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Financial regimes and uncertainty shocks

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ABSTRACT

Credit markets are an important link in the propagation of economic uncertainty. We study the nexus between the two using a nonlinear VAR where uncertainty is captured by the volatility of the economy's structural shocks and its transmission mechanism is allowed to change in periods of financial distress. We find that, in the USA, uncertainty shocks have recessionary effects at all times, but their impact on output is six times larger when the economy is going through a financial crisis. Uncertainty accounts for one percentage point of the contraction in industrial production observed in the Great Recession.

1. Introduction

Credit market disruptions and economic uncertainty are commonly listed among the main causes of the prolonged recession experienced by the US and other western economies after the outbreak of the financial crisis in 2007 (Stock and Watson, 2012). Financial markets are known to be capable of generating shocks that are as powerful as those analyzed by the traditional real business cycle literature.[1] Uncertainty or 'risk' shocks have also recently come to the fore in policy and research debates as an important source of economic cycles.[2] There is a clear link between the two: since investors price risk, financial markets seize up when economic uncertainty is high. Indeed, while the role of uncertainty has been traditionally linked to real frictions (Bernanke, 1983; Bloom, 2009; 2014), recent research has placed financial frictions at the centre of the transmission mechanism arguing that credit markets are the crucial link in the propagation of uncertainty shocks (Arellano et al., 2012; Caldara et al., 2016; Christiano et al., 2014; Gilchrist et al., 2014). This paper examines a conjecture that follows naturally from the 'financial view' of the transmission mechanism. If uncertainty affects the real economy mainly through financial markets, its impact might vary significantly over the cycle under the influence of fluctuations in asset prices and balance sheet conditions. In particular, weak balance sheets and 'thin' financial markets could boost the transmission mechanism and leave the economy particularly vulnerable to an increase in uncertainty. To

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[1] See e.g. Nolan and Thoenissen (2009), Jermann and Quadrini (2012), Gilchrist and Zakrajsek (2012) among others.

[2] The research on uncertainty is reviewed below and in Section 2; for the policy side of the debate, see for instance (FOMC) and Blanchard (2009).

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investigate this possibility we estimate a nonlinear VAR using monthly data covering the period between January 1973 and May 2014, and study how the response of the US economy to uncertainty shocks depends on aggregate financial conditions. The model has two distinguishing features. First, aggregate uncertainty is captured directly by the average volatility of the structural shocks, and it affects the dynamics of the economy through a volatility-in-mean type of mechanism (Mumtaz and Surico, 2018; Mumtaz and Theodoridis, 2015; 2017; Mumtaz and Zanetti, 2013) . Second, the dynamics can change when financial markets are dysfunctional: the model includes a financial distress indicator and it allows the parameters to shift when this crosses an endogenously-determined critical threshold. This combination of stochastic volatility and multiple regimes, which finds a natural justification in this context, represents a methodological novelty that could be of wider interest to empirical macroeconomists.

Our estimates show that the implications of an uncertainty shock differ significantly across financial regimes. In normal times uncertainty shocks are inflationary and have relatively little impact on output. When financial markets are in distress, on the contrary, they are deflationary, and their impact on output is roughly six times larger. The share of output variance explained by the shocks is modest in absolute terms, but twice as big in times of financial turmoil compared to calm periods (8% versus 4%). Once the nonlinearity is taken into account, the shocks appear to be responsible for about one percentage point of the peak fall in output observed in the Great Recession. These results provide new evidence on the pivotal role played by financial markets in propagating uncertainty shocks. They also point to an important complication to be taken into account when studying the role of uncertainty and financial conditions in driving macroeconomic fluctuations: the two are not easily separable, because uncertainty becomes more relevant if and when the economy has previously been hit by a sequence of adverse financial shocks. The Great Recession provides a powerful illustration of this issue.

The remainder of the paper is organized as follows. After reviewing the literature in Section 2, in Section 3 we introduce the nonlinear VAR framework and discuss its relation with DSGE models featuring uncertainty shocks. Our main results are illustrated in Section 5. Section 6 examines the robustness of our conclusions to various data choices and modelling assumptions. Section 7 concludes.

2. Literature

Uncertainty shocks are known to have powerful recessionary effects (see Bloom, 2014, for a survey of the evidence). While the traditional view of the transmission mechanism relies on some form of irreversibility in the firms' investment and hiring decisions (Bernanke, 1983; Bloom, 2009) Bloom et al., 2012, more recent studies place financial frictions at the centre of the transmission mechanism (Arellano et al., 2012; Christiano et al., 2014; Gilchrist et al., 2014) .[3] When financial contracts are subject to agency or moral hazard problems, a rise in uncertainty increases the premium on external finance, leading to an increase in the cost of capital and a fall in firms' investment. This 'financial view' of the transmission mechanism implies that asset prices and credit aggregates are crucial in propagating uncertainty shocks to the real economy. Consistent with this prediction, Gilchrist et al. (2014) find that uncertainty has a modest impact on output in a financially frictionless economy, while Carrière-Swallow and Céspedes (2013) show that uncertainty shocks are more powerful in countries with underdeveloped financial markets. This paper examines the 'financial view' along a different dimension, testing whether the impact of uncertainty shocks in the US has changed over time in connection with the state of the financial cycle. Our work is motivated by the consideration that, although the underlying frictions are structural in nature, the liquidity of financial markets and the availability of external finance obviously depend on the state of both borrowers' and lenders' balance sheets, and this changes significantly over time under the influence of fluctuations in real and financial asset prices.[4]

The connection between uncertainty and financial conditions has been typically neglected in the VAR literature (Bachmann et al., 2013; Bloom, 2009; Carriero et al., 2015; Leduc and Liu, 2016; Mumtaz and Surico, 2018) . We are aware of three exceptions to this rule. Popescu and Smets (2010) and Luca (2013) note that the coexistence of credit spreads and uncertainty proxies in a VAR raises significant identification issues and suggest that uncertainty shocks play a minor role once financial shocks are taken into account. Caldara et al. (2016) document that allowing credit conditions to respond to changes in uncertainty is critical in order for these shocks to affect economic activity. We examine the same issues but resort to a nonlinear model to study the state-dependent link between financial conditions and uncertainty.

The evidence regarding variation in the transmission of uncertainty shocks over time is relatively scant. Beetsma and Giuliodori (2012) and Mumtaz and Theodoridis (2017) find that the impact of uncertainty on output in the US has decreased over the last five decades. Caggiano et al. (2014) estimate a Smooth-Transition VAR on post-war US data, finding that uncertainty had a stronger impact on unemployment during recessions. None of these papers models the interdependence between uncertainty and financial conditions highlighted by the 'financial view' of the transmission mechanism. A step in this direction is attempted by Lhuissier and Tripier (2016), who use a Markov-switching VAR and find that shocks to the VIX index are more powerful during periods that ex post appear to be associated to financial tensions. Two methodological choices set our work apart from theirs': the measurement of uncertainty, which is more grounded in theory, and the nature of the regime-switching mechanism, which explicitly links the regimes to credit conditions. Both are discussed

[3] The real/financial divide sketched here is of course a stark simplification of the views that have been put forward on the topic: in Fernandez-Villaverde et al. (2011) uncertainty affects real aggregates because of a hedging motive, while Basu and Bundick (2017) study the role of nominal frictions.

[4] The general role of financial markets as shock amplifiers is examined *inter alia* in Brunnermeier and Sannikov (2014); Hubrich and Tetlow (2015); Mendoza (2010).

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extensively in Section 3.2. Although establishing why and how the impact of uncertainty shocks has changed over time is not trivial, our estimates indicate clearly that financial markets 'matter' and that credit constraints are a credible alternative to the explanations examined by Caggiano et al. (2014) and Mumtaz and Theodoridis (2017) (see Section 5.3).

Our econometric approach and our measure of uncertainty mark an important departure from the literature. Instead of relying on observable proxies such as realized equity price volatility or the VIX index we measure uncertainty as the average volatility of the economy's structural shocks, which in our framework can be estimated directly from the data. Time-varying volatilities are a pervasive feature of macroeconomic data (see e.g. (Justiniano and Primiceri, 2008)). More importantly, conditional volatilities are directly related to the overall predictability of the economic environment, which is ultimately the key uncertainty factor in households' and firms' decisions.[5] The idea of using a scalar volatility process in a multivariate model has been introduced by Carriero et al. (2016), while volatility-in-mean effects are studied in the context of otherwise linear VAR models by Mumtaz and Surico (2018); Mumtaz and Theodoridis (2015, 2017); Mumtaz and Zanetti (2013). The combination of stochastic volatility and regime switches is a novelty of this paper.

3. A VAR with financial regimes and volatility effects

The next subsection introduces our nonlinear VAR model and describes estimation and calculation of the impulse-response functions. The following one relates the model to the theoretical literature on uncertainty, providing a more detailed discussion of our identification assumptions.

