

Financial regimes and uncertainty shocks.

Piergiorgio Alessandri^{a,*}; Haroon Mumtaz^{b†}

^a Banca d'Italia; ^b Queen Mary University of London

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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.

Keywords: Uncertainty, Stochastic volatility, Financial markets, Threshold VARs

JEL classification: C32, E32, E44, G01

*Corresponding author: Banca d'Italia, Financial Stability Directorate, Via Nazionale 91, 00184 Rome, Italy. +39 0647922325 piergiorgio.alessandri@bancaditalia.it

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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 1993; 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; Christiano *et al.*, 2014; Gilchrist *et al.*, 2014; Caldara *et al.*, 2016). 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 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

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

²The research on uncertainty is reviewed below and in Section 2.; for the policy side of the debate, see for instance FOMC (2008) and Blanchard (2009).

1 through a volatility-in-mean type of mechanism (Mumtaz and Zanetti, 2013; Mumtaz and
2 Theodoridis, 2015, 2017; Mumtaz and Surico, 2018). Second, the dynamics can change
3 when financial markets are dysfunctional: the model includes a financial distress indicator
4 and it allows the parameters to shift when this crosses an endogenously-determined critical
5 threshold. This combination of stochastic volatility and multiple regimes, which finds a nat-
6 ural justification in this context, represents a methodological novelty that could be of wider
7 interest to empirical macroeconomists.

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

22 The remainder of the paper is organized as follows. After reviewing the literature in Sec-
23 tion 2., in Section 3. we introduce the nonlinear VAR framework and discuss its relation with
24 DSGE models featuring uncertainty shocks. Our main results are illustrated in Section 5..
25 Section 6. examines the robustness of our conclusions to various data choices and modelling
26 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 Carriere-Swallow and Cespedes (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 (Bloom, 2009; Bachmann *et al.*, 2013; Carriero *et al.*, 2015; Leduc and Liu, 2016; Mumtaz and Surico, 2018). We are aware of three exceptions to this rule.

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

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

1 Popescu and Smets (2010) and Benati (2013) note that the coexistence of credit spreads
2 and uncertainty proxies in a VAR raises significant identification issues and suggest that
3 uncertainty shocks play a minor role once financial shocks are taken into account. Caldara
4 *et al.* (2016) document that allowing credit conditions to respond to changes in uncertainty is
5 critical in order for these shocks to affect economic activity. We examine the same issues but
6 resort to a nonlinear model to study the state-dependent link between financial conditions
7 and uncertainty.

8 The evidence regarding variation in the transmission of uncertainty shocks over time
9 is relatively scant. Beetsma and Giuliodori (2012) and Mumtaz and Theodoridis (2017)
10 find that the impact of uncertainty on output in the US has decreased over the last five
11 decades. Caggiano *et al.* (2014) estimate a Smooth-Transition VAR on post-war US data,
12 finding that uncertainty had a stronger impact on unemployment during recessions. None
13 of these papers models the interdependence between uncertainty and financial conditions
14 highlighted by the ‘financial view’ of the transmission mechanism. A step in this direction
15 is attempted by Lhuissier and Tripier (2016), who use a Markov-switching VAR and find
16 that shocks to the VIX index are more powerful during periods that *ex post* appear to be
17 associated to financial tensions. Two methodological choices set our work apart from theirs’:
18 the measurement of uncertainty, which is more grounded in theory, and the nature of the
19 regime-switching mechanism, which explicitly links the regimes to credit conditions. Both
20 are discussed extensively in Section 3.2.. Although establishing why and how the impact
21 of uncertainty shocks has changed over time is not trivial, our estimates indicate clearly
22 that financial markets ‘matter’ and that credit constraints are a credible alternative to the
23 explanations examined by Caggiano *et al.* (2014) and Mumtaz and Theodoridis (2017) (see
24 Section 5.3.).

