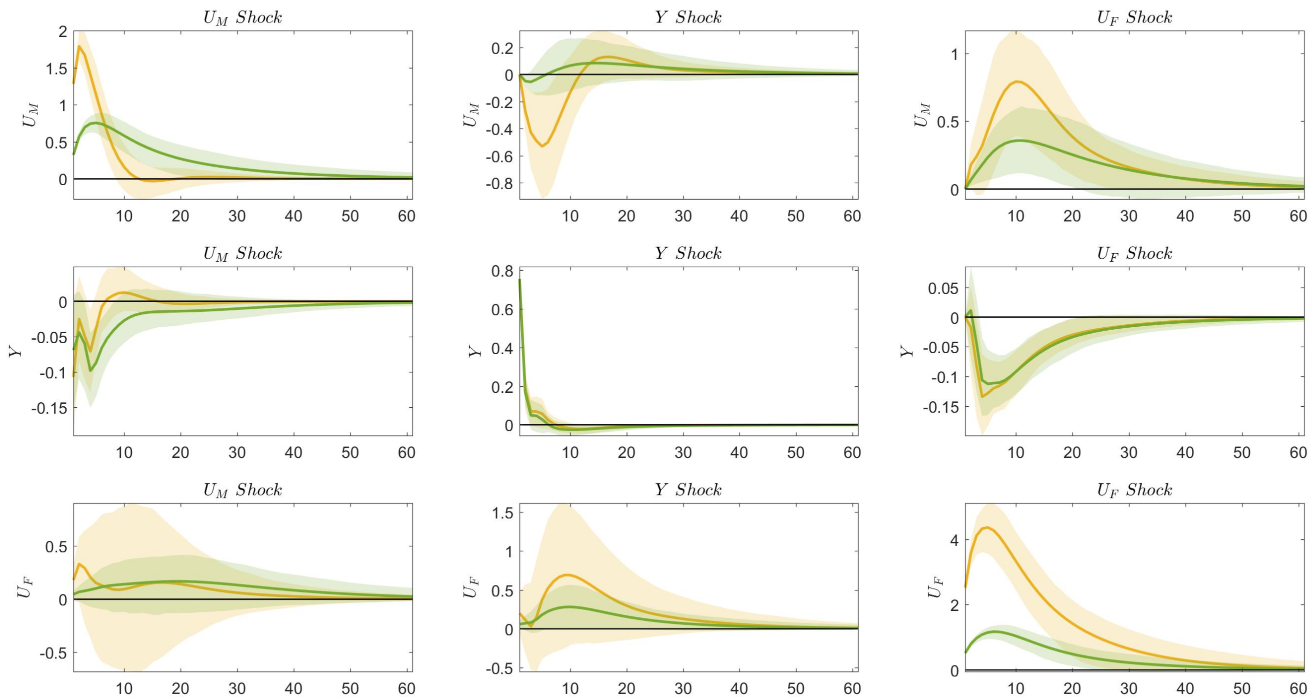

FIGURE TS.7: **Robustness check:** IRFs obtained in the first volatility regime (Great Inflation, 1960M8-1984M3) from the non-recursive SVAR for $X_t^p := \left(U_{Mt}^p, Y_t, U_{Ft}\right)'$, $Y_t = \Delta ip_t$ (industrial production growth), specified in eq. (17) of the paper. U_{Mt}^p is the measure of real uncertainty of Ludvigson *et al.* (2017). The yellow lines refer to the one-month ($f = 1$) uncertainty horizon and yellow shaded areas denote the associated 90% bootstrap confidence bands; the green lines refer to the one-year ($f = 12$) uncertainty horizon and green shaded areas denote the associated 90% bootstrap confidence bands; bootstrap confidence bands are computed using Kilian's (1998) method. Responses are measured with respect to one standard deviation changes in structural shocks.