3.1. Structure of the model

Our starting point is a VAR model where the structural shocks have time-varying, stochastic volatilities which influence the first-moment dynamics of the system (Mumtaz and Surico, 2018; Mumtaz and Theodoridis, 2015; 2017; Mumtaz and Zanetti, 2013). The framework is extended here in order to allow for these dynamics to be characterized by two distinct regimes, corresponding to periods of calm and tense financial markets. The model is defined as follows:

$$\begin{aligned} Z_t = & \left(c_1 + \sum_{j=1}^{P} \beta_{1j} Z_{t-j} + \sum_{j=0}^{J} \gamma_{1j} \ln \lambda_{t-j} + \Omega_{1t}^{1/2} e_t \right) \tilde{S}_t \\ & + \left(c_2 + \sum_{j=1}^{P} \beta_{2j} Z_{t-j} + \sum_{j=0}^{J} \gamma_{2j} \ln \lambda_{t-j} + \Omega_{2t}^{1/2} e_t \right) (1 - \tilde{S}_t) \end{aligned} \tag{1}$$

where $Z_t = \{Y_t, P_t, R_t, F_t\}$ is a set of (at least) four endogenous variables: industrial production growth, consumer price inflation, the three-month Treasury Bill rate and an indicator of financial conditions, such as a corporate bond spread (the data is described in Section 4). Uncertainty is represented by λ_t : as we clarify below, this is treated as an unobservable state variable and estimated exploiting the volatility of the shocks that occurred over the sample period. By introducing $\tilde{S}_t$ we allow for the existence of two economic "regimes" characterized by potentially different dynamics. In particular, the regime is determined in this application by the level of the financial distress indicator relative to some unobserved threshold Z^*:

$$\tilde{S}_t = 1 \Longleftrightarrow F_{t-d} \leq Z^*, \tag{2}$$

where both the delay d and the threshold Z^* are unknown parameters. Eq. (1) shows that, as in standard threshold models, all parameters are allowed to change across regimes. The covariance matrix of the residuals plays a central role in our analysis. It is defined as follows:

$$\begin{aligned} \Omega_{1t} &= A_1^{-1} H_t A_1^{-1'} \\ \Omega_{2t} &= A_2^{-1} H_t A_2^{-1'}, \end{aligned} \tag{3}$$

where A_1 and A_2 are lower triangular matrices. Finally, the volatility process is defined as:

$$\begin{aligned} H_t &= \lambda_t S \\ S &= diag(s_1, s_2, s_3, s_4) \\ \ln \lambda_t &= \alpha + F \ln \lambda_{t-1} + \eta_t, \end{aligned} \tag{4}$$

where η_t is an *i.i.d.* innovation with variance Q. Following Carriero et al. (2016), we thus assume that a single, scalar volatility process λ_t drives time variation of the entire variance-covariance matrix of the structural shocks. We take this process to represent economic uncertainty.[6] Intuitively, a volatility or uncertainty shock $\eta_t > 0$ raises λ_t, causing an upward shift in the

[5] See also Jurado et al. (2015). We discuss these points further in Section 3, and provide a comparison between our estimate of uncertainty and that by Jurado et al. (2015) in Section 5.

[6] In our benchmark model we set $P = 13$ (a standard choice with monthly data) and $J = 3$ (meaning that the state of the economy can be affected by the levels of uncertainty that prevailed over the past quarter). Allowing for $P = 18$ does not change the results. The definition and timing of the volatility process λ_t is discussed further in Section 6.

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covariance matrix of the innovations e_t, and hence a sudden deterioration of the accuracy with which agents can forecast Z_{t+k}. By letting λ_t enter Eq. (1), our framework allows output, asset prices and monetary policy to adjust endogenously to the new, riskier (and less predictable) state of the economy. The occurrence of regime shifts associated to periods of financial distress captures the time-varying nature of the underlying transmission mechanisms: the two sets of parameters $\{c_i, \beta_{ij}, \gamma_{ij}, \Omega_i\}_{i=1,2}$ can be thought of as capturing the behavior of the economy in periods of "tense" and "calm" financial markets, or binding and non-binding borrowing constraints. No restrictions are placed on how the primitive shocks e_t and η_t play out in different regimes.[7]

The Gibbs sampling algorithm for the estimation of the model in described in detail in the Appendix to the paper. The main intuition behind it is straightforward. Given a draw for λ_t, the model collapses to a threshold VAR, albeit with a known form of heteroscedasticity. After a GLS transformation of the model, the conditional posterior distributions of the regime dependent VAR parameters, the threshold and delay are identical to those of a standard threshold VAR (see Alessandri and Mumtaz, 2017). In particular, as described in Chen and Lee (1995), the conditional posterior of the delay parameter is a Multinomial distribution, while the threshold value can be drawn from its non-standard posterior via a Metropolis step. Then the data can be split into regime-specific observations, and the VAR autoregressive coefficients sampled from the normal distribution. Given the residuals of the VAR and λ_t, the conditional posterior for A is standard and described in several recent papers (e.g. Cogley and Sargent, 2005). The variances S can be drawn from the inverse Gamma distribution. Given these parameters, the model admits a non-linear state-space representation. The state-variable λ_t is drawn using the independence Metropolis algorithm introduced in Jacquier et al. (1994) for stochastic volatility models.

Once the posterior distribution of all parameters is available, "generalized" impulse-responses are obtained using Montecarlo integration as described in Koop et al. (1996). In practice the responses are calculated as differences between conditional expectations obtained by simulating the model under a shock scenario and under a baseline, no-shocks scenario. For a given regime $(S = 0, 1)$ and regime-specific history (Y^S_{t-1}), the responses are defined as $IRF^S_t = E\left(Y_{t+k} \backslash \Psi_t, Y^S_{t-1}, \mu\right) - E\left(Y_{t+k} \backslash \Psi_t, Y^S_{t-1}\right)$, where Ψ_t represents all the parameters and hyperparameters of the model, k is the horizon under consideration and μ denotes the shock of interest (in our case, an increase in uncertainty). Two points are worth emphasizing. First, the switch among regimes is treated as endogenous in this calculation: the economy can freely transition from calm to crisis dynamics or *viceversa* over the simulation horizon, depending on the sign and size of the shock. In other words, the simulation takes into account the dynamics of both the endogenous variables Y_t and the parameters Ψ_t. Second, even within a given initial regime S, the responses depend on the specific history of the system prior to the shock (Y^S_{t-1}). Intuitively, the economy may respond differently when the financial distress indicator is at its historical minimum and when it is just below its critical threshold, even though both constitute instances of "normal times". We focus throughout on the average responses in each regime. The normal-time response (respectively, crisis response) is thus calculated as the average response to the shock of interest across all histories that belong into regime $S = 1$ (respectively, $S = 0$). By averaging over histories we aim to obtain the most representative picture of the dynamics associated to each regime. The online annex to the paper provides results obtained conditioning separately on all histories in our sample (see section F). We find that regime-specific averages deliver an accurate description of the overall behavior of the economy. For industrial production, for instance, the cumulative 12-month response to a one standard deviation uncertainty shock varies between −0.2% and -0.4% in normal times and exceeds −1.2% in all distress episodes but two (the exceptions are the short-lived financial tensions of 1984 and 1987). Furthermore, the Great Recession responses are of the same order of magnitude as those observed in the early 1980s crisis (−1.9% versus −1.7%). In short, the variation within regimes is negligible compared to the variation across regimes.

3.2. Theoretical background

Like Jurado et al. (2015), we use a model-based measure of uncertainty that is directly linked to the agents' (in)ability to form predictions on the fundamentals of the economy. This allows us to avoid using proxies that are at best weakly related to macroeconomic predictability, such as the VIX index. Relative to the factor model by Jurado et al. (2015), the volatility-in-mean specification employed in this paper has the advantage of modeling the economy's first and second moments in a unified, internally-consistent framework. In our model agents form expectations $E_t Z_{t+h}$ treating uncertainty as an ordinary state variable: they estimate λ_t, project it forward considering its persistence (F), and take into account its influence on the economy ($\gamma_{ij} \neq 0$). These expectations are then integrated out in the impulse-response analysis. Clearly this would not possible in a two-step procedure where uncertainty is first estimated using a forecasting model and then linked to macroeconomic fundamentals through a separate set of regressions. This improvement comes at the cost of a dimensionality problem, as our set up forces us to model a far smaller number of variables than Jurado et al. (2015). However, we find this cost to be quantitatively small (see Sections 5.1 and 6).

The volatility-in-mean feature also takes our set up closer to the theoretical literature on uncertainty. In the model uncertainty (i) stems directly from the volatility of the structural shocks in the economy, (ii) follows an AR(1) process, and (iii) is exogenous to the first-moment dynamics of the economy. The model thus closely resembles the reduced-form of a

[7] The model nests a linear VAR with volatility effects, a TAR without volatility effects and a fully linear VAR, all of which provide useful benchmarks for our analysis (see Section 5.3).

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DSGE model with stochastic volatility. There are two main differences between the two: first, the focus is on the average volatility of the shocks rather than the volatility of a specific structural shock; second, the threshold structure neglects some of the interactions that arise naturally in (high-order solutions to) a nonlinear DSGE model.[8] To check whether these modelling choices introduce a bias in the impulse-responses we run a Montecarlo experiment using as data-generating process the model of Carriero et al. (2015). The model represents a simple new-keynesian economy where uncertainty is introduced via heteroscedastic innovations in the Taylor rule followed by the central bank. Model and simulation are described in more detail in the online annex to the paper (see section C). We simulate artificial data from a third-order approximation to the model and then estimate the vol-in-mean VAR on the simulated data. Conditioning on a volatility shock, the VAR generates responses that closely match those of the theoretical model: the theoretical IRFs lie within a one standard deviation confidence band of the VAR responses for all variables throughout a 5 year simulation horizon. The responses are particularly accurate for aggregate output, which is our main variable of interest.

Identification is achieved in our model by assuming that λ_t is not affected by lags of Y_t and that first- and second-moment shocks are orthogonal, i.e. $E(e_t\eta_t) = 0$. This implies that uncertainty is exogenous to the level dynamics of the economy. This assumption is consistent with the dominant theoretical approach to modeling risk and uncertainty (see Section 2) and it is supported by the empirical evidence in Carriero et al. (2017), which suggests that macroeconomic uncertainty does not respond to changes in cyclical conditions in the US. Exogeneity greatly simplifies the estimation of the impulse-responses. However, our results do not hinge on it. The robustness analysis of Section 6 considers a more general model where $E(e_t\eta_t)$ is left unrestricted and identification is achieved through narrative sign restrictions à la Ludvigson et al. (2017). Although the estimates are overall less accurate, this model confirms the conclusion that uncertainty shocks have a stronger impact on FCI and output in periods of financial distress. Finally, notice that the framework does not require the identification of the structural shocks that drive the level dynamics of the system. Since (i) we are not interested in level shocks *per se*, and (ii) we study changes in the average volatility of the economy, rather than the volatility of distinct structural shocks, we do not need to impose specific theory-based restrictions on the residual covariance matrices of the observation equation of the VAR. The recursive factorization of the matrices in Eq. (3) can play a role in our analysis too, but only insofar as it affects the estimation of the average volatility process λ_t (Cogley and Sargent, 2005). This indirect influence turns out to be negligible. If we swap FCI and R, for instance, we obtain a $\hat{\lambda}$ that correlates at 92% with the baseline estimate and generates nearly identical IRFs. Under alternative orderings the correlation can drop to 50–60%, but the IRFs remain again qualitatively similar to the baseline, particularly in terms of asymmetries across financial regimes (the results are available upon request). This form of robustness is particularly valuable in this context because identifying uncertainty shocks from the first-moment dynamics of a VAR is notoriously problematic Caldara et al. (2016).