25 Our econometric approach and our measure of uncertainty mark an important departure
26 from the literature. Instead of relying on observable proxies such as realized equity price

1 volatility or the VIX index we measure uncertainty as the average volatility of the econ-
2 omy's structural shocks, which in our framework can be estimated directly from the data.
3 Time-varying volatilities are a pervasive feature of macroeconomic data (see e.g. Justiniano
4 and Primiceri, 2008). More importantly, conditional volatilities are directly related to the
5 overall predictability of the economic environment, which is ultimately the key uncertainty
6 factor in households' and firms' decisions.⁵ The idea of using a scalar volatility process in a
7 multivariate model has been introduced by Carriero *et al.* (2016), while volatility-in-mean
8 effects are studied in the context of otherwise linear VAR models by Mumtaz and Zanetti
9 (2013), Mumtaz and Theodoridis (2015, 2017), Mumtaz and Surico (2018). The combination
10 of stochastic volatility and regime switches is a novelty of this paper.

11 **3. A VAR with financial regimes and volatility effects**

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

16 *3.1. Structure of the model*

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

⁵See 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..

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

Here $Z_t = \{Y_t, P_t, R_t, F_t\}$ 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^* :

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

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

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

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

1 as:

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

2 where η_t is an *i.i.d.* innovation with variance Q . Following Carriero *et al.* (2016), we thus
 3 assume that a single, scalar volatility process λ_t drives time variation of the entire variance-
 4 covariance matrix of the structural shocks. We take this process to represent economic
 5 uncertainty.⁶ Intuitively, a volatility or uncertainty shock $\eta_t > 0$ raises λ_t , causing an
 6 upward shift in the covariance matrix of the innovations e_t , and hence a sudden deterioration
 7 of the accuracy with which agents can forecast Z_{t+k} . By letting λ_t enter equation (1), our
 8 framework allows output, asset prices and monetary policy to adjust endogenously to the
 9 new, riskier (and less predictable) state of the economy. The occurrence of regime shifts
 10 associated to periods of financial distress captures the time-varying nature of the underlying
 11 transmission mechanisms: the two sets of parameters $\{c_i, \beta_{ij}, \gamma_{ij}, \Omega_i\}_{i=1,2}$ can be thought of
 12 as capturing the behavior of the economy in periods of "tense" and "calm" financial markets,
 13 or binding and non-binding borrowing constraints. No restrictions are placed on how the
 14 primitive shocks e_t and η_t play out in different regimes.⁷

15 The Gibbs sampling algorithm for the estimation of the model is described in detail in the
 16 Appendix to the paper. The main intuition behind it is straightforward. Given a draw for
 17 λ_t , the model collapses to a threshold VAR, albeit with a known form of heteroscedasticity.

⁶In 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.

⁷The 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.).

1 After a GLS transformation of the model, the conditional posterior distributions of the
 2 regime dependent VAR parameters, the threshold and delay are identical to those of a
 3 standard threshold VAR (see Alessandri and Mumtaz, 2017). In particular, as described
 4 in Chen and Lee (1995), the conditional posterior of the delay parameter is a Multinomial
 5 distribution, while the threshold value can be drawn from its non-standard posterior via a
 6 Metropolis step. Then the data can be split into regime-specific observations, and the VAR
 7 autoregressive coefficients sampled from the normal distribution. Given the residuals of the
 8 VAR and λ_t , the conditional posterior for A is standard and described in several recent
 9 papers (e.g. Cogley and Sargent, 2005). The variances S can be drawn from the inverse
 10 Gamma distribution. Given these parameters, the model admits a non-linear state-space
 11 representation. The state-variable λ_t is drawn using the independence Metropolis algorithm
 12 introduced in Jacquier et al. (1994) for stochastic volatility models.