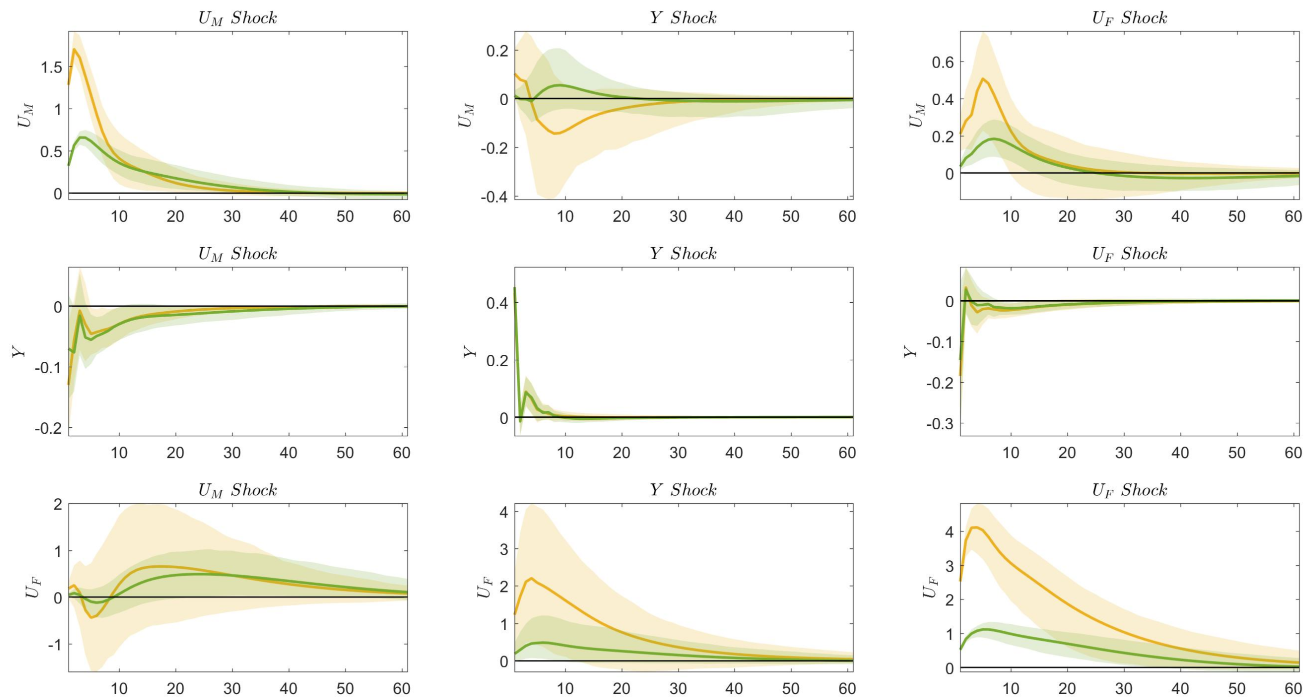

FIGURE TS.8: **Robustness check:** IRFs obtained in the second volatility regime (Great Moderation, 1984M4-2007M12) from the non-recursive SVAR for $X_t^p := \left(U_{Mt}^p, Y_t, U_{Ft}\right)'$, $Y_t = \Delta ip_t$ (industrial production growth), specified in eq. (17) of the paper. U_{Mt}^p is the measure of real uncertainty of Ludvigson *et al.* (2017). The yellow lines refer to the one-month ($f = 1$) uncertainty horizon and yellow shaded areas denote the associated 90% bootstrap confidence bands; the green lines refer to the one-year ($f = 12$) uncertainty horizon and green shaded areas denote the associated 90% bootstrap confidence bands; bootstrap confidence bands are computed using Kilian's (1998) method. Responses are measured with respect to one standard deviation changes in structural shocks.