4. Data

The estimation employs monthly data covering the period from January 1973 to May 2014. Industrial production index, consumer price index and the nominal three-month Treasury bill rate are taken from the Federal Reserve Bank of St. Louis Database (FRED®). The choice of the financial indicator is clearly important given the objective of the exercise, and it is not straightforward. On the one hand, the indicator should capture the dynamics of a large set of financial variables: uncertainty can affect firms' funding through a number of markets at the same time; a broad indicator is likely to be more robust to structural instabilities affecting the link between financial and real economy Stock and Watson (2003); and controlling accurately for the state of financial markets is important to isolate uncertainty shocks in a credible way (Caldara et al., 2016). On the other hand, the indicator should not be too correlated with the business cycle. Since the analysis relies on our ability to isolate episodes of genuine financial distress in the data, a strong correlation between real and financial cycle would weaken our tests and make our null hypothesis indistinguishable from that examined by Caggiano et al. (2014). Insofar as broad indicators are more likely to be subject to endogeneity issues these two objectives are hard to reconcile. We circumvent the problem by using a range of alternative indicators. The first and broadest one is the Financial Condition Index (FCI), a real-time indicator of financial distress constructed and maintained by the Chicago Fed. The index is extracted using dynamic factor analysis from a set of 120 series that describe a broad range of money, debt and equity markets, as well as the leverage of the financial industry (Brave and Butters, 2012). To mitigate endogeneity, we also use a "purged FCI" obtained as the residual from a regression of FCI on the Chicago Fed National Activity Index. The third alternative is the Excess Bond Premium (EBP) constructed by Gilchrist and Zakrajsek (2012), which represents the excess return required by bond investors over and above their compensation for expected defaults. Finally, we also employ a simple, model-free measure of funding conditions, namely Moody's spread between BAA corporate bonds and 10-year Treasury bill rates. Section 6 also examines versions of the baseline model that include observable proxies of aggregate uncertainty, such as the VIX index (see e.g. Bloom, 2009) and the government debt-to-GDP ratio (Mumtaz and Surico, 2018).[9]

[8] The threshold structure captures the interaction between uncertainty λ_t and financial conditions F_t (and more generally all interactions of the form S_tF_{t-1}, where S_t is a shorthand for the shocks and predetermined state variables in the model), but ignores the interactions that are unrelated to financial markets.

[9] Mumtaz and Surico (2018) show that debt sustainability concerns represent a key component of policy uncertainty in the US. We interpolate the authors' quarterly debt-to-GDP series to a monthly frequency.

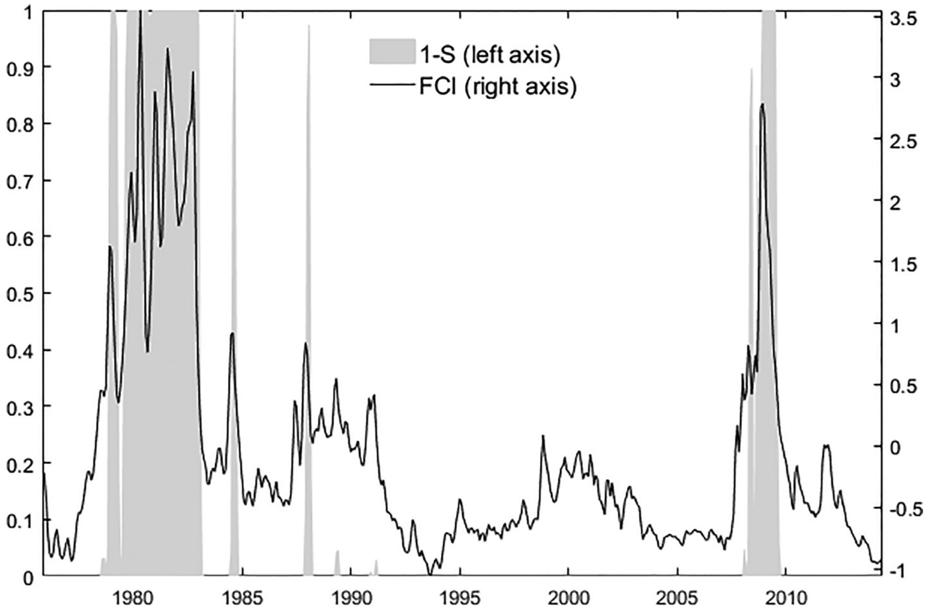

Fig. 1. Financial regimes. FCI is the Chicago Fed *Financial Condition Index*. Gray bands identify the subperiods when the US economy is estimated to be in a 'financial crisis', defined as a state where the index exceeds the critical threshold in the TAR model of Section 3.

5. Results

Our findings are organized in three subsections. The first one demonstrates that uncertainty shocks have a much larger impact on economic activity when credit conditions are tight. The second one shows that credit frictions also generate a sign asymmetry (uncertainty matters more on the way up than on the way down) and quantifies the contribution of uncertainty shocks to the US business cycle. The third and final one shows that financial regimes fit the data better than alternative views of the time-varying role of uncertainty that have been proposed in the literature.

5.1. A financial accelerator for uncertainty shocks

The periodization estimated by the Threshold VAR model is illustrated in Fig. 1, which shows the Financial Condition Index and the associated financial regimes. Gray bands identify periods when the FCI is above the estimated critical threshold Z^*, implying that the US economy is experiencing financial distress (see Eq. (2)). We refer to this as the 'crisis' regime. The delay parameter (d) has a median estimate of one month, with a 95% upper bound of two months only: this suggests that the economy tends to enter the crisis regime immediately once the threshold is breached. Fig. 2 reproduces the estimated average volatility $\hat{\lambda}_t$ together with the measure of economic uncertainty calculated by Jurado et al. (2015). Both indicators suggest that economic uncertainty was highest in the USA in the early 1980s and in 2007-2009. The correlation between the two series is generally very strong, confirming that the two approaches rely on similar assumptions for the measurement of uncertainty (see Section 3). This similarity also suggests that the volatilities of the (relatively small) set of variables included in the model provide a credible description of aggregate economic uncertainty, which Jurado et al. (2015) estimate using a much larger dataset (see also Section 6). Taken together, Figs. 1 and 2 clearly confirm the stylized fact that high volatility, financial tensions and low growth are often associated in the recent history of the USA. Fig. 3 plots the response of the US economy to an exogenous increase in uncertainty, defined as a positive one standard deviation shock to the λ_t process in Eq. (4). The responses associated to good and bad financial times, namely to periods of low and high FCI, are pictured respectively in black and in red. For each regime the figure reports the median generalized impulse-responses and the associated 68% confidence bands (see Section 3.1 and Koop et al., 1996 for details). Notice that the volatility dynamics, shown in the last panel on the right, are identical across regimes because the stochastic volatility process λ_t is not regime-dependent. In both regimes an increase in uncertainty leads to a financial tightening (panel 4) and a contraction in output (panel 1). The responses, however, are much more pronounced in the crisis regime: the contraction is more abrupt and the peak fall in output is roughly six times larger (–0.17% *versus* –0.02%). The key prediction of the 'financial view' of the transmission mechanism is thus supported by the data: uncertainty shocks are relatively inconsequential in normal times but their impact on credit markets and economic activity is greatly amplified during episodes of financial distress, when borrowing constraints

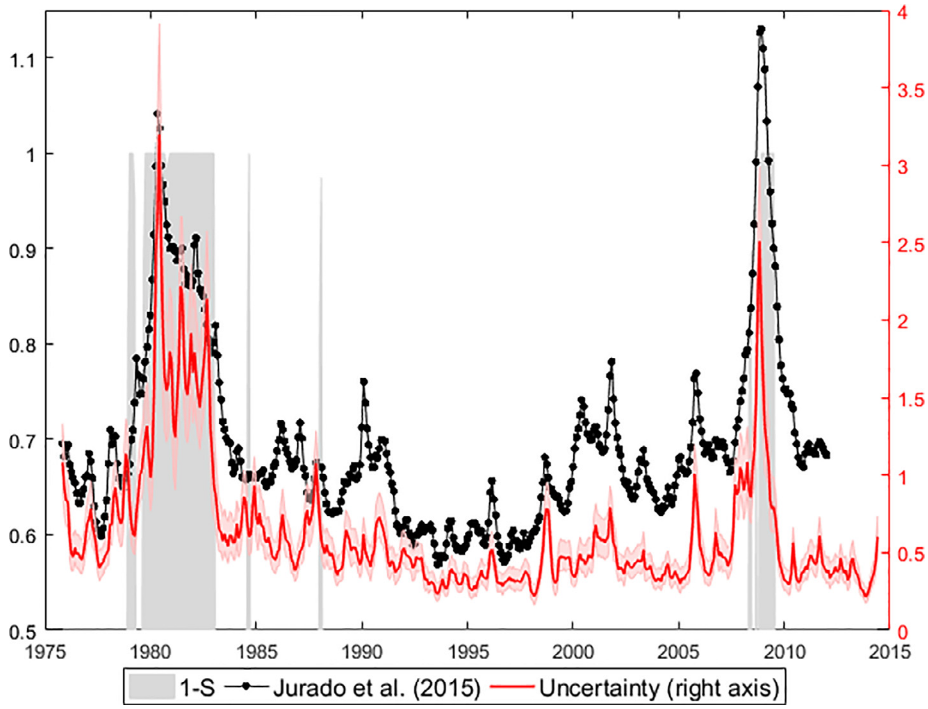

Fig. 2. Financial regimes and economic uncertainty. Gray bands denote the financial crises indentified by the TAR model discussed in Section 3. The black line is the uncertainty estimate of Jurado et al. (2015). The red line is uncertainty measured as the average volatility of the structural shocks in the US economy according to the TAR model (median estimate and 68% confidence band). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

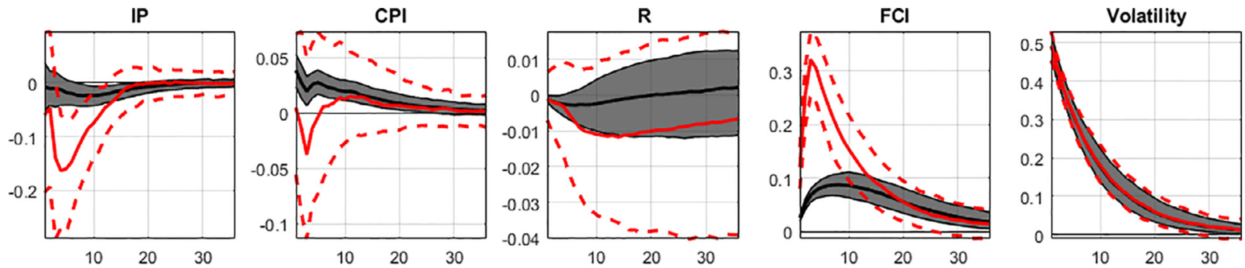

Fig. 3. Impact of volatility shocks in good and bad times. The black lines show the impact of a one standard deviation increase in the volatility of the US economy in normal times. The red line shows the impact of the same shock during episodes of financial distress, defined as periods when the Financial Condition Index (FCI) exceeds an endogenously-determined critical threshold (see Eq. (2) in Section 3). From left to right, the variables are industrial production (IP), consumer price inflation (CPI), the nominal 3-month Treasury Bill rate (R), FCI and the model-based volatility estimate. For each variable and regime the figure reports the median response and a 68% confidence band.The horizontal axis is time, measured in months. The estimation period is January 1973 – May 2014. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

bind more severely.[10] Panel 2 shows that the response of inflation also changes dramatically across regimes: prices increase in normal times and fall in a crisis.[11] The literature offers mixed evidence on the relation between uncertainty and inflation. Uncertainty shocks are deflationary for instance in Basu and Bundick (2017), Christiano et al. (2014), and Leduc and Liu (2016), where they act as aggregate demand shocks, but they are inflationary in Fernandez-Villaverde et al. (2015) and Mumtaz and Theodoridis (2015), where uncertainty on future demand and marginal costs introduces a precautionary upward bias in the firms' pricing decisions. Our result suggests that this precautionary mechanism prevails in good times but is dominated by the standard channel in bad times, when aggregate demand is more sensitive to uncertainty because of binding borrowing constraints. Finally, notice that, although the short-term interest rate does not respond significantly to the

[10] We find no evidence of the 'overshooting' in economic activity documented in Bloom (2009). Such overshooting can be an artifact of using filtered data (Jurado et al., 2015). Since it is a specific trademark of real as opposed to financial frictions, it may also vary across estimation samples owing to changes in the relative importance of these factors – see the discussion in Bloom (2009) and Gilchrist et al. (2014).

[11] Inflation responds contemporaneously to the shock. An alternative specification where this effect is excluded by assuming that only lags of λ_t enter Eq. (1) produces analogous results (see Section 6).

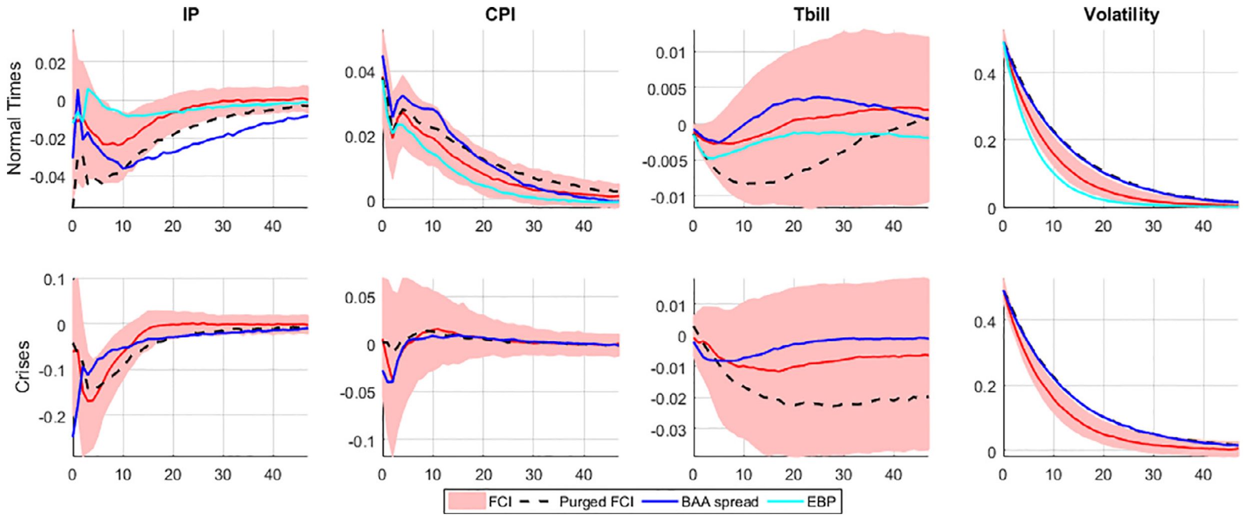

Fig. 4. Impact of volatility shocks under alternative financial conditions indicators. The figure shows the response of industrial production growth, consumer price inflation and 3-month T-Bill rate (columns 1 to 3) to a one standard deviation increase in the average volatility of the US economy (column 4). The estimates are based on a Threshold-VAR model that separates normal times (row 1) from financial crises (row 2). These are identified as periods when one of four alternative financial distress indicators exceeds an endogenously-determined critical threshold. FCI is the baseline Chicago Fed Financial Condition Index used in Fig. 3 (median responses and 68% confidence bands). Purged FCI is the residual from a regression of FCI on the Chicago Fed National Activity Index. BAA spread is the spread between BAA corporate bonds and the 10 year T-Bill rate. EBP is the Excess Bond Premium of Gilchrist and Zakrajsek (2012). All models are estimated over the period from January 1973 to May 2014.

shock (panel 3), its qualitative behavior can be easily rationalized in the light of this discussion. In a crisis both output and prices fall, so monetary policy can work countercyclically and interest rates tend to drop (the distribution of the responses lies mostly below the zero line). In normal times instead the shock generates stagflation and the responses are symmetrically distributed around zero. Truncating the sample to December 2008, so to exclude the ‘zero lower bound’ period, does not affect any of these results.

We next replicate the analysis using three alternative indicators to identify financial regimes in US history: a “purged” FCI obtained as the residual from a regression of FCI on economic activity, the Excess Bond Premium by Gilchrist and Zakrajsek (2012), and the spread between Moody’s BAA corporate bond yield and the 10-year T-Bill rate (see Section 4).[12] The results are summarized in Fig. 4. This is similar to Fig. 3, except that the regimes are displayed on two separate rows and financial variables are omitted to improve clarity. To further facilitate the comparison across models we simulate in all cases an increase in volatility of approximately 0.5 units, which corresponds to one standard deviation in the benchmark model. As column 4 shows, the dynamics of the volatility process λ_t are very similar across models. All specifications produce output and inflation responses that are in line with those of the benchmark model. The fall in industrial production (column 1) is larger in the crisis regime irrespective of which indicator is used to identify the regimes. In absolute terms, purged FCI and EBP generate smaller crisis-times responses than FCI, suggesting that some of the amplification effects in our baseline analysis might be associated to recessions rather than financial tensions. However, the asymmetry between good and bad times is clear and sizable for these indicators too. In the EBP-based model, for instance, the trough in output is approximately five times larger in the bad regime. The sign asymmetry in the inflation response (column 2) is equally robust: in all models consumer prices rise in good times (row 1) and fall marginally in bad times (row 2).[13] The TAR models assume that the transitions across financial regimes are abrupt, which is broadly consistent with the onset of the periods of financial distress in our sample. The results do not change if we use a ‘smooth’ transition mechanism, modeling the regimes through a logistic function that allows for gradual changes in credit conditions. The estimated regimes turn out to be very similar to those obtained from the benchmark TAR model and the responses of output and inflation are again strongly asymmetric (see section D of the online annex for details).

5.2. Large shocks and the great recession

Given the nonlinear nature of the model, the implications of a change in uncertainty might in principle also depend on sign and size of the shock. Fig. 5 compares the response of industrial production to (i) ‘small’ and ‘large’ perturbations,

[12] In each of these specifications (i) both FCI and the alternative indicator are included in the Y vector, and (ii) the alternative indicator is used to estimate the threshold Z^* in Eq. (2). Hence, the information sets are very similar across models. What changes is the mechanism that determines the endogenous switches across regimes.

[13] Part D of the online annex reports the regime estimates for the alternative TAR specifications. Relative to the FCI, both EBP and the BAA spread tend to downweigth the financial tightening of the early 1980s, emphasizing instead the 2001-2002 period.