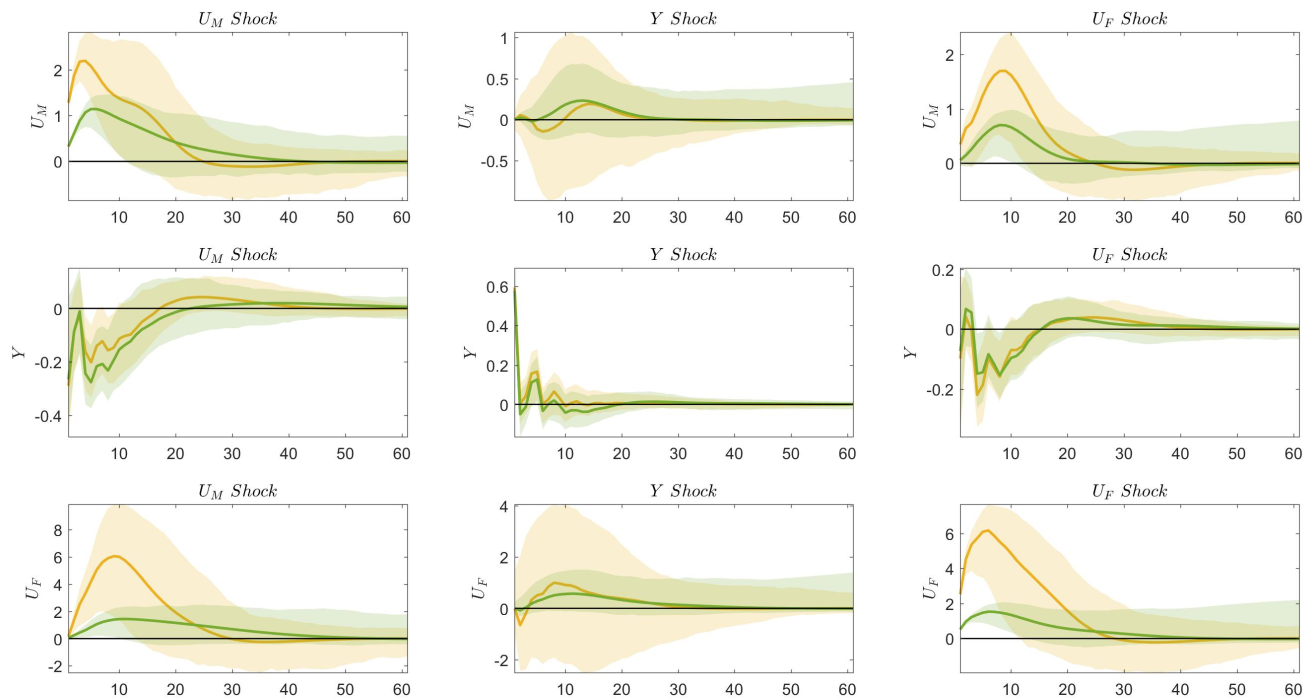

FIGURE TS.9: **Robustness check:** IRFs obtained in the third volatility regime (Great Recession + Slow Recovery, 2008M1-2015M4) from the non-recursive SVAR for $X_t^p := \left(U_{Mt}^p, Y_t, U_{Ft}\right)'$, $Y_t = \Delta ip_t$ (industrial production growth), specified in eq. (17) of the paper. U_{Mt}^p is the measure of real uncertainty of Ludvigson *et al.* (2017). The yellow lines refer to the one-month ($f = 1$) uncertainty horizon and yellow shaded areas denote the associated 90% bootstrap confidence bands; the green lines refer to the one-year ($f = 12$) uncertainty horizon and green shaded areas denote the associated 90% bootstrap confidence bands; bootstrap confidence bands are computed using Kilian's (1998) method. Responses are measured with respect to one standard deviation changes in structural shocks.