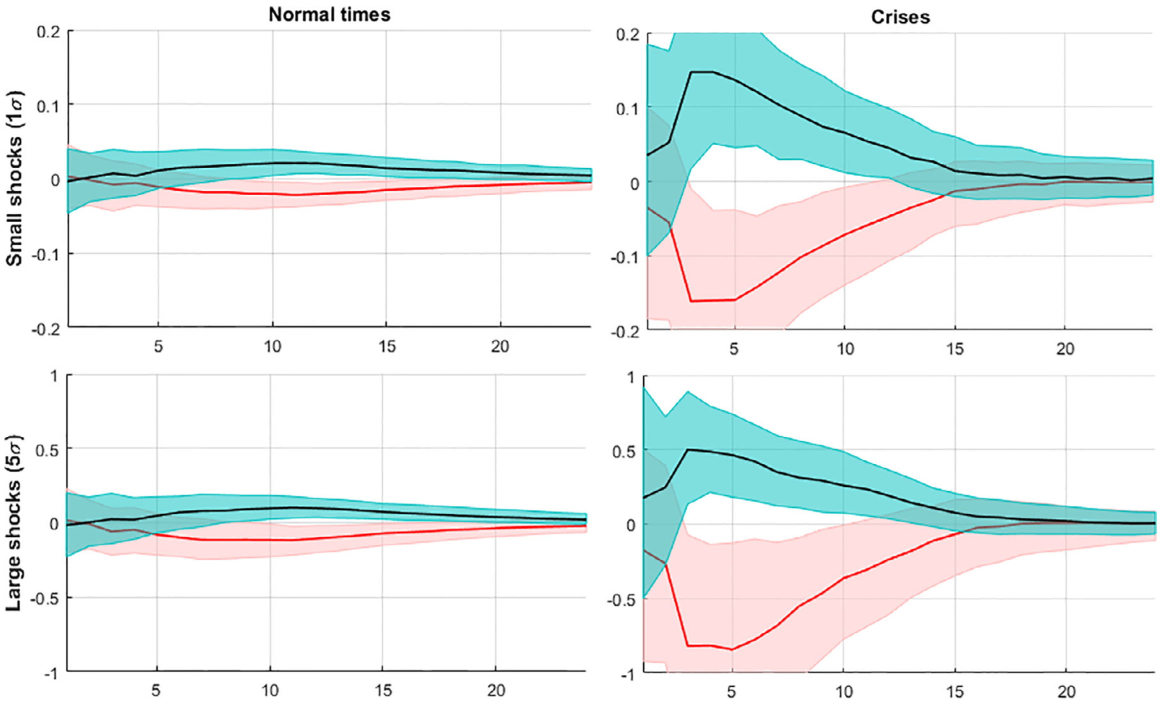

Fig. 5. Sign asymmetries. The first row shows the response of US industrial production to a one standard deviation volatility shock in normal times (left colum) and in financial crises (right column). Green and red shades represent the 68% confidence bands associated respectively to decreases and increases in volatility. The second row shows the response of industrial production to a five standard deviation volatility shock, distinguishing again between normal and crisis times and between positive and negative shocks. All estimates are obtained with the Threshold VAR of Section 3.1, estimated using data from January 1973 to May 2014. The horizontal axis is time, measured in months. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

defined respectively as one and five standard deviation shocks, and (ii) positive and negative perturbations, i.e. rises and falls in the volatility of the US economy.[14] All responses are obtained from the benchmark specification of the TAR model that includes the FCI. The left column shows that normal-time responses are essentially linear in the sign and size of the shock. Furthermore, the comparison between left and right column reveals that financial crises amplify the shock irrespective of its size and direction. In the crisis regime, however, large shocks give place to an interesting sign asymmetry: a drop in volatility causes a smaller change in output than a rise in volatility of equal size (see bottom right panel). A similar form of asymmetry between positive and negative uncertainty shocks is documented by Foerster (2014). According to the model this asymmetry is the product of two factors: the strong impact that volatility has on financial markets, and the state-contingent nature of the linkage between financial markets and the real economy. In bad times, an increase in volatility keeps the economy in a state where financial markets are tight and the 'volatility multiplier' is large. A fall in volatility, on the other hand, generates a relaxation in financial conditions that can push the economy back into the good regime, where borrowing constraints bind less and the 'volatility multiplier' is lower. The upshot is that volatility matters more on the way up than on the way down.

To quantify the overall role of uncertainty in the business cycle we resort to a forecast error variance (FEV) decomposition. Fig. 6 shows the contribution of volatility shocks to the FEVs of all endogenous variables in the benchmark specification. The shocks are a powerful driver of financial conditions in both regimes (column 4). For output and inflation, not surprisingly, they are more relevant in bad times (columns 2 and 3). The fraction of output variance accounted for by volatility shocks is twice as big in the crisis regime, approximately 8% versus 4%. These estimates are broadly consistent with those of Caldara et al. (2016), who find that uncertainty accounts for about 10% of the FEV for industrial production and employment. They are instead far smaller than those reported by Caggiano et al. (2014), according to whom uncertainty explains 23% of the FEV of US unemployment in a linear VAR and as much as 62% of it in a smooth-transition VAR conditioning on recessions. Although this discrepancy might partly depend on data and sampling issues, the nexus between uncertainty and financial markets is likely to be one of its causes. Since uncertainty and credit conditions co-move very strongly, the baseline

[14] A full set of responses to five standard deviation shocks is provided in the online annex to the paper.

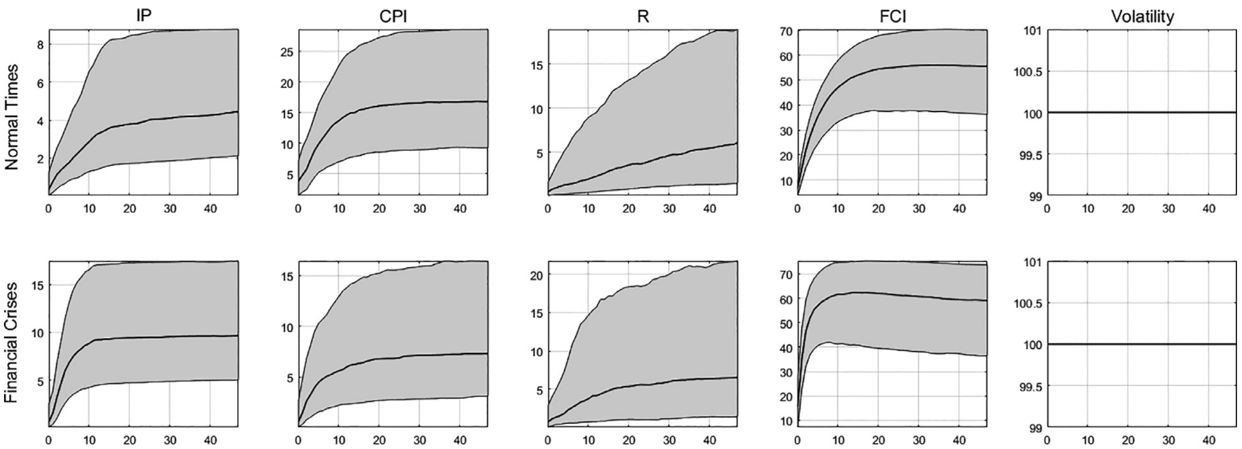

Fig. 6. Forecast error variance decomposition. Each panel shows the fraction of forecast error variance explained by volatility shocks for one of the variables included in the Threshold VAR of Section 3. The first row corresponds to calm periods and the second row corresponds to financial crises, defined as periods when the financial distress indicator FCI exceeds an endogenously-determined critical threshold (see Eq. (2)). The horizontal axis is the forecast horizon measured in months.

model of Caggiano et al. (2014), which does not include financial variables, might mix credit and uncertainty shocks and thus overestimate the economic relevance of the latter.[15]

We conclude this section with a counterfactual exercise that provides a model-based narrative on the historical role of uncertainty shocks in the US. The counterfactual world we consider is one where uncertainty shocks do not occur (i.e. $\eta_t = 0$ in Eq. (4)), so the volatilities of all level shocks in the economy are constant at their sample means. This "constant uncertainty" world is simulated using both the baseline Threshold VAR and an otherwise identical VAR without threshold effects. For each model we first simulate the data under the counterfactual and then calculate the difference between actual and simulated series. This difference is a direct gauge of the role played by uncertainty shocks in the two frameworks; or, equivalently, of the loss of fit caused in each model by the counterfactual assumption that volatility remained constant over time. The results are illustrated in Fig. 7. The Threshold VAR (*Threshold*) and the volatility-in-mean VAR without threshold effects (*No Threshold*) are represented respectively by red and black lines. The top left panel reports the results for Industrial Production. The negative values observed in the early 1980s and between 2007 and 2009 indicate that in both models shutting down volatility shocks causes an underestimation of the observed drop in output. However, this effect is much larger in the threshold model: in the Great Recession period, the gap amounts to only 0.2% for the VAR and over 1% for the TAR. The bottom left panel focuses on financial market dynamics. Without volatility shocks, the TAR entirely misses the spikes in FCI that occurred in the early 1980s and in 2008. The results are qualitatively similar for the VAR (FCI is again too low in those periods), but the discrepancies are far less significant from a quantitative point of view. In short, ignoring financial thresholds leads to a partial and heavily downward-biased picture of the contribution of uncertainty shocks to financial and real cycles in the USA.

5.3. *Is it really about financial markets?*

Caggiano et al. (2014) find that the impact of uncertainty on economic activity in post-war US history has been higher in periods of low growth and high unemployment. According to Mumtaz and Theodoridis (2017), uncertainty shocks have generally become less powerful over the last decades, possibly under the influence of a flatter Phillips curve and a more aggressive monetary policy stance. This raises a question: why does the transmission of uncertainty change over time, and how does the 'financial view' hold up against these alternative explanations? This issue is investigated below by comparing the Threshold VAR to a range of alternative time-varying models of the transmission mechanism. The model comparison is based on the Deviance Information Criterion (DIC) of Spiegelhalter et al. (2002). DIC is calculated using the mean likelihood of a model and a penalty correction that penalizes the model's complexity, measured by the number of effective parameters. As such, it is particularly suited to situations where the models under scrutiny are highly nonlinear, or differ significantly in terms of complexity, as in this case. To assess the overall importance of the nonlinearities in the data, we first compare the benchmark TAR model used in the previous section (*Benchmark*) to three simpler specifications. In the first one we retain the double-regime structure but rule out a direct impact of uncertainty on the endogenous variables by setting $\gamma_{ij} = 0$ in Eq. (1) (*No Uncertainty*). This restriction delivers a model that accounts for the nonlinearities stem-

[15] Caggiano et al. (2014) find indeed that the impact of uncertainty on employment is halved if the S&P500 index is included in the model. None of the specifications examined by the authors includes however corporate credit spreads, which are a key ingredient in Caldara et al. (2016), Gilchrist et al. (2014) and in this paper.

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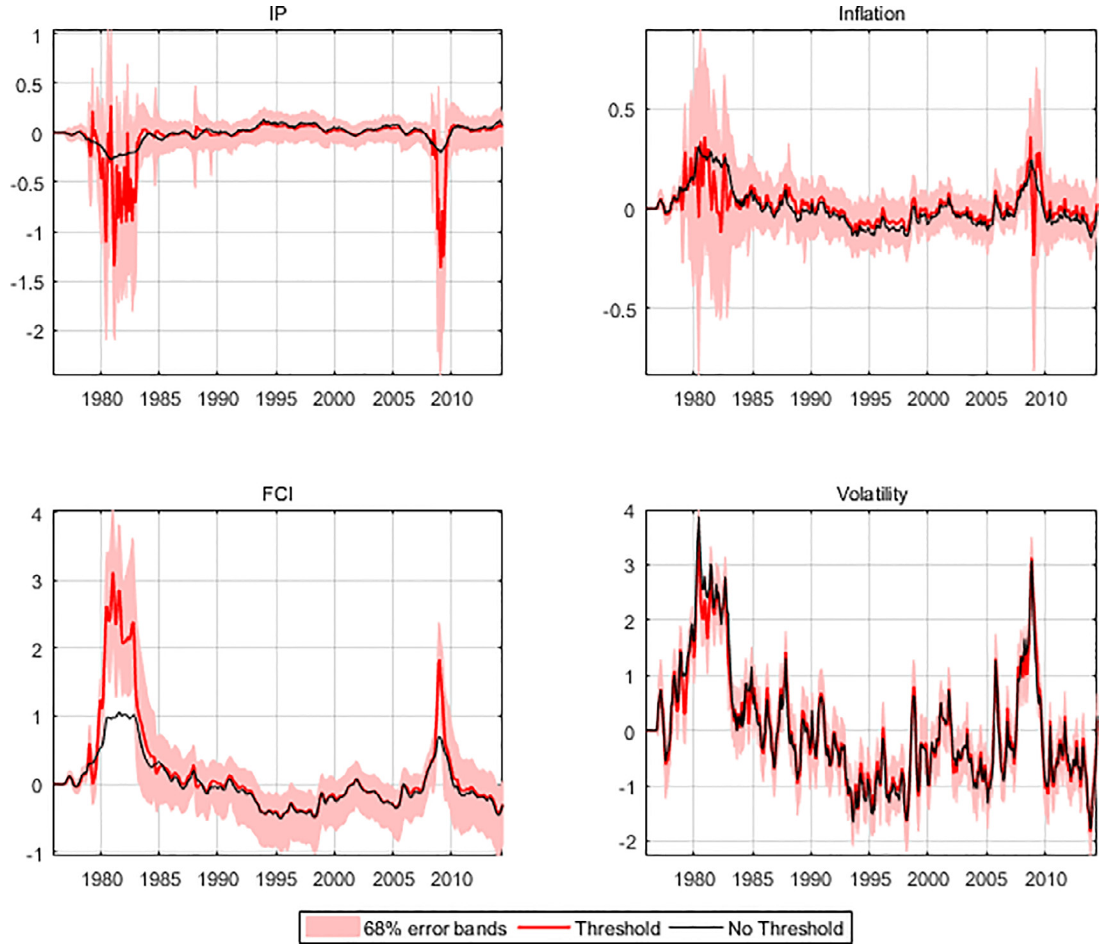

Fig. 7. A counterfactual without uncertainty shocks. For each variable, the figure shows the difference between actual data and model-generated series under the assumption of no volatility shocks ($\eta_t = 0$ in Eq. (4)). The black lines are based on a linear VAR. The red lines and the associated 68% confidence bands are based on a Threshold VAR that separates periods of calm and distressed financial conditions. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

ming from credit or collateral constraints but does not assign any role to uncertainty. In the second one, symmetrically, we allow for uncertainty effects but remove the threshold structure, obtaining a volatility-in-mean VAR à la Mumtaz and Theodoridis (2015) (*No Threshold*) . In the third experiment we combine these two restrictions obtaining a linear VAR without uncertainty (*No Threshold & No Uncertainty*). We then consider two alternative ways of modelling the nonlinearity. The first one (*IP-based Threshold*) is a version of the benchmark TAR where the regimes are identified using annual growth in industrial production instead rather than financial conditions (i.e. we replace F_t with $\Delta^{12} IP_t$ in Eq. (2)). This mimics the model of Caggiano et al. (2014), where the regimes are linked to the state of the business cycle. The second alternative (*TVP VAR*) is a VAR where all parameters are treated as random walks, reproducing the smooth structural change modeled by Mumtaz and Theodoridis (2017). The results are reported in Table 1. The restrictions that shut down the uncertainty channel (*No Uncertainty*), remove the differences across regimes (*No Threshold*) or turn the model into a linear VAR (*No Threshold & No Uncertainty*) all lead to a significant increase – i.e. a worsening – of the DIC relative to the benchmark model. This corroborates the empirical relevance of both volatility shocks and financial regimes in the data. Furthermore, *Benchmark* has a lower DIC than *IP-based Threshold*. This means that, in our sample, breaks associated to periods of financial distress capture structural change relatively better than a boom-recession type of periodization. Finally, *Benchmark* also dominates *TVP VAR*: financial regimes thus fit the data better than smoothly-changing parameters. In fact, *TVP VAR* turns out to have the highest DIC of all models included in Table 1, which suggests that its high complexity pays off relatively poorly in terms of explaining the patterns in the data.[16]

[16] The TVP VAR includes 6 lags instead of 13: the estimation of random-walk parameters becomes unfeasible when the dimensionality of the model grows too large. However, we find that a benchmark TAR restricted to 6 lags has again a far lower DIC than the TVP VAR with 6 lags (−5,761.7 versus −4,906.1). The better performance of the TAR is thus unrelated to the number of lags.

Table 1
Deviance Information Criterion. The table reports the Deviance Information Criterion of Spiegelhalter et al. (2002) for seven alternative models. Benchmark is the TAR described in Section 3. Model (i) assumes that uncertainty has no impact on the economy. Model (ii) assumes a single regime. Model (iii) combines the two restrictions. Model (iv) is a TAR with the same structure as the benchmark, except that the switches between regimes are driven by annual growth in industrial production rather than the Financial Condition Index. Model (v) is a Time-Varying Parameter VAR where uncertainty has a direct impact on the endogenous variables, as in the benchmark, and all parameters are treated as random walks. All models are estimated using monthly data on industrial production, consumer price inflation, the three-month Treasury Bill rate and the Financial Condition Index between January 1973 and May 2014

	Model	*DIC*
	Benchmark	-5,700.4
i.	No Uncertainty	-5,680.2
ii.	No Threshold	-5,687.5
iii.	No Threshold & No Uncertainty	-5,669.7
iv.	IP-based Threshold	-5,291.5
v.	TVP VAR	-4,906.1

Discriminating between financial thresholds, real thresholds and smooth, persistent forms of structural change is intrinsically difficult. Since financial conditions are strongly countercyclical, recessions and episodes of financial distress tend to overlap, blurring the line between 'financial' and 'real' cycles. Furthermore, financial conditions improved steadily during the Great Moderation period (see e.g. Fig. 1): this implies that the time-varying parameter VAR of Mumtaz and Theodoridis (2017) might also partly pick up a weaker transmission of uncertainty shocks through financial markets. A clean separation between these possibilities would thus require an encompassing structural model. From a purely statistical standpoint, however, the finance-driven interpretation of the amplification mechanism receives more support from the data. Furthermore, financial frictions and occasionally binding credit constraints are now widely recognized as a quantitatively important amplification mechanism for standard business cycle shocks (see e.g. Hubrich and Tetlow, 2015). Our analysis demonstrates that this mechanism also applies to volatility shocks.

6. Sensitivity analysis

The conclusions reached in the previous section are robust to various changes in the specification of the benchmark model. In particular, the results survive the inclusion of additional variables or estimated factors to the system, changes in the timing assumptions and/or definition of the volatility process, and the use of narrative sign restrictions à la Ludvigson et al. (2017) for the identification of uncertainty shocks. These exercises are described in turn below. The results are summarized in Fig. 8. For each of the specifications introduced in this section the figure reports the responses of output and inflation to a one standard deviation increase in uncertainty (columns 1 and 2 respectively) and the estimated uncertainty series (column 3).

6.1. Expanding the information set

The benchmark model relies on an information set that is very rich on the financial side, due to the presence of the Financial Conditions Index, but is relatively weak on the real side, due to the small number of variables, and does not include any observable proxy of aggregate uncertainty. As a first robustness check we thus replicate the benchmark analysis adding to the vector of observables Y_t either the VIX index or the debt-to-GDP ratio, an indicator of fiscal uncertainty (Mumtaz and Surico, 2018). The results are reported in rows 1 and 2 of Fig. 8**.** Neither of these extensions alters our key results. In particular, the responses of output and inflation to a rise in uncertainty still display a strong asymmetry across financial regimes. The results are also unaffected if economic activity is measured by the unemployment rate instead of industrial production (details are available upon request). We then go a step further and replace the benchmark model with a Factor-Augmented TAR. The introduction of a factor structure allows us to expand the information set in a far more significant way, correcting for any missing variable bias and accounting for the possibility of non-fundamentalness of shocks (Forni and Gambetti, 2014). The extended model is defined as follows:

$$\begin{pmatrix} X_{it} \\ F_t \end{pmatrix} = \begin{pmatrix} B_i & 0 \\ 0 & 1 \end{pmatrix} \begin{pmatrix} \tilde{F}_t \\ F_t \end{pmatrix} + v_{it}, v_{it} \tilde{} N(0, R_i) \tag{5}$$

$$\begin{aligned} \tilde{Z}_t = & \left(c_1 + \sum_{j=1}^{P} \beta_{1j} \tilde{Z}_{t-j} + \sum_{j=0}^{J} \gamma_{1j} \ln \lambda_{t-j} + \Omega_{1t}^{1/2} e_t \right) \tilde{S}_t \\ & + \left(c_2 + \sum_{j=1}^{P} \beta_{2j} \tilde{Z}_{t-j} + \sum_{j=0}^{J} \gamma_{2j} \ln \lambda_{t-j} + \Omega_{2t}^{1/2} e_t \right) (1 - \tilde{S}_t) \end{aligned} \tag{6}$$