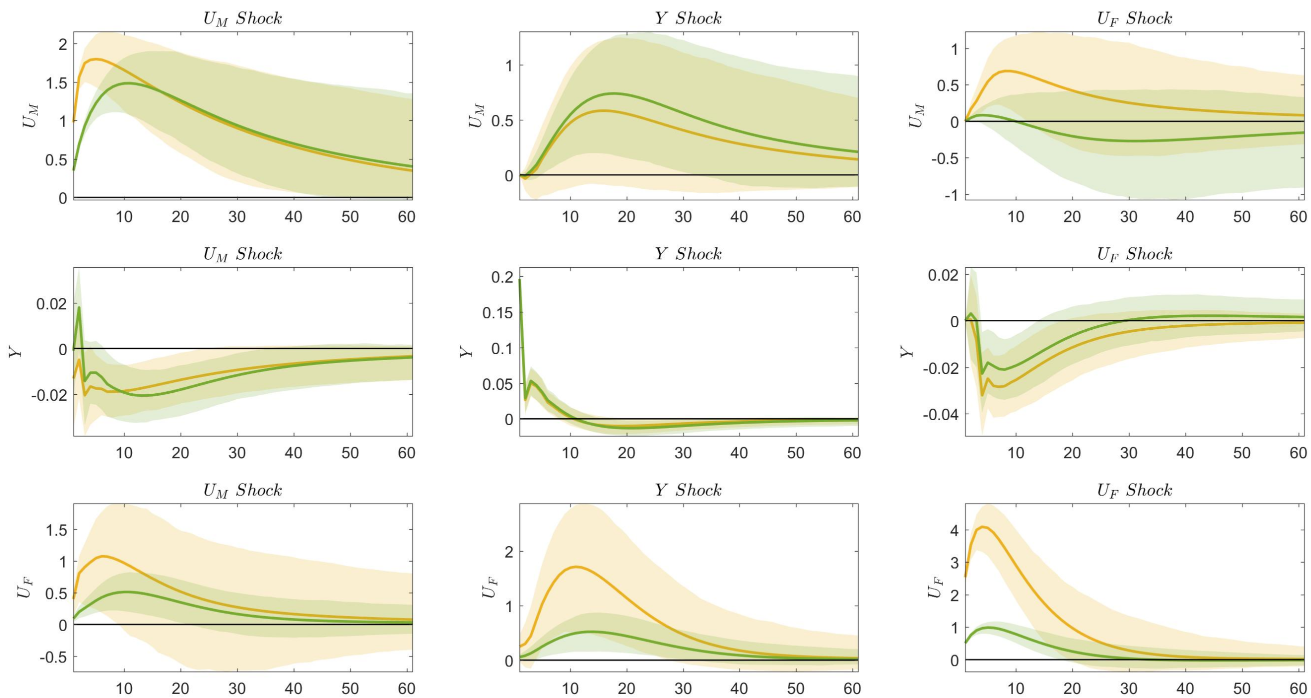

FIGURE TS.10: **Robustness check:** IRFs obtained in the first volatility regime (Great Inflation, 1960M8-1984M3) from the non-recursive SVAR for $X_t := (U_{Mt}, Y_t, U_{Ft})'$, $Y_t = \Delta emp_t$ (employment growth) specified in eq. (17) of the paper. The yellow lines refer to the one-month ($f = 1$) uncertainty horizon and yellow shaded areas denote the associated 90% bootstrap confidence bands; the green lines refer to the one-year ($f = 12$) uncertainty horizon and green shaded areas denote the associated 90% bootstrap confidence bands; bootstrap confidence bands are computed using Kilian's (1998) method. Responses are measured with respect to one standard deviation changes in structural shocks.