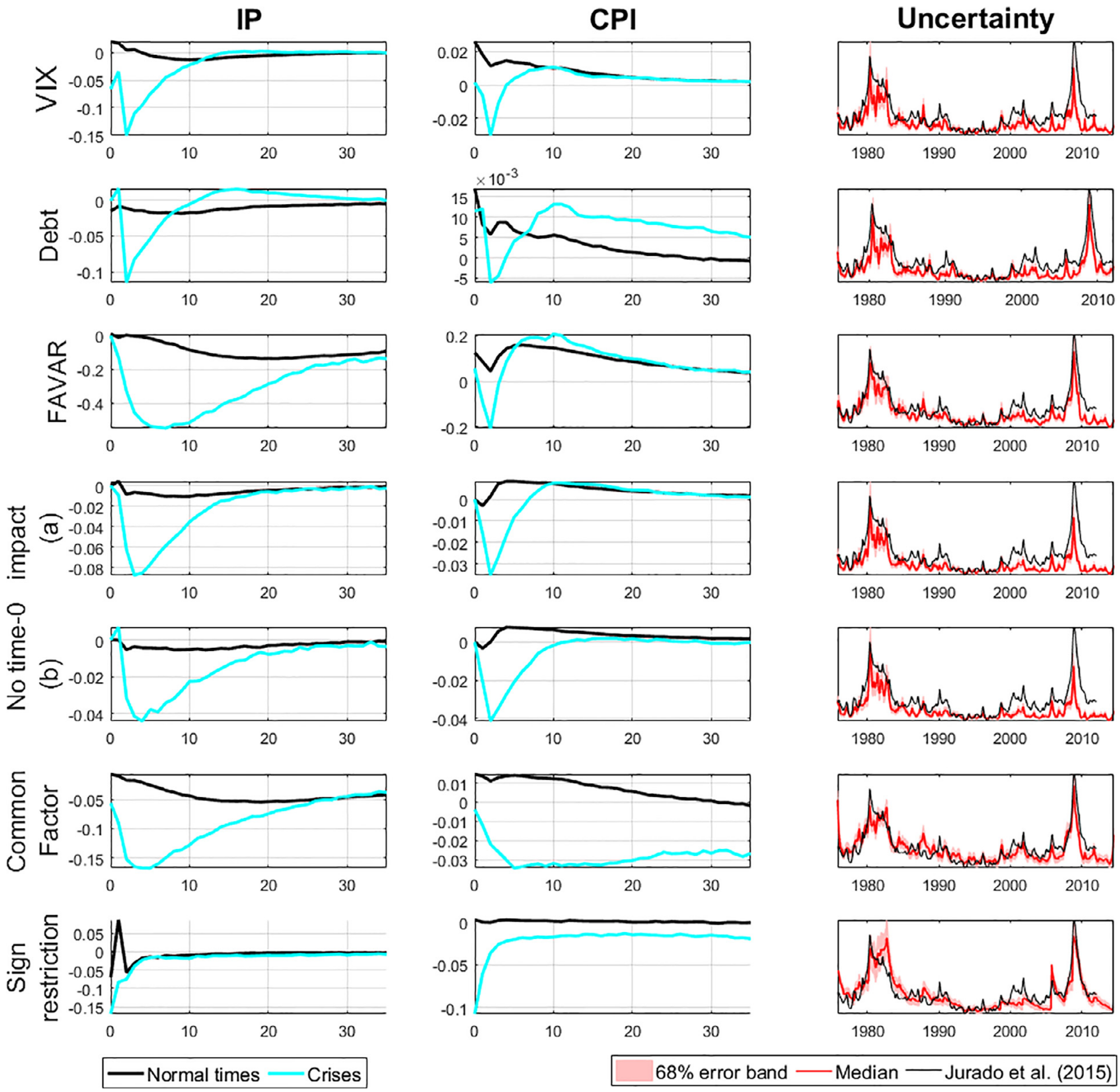

Fig. 8. Robustness analysis. Each row refers to an alternative specification of the benchmark TAR model studied in Section 5.1. For each specification the figure shows the estimated average volatility series (column 3) and the responses of industrial production and inflation to a one-standard-deviation volatility shock (columns 1 and 2). Good time and bad time responses are represented by black and cyan lines. Starting from the top row, the models are: a TAR model that includes the VIX index or the public debt-to-GDP ratio (rows 1, 2); a Factor-Augmented TAR (row 3); a TAR where volatility has no contemporaneous impact on industrial production and inflation (row 4) or on any of the variables included in the model (row 5); a TAR where uncertainty is captured by the common factor of the volatilities of the structural shocks (row 6); a TAR where uncertainty shocks are identified using narrative sign restrictions (row 7). See Section 6 for details.

In the observation Eq. (5) X_{it} is a panel of 111 macroeconomic variables taken from Stock and Watson (2004) that incorporate information about real activity, inflation and the yield curve and include variables such as production and employment in various sectors, consumer prices, producer and commodity prices and government bond yields (a full list is available on request). $\tilde{F}_t = \{\tilde{f}_{1t}, \tilde{f}_{2t}, \dots \tilde{f}_{Kt}\}$ are a set of K unobserved factors that summarize the information in X_{it} and B_i denote the associated factor loadings. The model treats the financial conditions index F_t as an observed factor. The transition equation of the model is a TVAR in $\tilde{Z}_t = \{\tilde{f}_{1t}, \tilde{f}_{2t}, \dots \tilde{f}_{Kt}, F_t\}$ with stochastic volatility in mean as in the benchmark model above. The dynamics of λ_t are described in Eq. (4). In summary, this extended model incorporates additional information through the factors $\tilde{F}_t$ while retaining the threshold dynamics and stochastic volatility of the benchmark model.[17] We fix

[17] Details on the estimation of the Factor-Augmented TAR are available upon request.

$K = 3$ and use the same lag specification as in the benchmark case. This value for K ensures that the number of regime-specific parameters to be estimated in the transition equation remains feasible given the number of observations in each regime. The results from this model are reported in row 3 of Fig. 8.[18] As in the benchmark model, industrial production falls significantly more during crises, while the response of inflation is negative in the crisis regime and mildly positive in normal times. The volatility estimate obtained from this model (panel 3) is very similar to the benchmark estimate.

6.2. Volatility: measurement, timing and exogeneity.

The benchmark model assumes that (i) aggregate uncertainty is captured by the average volatility of the shocks in the economy; (ii) uncertainty shocks can have a contemporaneous impact on the economy; (iii) uncertainty shocks are orthogonal to the level shocks in the economy. We probe these assumptions sequentially below. Row 4 of Fig. 8 reports estimates obtained from a version of the model where the contemporaneous impact of λ_t on industrial production and inflation is restricted to be zero, while still allowing financial variables to be affected contemporaneously. Row 5 is based on an even stronger restriction that forces all variables in the system to respond to uncertainty with a one-month lag. Intuitively, this extreme case mimics a recursive VAR where uncertainty is ordered last rather than first. Except for the time-zero responses, in both cases the dynamics of output and inflation match those generated by the benchmark model very closely.

Modelling aggregate uncertainty as the *average* volatility of the shocks hitting the US economy is intuitive and computationally convenient (see Section 3.2). In principle, however, one could also think of uncertainty as the *common factor* behind changes in the shock covariance matrix. To study this possibility we estimate a version of the model where variation in the error covariance matrix is driven by $H_t = diag(h_{it} s_i)$, where $\ln h_{it} = b_i \ln \lambda_t + \ln e_{it}$. The factor loadings are denoted by b_i, the common factor $\ln \lambda_t$ follows the transition equation defined in Eq. (4), and e_{it} is assumed to be white noise. In this set up the log-volatility of each shock h_{it} is decomposed into a common and an idiosyncratic component and, unlike in the baseline specification, λ_t is estimated (i) stripping out all idiosyncratic components and (ii) allowing for shock-specific loadings b_i.[19] The impulse-responses from this model are reported in row 6 of Fig. 8. The responses are very similar to the benchmark case, with the crisis regime generating a much larger contraction in industrial production and a significant drop in inflation. As the the last panel shows, the common volatility component turns out to be highly correlated with the average volatility estimated by the benchmark model.

Another assumption we borrow from the DSGE literature is that uncertainty is exogenous, so that $E(e_{jt}\eta_t) = 0$ for all variables $j = 1,..., N$ included in the measurement equation of the VAR. Relaxing this assumption requires a more marked departure from the benchmark model. The online appendix to the paper discusses the estimation of a generalized model that allows for unrestricted, regime-dependent covariances across residuals (see section H). In essence, the structure defined by Eqs. (1), (2) and (4) remains unchanged, but the distribution of the innovations is defined in this case as follows:

$$\begin{pmatrix} \eta_t \\ e_t \end{pmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \Sigma_{i,\eta_t\eta_t} & \Sigma'_{i,\eta_t e_t} \\ \Sigma_{i,\eta_t e_t} & \Sigma_{i,e_t e_t} \end{bmatrix} \right) \tag{7}$$

where $i = 1, 2$ denotes the two financial regimes and $\Sigma_{i,\eta_t e_t}$ parameterizes the covariance between level and volatility shocks in regime i. The distinguishing feature of this setup is that first- and second-moment shocks are correlated and uncertainty can respond endogenously to changes in macroeconomic fundamentals. It follows that uncertainty shocks cannot be distinguished from level shocks without further assumptions. To that end, we use narrative sign restrictions in the spirit of Ludvigson et al. (2017). We assume that uncertainty shocks (i) raise volatility, (ii) have a (weakly) negative impact on output, and (iii) are negatively correlated to unexpected changes in the US stock price index. We further assume that (iv) large uncertainty shocks (two standard deviations or above) took place in October 1987 and at least once during the Great Recession.[20] The responses are depicted in the last row of Fig. 8. The confidence bands are generally wider in this case, owing to the increase in the complexity of the model and the switch to set identification. However, the crisis regime is again associated to a larger drop in output and a flip in the sign of the inflation response. After 12 months, the cumulative drop in output is approximately 0.2% in normal times and 0.5% in bad times, and the fall in inflation in bad times is 0.5% (see section H of the annex for details).

7. Conclusions

Financial frictions are known to play an important role in the transmission of uncertainty shocks. This paper documents a new aspect of the interaction between the two by showing that an exogenous increase in economic uncertainty can have radically different macroeconomic implications depending on the conditions that prevail in financial markets when the shock materializes. Using monthly US data covering the period from January 1973 to May 2014, we estimate a nonlinear VAR where

[18] The variables in X_{it} are standardised and the impulse responses are converted back to percentages. However, because of the initial standardisation, the scale of λ_t can be different from the original model. In Fig. 8 we rescale the responses to match the average difference in the scale of λ_t estimated using the FAVAR and the benchmark model.

[19] While this model can be easily estimated using a slight modification of the MCMC algorithm described in the appendix, we found (for our dataset) that identifying the unobserved components in the shock volatility requires tight priors on the dynamics and scale of $\ln \lambda_t$ and $\ln e_{it}$.

[20] The restrictions are based on Ludvigson et al. (2017). Both restriction and estimation method are illustrated in detail in section H of the annex.

uncertainty is captured by the average volatility of the economy's structural shocks, and a regime change occurs whenever financial markets are in distress. The regime associated to high financial distress identifies periods in US history where financial constraints were relatively more severe because balance sheets in the private sector were strained, such as the early 1980s and 2008-2009. The estimates show that, although exogenous increases in uncertainty have recessionary effects at all times, their impact on output is roughly six times larger during a 'financial crisis'. Accounting for this nonlinearity, uncertainty shocks explain one percentage point of the peak fall in industrial production observed in the Great Recession. These results provide further support for the financial view of the transmission mechanism of uncertainty shocks (Christiano et al., 2014; Gilchrist et al., 2014). They also point to a complication that must be taken into account when examining the role of uncertainty and credit conditions in the business cycle: the two are not easily separable, because uncertainty becomes more relevant if and when the economy has previously been hit by adverse financial shocks. Finally, the results suggest that, although uncertainty shocks can cause significant macro-financial fluctuations, policy makers could limit their propagation by preserving the resilience of the financial sector through appropriate macroprudential policy interventions.

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Supplementary material

Supplementary material associated with this article can be found, in the online version, at 10.1016/j.jmoneco.2018.05.001

References

Alessandri, P., Mumtaz, H., 2017. Financial conditions and density forecasts for US output and inflation. Rev. Econ. Dyn. 24, 66–78.
Arellano, C., Bai, Y., Kehoe, P., 2012. Financial markets and fluctuations in uncertainty, federal reserve bank of minneapolis staff report, march.
Bachmann, R., Elstner, S., Sims, E.R., 2013. Uncertainty and economic activity: evidence from business survey data. Am. Econ. J. 5 (2). 217–49.
Basu, S., Bundick, B., 2017. Uncertainty shocks in a model of effective demand. Econometrica 85 (3), 937–958.
Bernanke, B.S., 1983. Irreversibility, Uncertainty and cyclical investment. Q. J. Econ. 98, 85–106.
Beetsma, R., Giuliodori, M., 2012. The changing macroeconomic response to stock market volatility shocks. J. Macroecon. 34, 281–293.
Blanchard, O., 2009. (nearly) nothing to fear but fear itself. The Economist, January 29th.
Bloom, N., 2009. The impact of uncertainty shocks. Econometrica 77, 623–685.
Bloom, N., 2014. Fluctuations in uncertainty. J. Econ. Perspect. 28 (2), 153–176.
Brave, S., Butters, A.R., 2012. Diagnosing the financial system: financial conditions and financial stress. Int. J. Central Bank. 8 (2), 191–239.
Brunnermeier, M.K., Sannikov, Y., 2014. A macroeconomic model with a financial sector. Am. Econ. Rev. 104 (2), 379–421.
Caggiano, G., Castelnuovo, E., Groshenny, N., 2014. Uncertainty shocks and unemployment dynamics in U.S. recessions. J. Monetary Econ. 67 (0), 78–92.
Caldara, D., Fuentes-Albero, C., Gilchrist, S., Zakrajsek, E., 2016. The macroeconomic impact of financial and uncertainty shocks. Eur. Econ. Rev. 88, 185–207.
Carrière-Swallow, Y., Céspedes, L.F., 2013. The impact of uncertainty shocks in emerging economies. J. Int. Econ. 90, 316–325.
Carriero, A., Clark, T.E., Marcellino, M., 2016. Common drifting volatility in large Bayesian VARs. J. Bus. Econ. Stat. 34 (3), 375–390.
Carriero, A., Mumtaz, H., Theodoridis, K., Theophilopoulou, A., 2015. The impact of uncertainty shocks under measurement error: a proxy SVAR approach. J. Money Credit Bank. 47 (6), 1223–1238.
Carriero, Andrea, Clark, Todd E., and Marcellino, Massimiliano, 2017, Endogenous Uncertainty?, manuscript.
Chen, C.W., Lee, J.C., 1995. Bayesian inference of threshold autoregressive models. J. Time Ser. Anal. 16 (5), 483–492.
Christiano, L.J., Motto, R., Rostagno, M., 2014. Risk shocks. Am. Econ. Rev. 104 (1), 27–65.
Cogley, T., Sargent, T.J., 2005. Drifts and volatilities: monetary policies and outcomes in the post WWII US. Rev. Econ. Dyn. 8 (2), 262–302.
Fernandez-Villaverde, J., Guerron-Quintana, P., Kuester, K., Rubio-Ramirez, J., 2015. Fiscal volatility shocks and economic activity. Am. Econ. Rev. 105. 3352–84
Fernandez-Villaverde, J., Guerron-Quintana, P., Rubio-Ramirez, J., Uribe, M., 2011. Risk matters: the real effects of volatility shocks. Am. Econ. Rev. 101 (6), 2530-61.
Foerster, A.T., 2014. The asymmetric effects of uncertainty. Federal Reserve Bank of Kansas City Economic Review 2014. (3).
(FOMC), F.O.M.C., 2008. Federal Open Market Committee Minutes, pp. 29–30. April
Forni, M., Gambetti, L., 2014. Sufficient information in structural VARs. J. Monet. Econ. 66, 124–136.
Gilchrist, S., Sim, J. W., Zakrajsek, E., 2014. Uncertainty, financial frictions and investment dynamics, NBER working paper no.20038, April.
Gilchrist, S., Zakrajsek, E., 2012. Credit spreads and business cycle fluctuations. Am. Econ. Rev. 102 (4). 1692–720.
Hubrich, K., Tetlow, R.J., 2015. Financial stress and economic dynamics: the transmission of crises. J. Monet. Econ. 70 (0), 100–115.
Jacquier, E., Polson, N., Rossi, P., 1994. Bayesian analysis of stochastic volatility models. J. Bus. Econ. Stat. 12, 371–418.
Jermann, U., Quadrini, V., 2012. Macroeconomic effects of financial shocks. Am. Econ. Rev. 102 (1). 238–71.
Jurado, K., Ludvigson, S.C., Ng, S., 2015. Measuring uncertainty. Am. Econ. Rev. 105 (3), 1177–1216.
Justiniano, A., Primiceri, G., 2008. The time-varying volatility of macroeconomic fluctuations. Am. Econ. Rev. 98 (3). 604–41.
Koop, G., Pesaran, M.H., Potter, S.M., 1996. Impulse response analysis in nonlinear multivariate models. J. Econ. 74 (1), 119–147.
Leduc, S., Liu, Z., 2016. Uncertainty shocks are aggregate demand shocks. J. Monet. Econ. 82, 20–35.
Lhuissier, S., Tripier, F., 2016. Do uncertainty shocks always matter for business cycles? Manuscript.
Luca, B., 2013. Economic policy uncertainty and the great recession, manuscript.
Ludvigson, S.C., Ma, S., Ng, S., 2017. Uncertainty and Business Cycles: Exogenous Impulse or Endogenous Response? In: NBER Working Paper No. 21803.
Mendoza, E.G., 2010. Sudden stops, financial crises, and leverage. Am. Econ. Rev. 100 (5). 1941–66.
Mumtaz, H., Surico, P., 2018. Policy uncertainty and aggregate fluctuations. J. Appl. Econ. 33, 319–331.
Mumtaz, H., Theodoridis, K., 2015. The international transmission of volatility shocks: an empirical analysis. J. Eur. Econ. Assoc. 13, 512–533.
Mumtaz, H., Theodoridis, K., 2017. The changing transmission of uncertainty shocks in the U.S. J. Bus. Econ. Stat. 0 (0), 1–14.
Mumtaz, H., Zanetti, F., 2013. The impact of the volatility of monetary policy shocks. J. Money Credit Bank. 45 (4), 536–558.
Nolan, C., Thoenissen, C., 2009. Financial shocks and the US business cycle. J. Monet. Econ. 56. 596–604.
Popescu, A., Smets, F.R., 2010. Uncertainty, risk-taking, and the business cycle in germany. CESifo Econ. Stud. 56, 596–626.

Spiegelhalter, D.J., Best, N.G., Carlin, B.P., van der Linde, A., 2002. Bayesian measures of model complexity and fit. J. R. Stat. Soc. Ser. B (Stat. Methodol.) 64 (4), 583–639.
Stock, J.H., Watson, M.W., 2003. Forecasting output and in‡ation: the role of asset prices. J. Econ. Lit. 41 (3), 788–829.
Stock, J.H., Watson, M.W., 2004. An empirical comparison of methods for forecasting using many predictors. Manuscript.
Stock, J. H., Watson, M. W., 2012. Disentangling the Channels of the 2007–2009 Recession. In: NBER Working Paper no.18094, May.

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