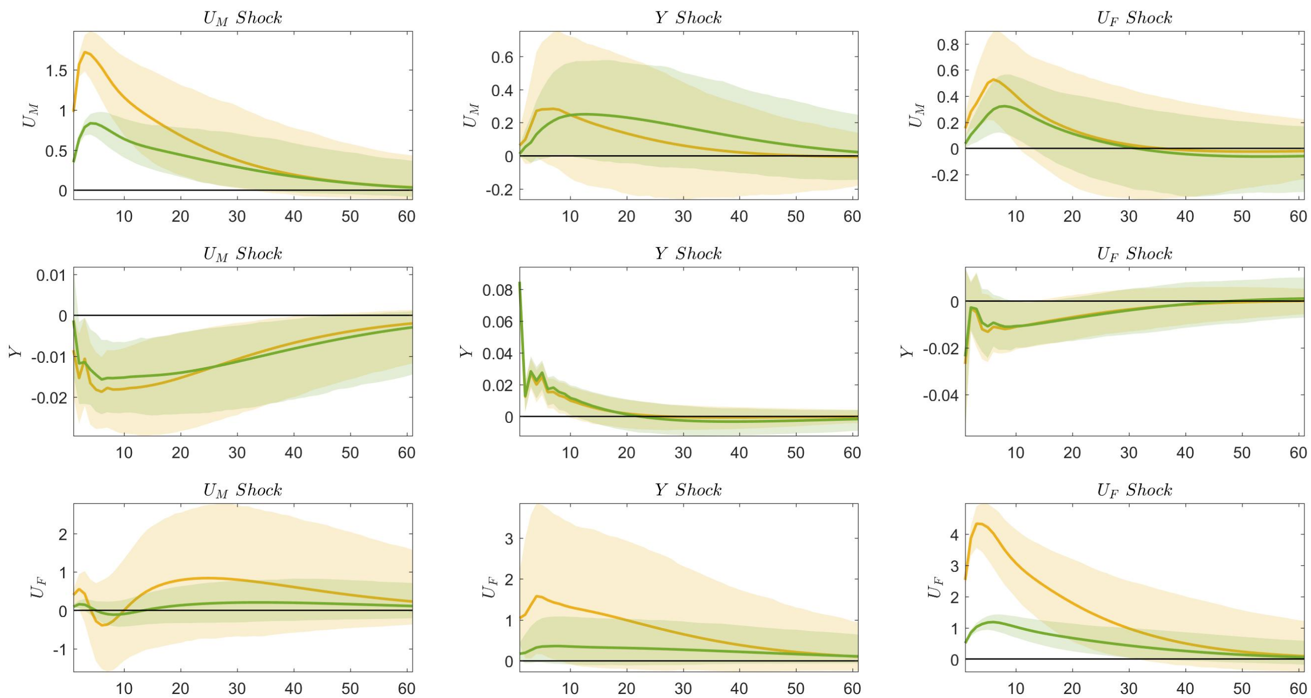

FIGURE TS.11: **Robustness check:** IRFs obtained in the second volatility regime (Great Moderation, 1984M4-2007M12) from the non-recursive SVAR for $X_t := (U_{Mt}, Y_t, U_{Ft})'$, $Y_t = \Delta emp_t$ (employment growth) specified in eq. (17) of the paper. The yellow lines refer to the one-month ($f = 1$) uncertainty horizon and yellow shaded areas denote the associated 90% bootstrap confidence bands; the green lines refer to the one-year ($f = 12$) uncertainty horizon and green shaded areas denote the associated 90% bootstrap confidence bands; bootstrap confidence bands are computed using Kilian's (1998) method. Responses are measured with respect to one standard deviation changes in structural shocks.

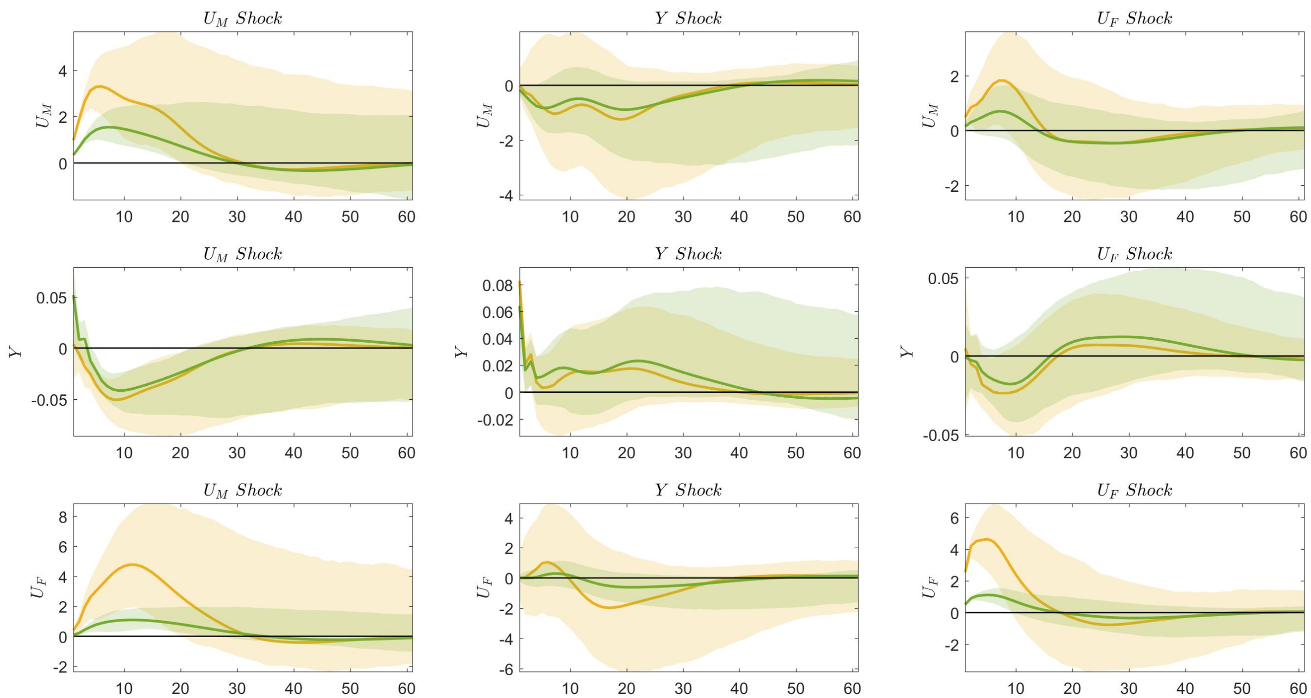

FIGURE TS.12: **Robustness check:** IRFs obtained in the third volatility regime (Great Recession + Slow Recovery, 2008M1-2015M4) from the non-recursive SVAR for $X_t := (U_{Mt}, Y_t, U_{Ft})'$, $Y_t = \Delta emp_t$ (employment growth) specified in eq. (17) of the paper. The yellow lines refer to the one-month ($f = 1$) uncertainty horizon and yellow shaded areas denote the associated 90% bootstrap confidence bands; the green lines refer to the one-year ($f = 12$) uncertainty horizon and green shaded areas denote the associated 90% bootstrap confidence bands; bootstrap confidence bands are computed using Kilian's (1998) method. Responses are measured with respect to one standard deviation changes in structural shocks.