13 Once the posterior distribution of all parameters is available, “generalized” impulse-
 14 responses are obtained using Montecarlo integration as described in Koop et al. (1996). In
 15 practice the responses are calculated as differences between conditional expectations obtained
 16 by simulating the model under a shock scenario and under a baseline, no-shocks scenario.
 17 For a given regime ($S = 0, 1$) and regime-specific history (Y_{t-1}^s), the responses are defined as
 18 $IRF_t^S = E(Y_{t+k} \setminus \Psi_t, Y_{t-1}^s, \mu) - E(Y_{t+k} \setminus \Psi_t, Y_{t-1}^s)$, where Ψ_t represents all the parameters and
 19 hyperparameters of the model, k is the horizon under consideration and μ denotes the shock
 20 of interest (in our case, an increase in uncertainty). Two points are worth emphasizing. First,
 21 the switch among regimes is treated as endogenous in this calculation: the economy can freely
 22 transition from calm to crisis dynamics or *viceversa* over the simulation horizon, depending
 23 on the sign and size of the shock. In other words, the simulation takes into account the
 24 dynamics of both the endogenous variables Y_t and the parameters Ψ_t . Second, even within a
 25 given initial regime S , the responses depend on the specific history of the system prior to the
 26 shock (Y_{t-1}^s). Intuitively, the economy may respond differently when the financial distress

1 indicator is at its historical minimum and when it is just below its critical threshold, even
 2 though both constitute instances of "normal times". We focus throughout on the average
 3 responses in each regime. The normal-time response (respectively, crisis response) is thus
 4 calculated as the average response to the shock of interest across all histories that belong
 5 into regime $S = 1$ (respectively, $S = 0$). By averaging over histories we aim to obtain the
 6 most representative picture of the dynamics associated to each regime. The online annex
 7 to the paper provides results obtained conditioning separately on all histories in our sample
 8 (see section F). We find that regime-specific averages deliver an accurate description of the
 9 overall behavior of the economy. For industrial production, for instance, the cumulative
 10 12-month response to a one standard deviation uncertainty shock varies between -0.2% and
 11 -0.4% in normal times and exceeds -1.2% in all distress episodes but two (the exceptions
 12 are the short-lived financial tensions of 1984 and 1987). Furthermore, the Great Recession
 13 responses are of the same order of magnitude as those observed in the early 1980s crisis
 14 (-1.9% versus -1.7%). In short, the variation within regimes is negligible compared to the
 15 variation across regimes.

16 3.2. *Theoretical background*

17 Like Jurado *et al.* (2015), we use a model-based measure of uncertainty that is directly
 18 linked to the agents' (in)ability to form predictions on the fundamentals of the economy.
 19 This allows us to avoid using proxies that are at best weakly related to macroeconomic
 20 predictability, such as the VIX index. Relative to the factor model by Jurado *et al.* (2015),
 21 the volatility-in-mean specification employed in this paper has the advantage of modeling
 22 the economy's first and second moments in a unified, internally-consistent framework. In our
 23 model agents form expectations $E_t Z_{t+h}$ treating uncertainty as an ordinary state variable:
 24 they estimate λ_t , project it forward considering its persistence (F), and take into account
 25 its influence on the economy ($\gamma_{ij} \neq 0$). These expectations are then integrated out in the

1 impulse-response analysis. Clearly this would not possible in a two-step procedure where
 2 uncertainty is first estimated using a forecasting model and then linked to macroeconomic
 3 fundamentals through a separate set of regressions. This improvement comes at the cost of
 4 a dimensionality problem, as our set up forces us to model a far smaller number of variables
 5 than Jurado *et al.* (2015). However, we find this cost to be quantitatively small (see Sections
 6 5.1. and 6.).

7 The volatility-in-mean feature also takes our set up closer to the theoretical literature on
 8 uncertainty. In the model uncertainty (i) stems directly from the volatility of the structural
 9 shocks in the economy, (ii) follows an AR(1) process, and (iii) is exogenous to the first-
 10 moment dynamics of the economy. The model thus closely resembles the reduced-form of
 11 a DSGE model with stochastic volatility. There are two main differences between the two:
 12 first, the focus is on the average volatility of the shocks rather than the volatility of a specific
 13 structural shock; second, the threshold structure neglects some of the interactions that arise
 14 naturally in (high-order solutions to) a nonlinear DSGE model.⁸ To check whether these
 15 modelling choices introduce a bias in the impulse-responses we run a Montecarlo experiment
 16 using as data-generating process the model of Carriero *et al.* (2015). The model represents
 17 a simple new-keynesian economy where uncertainty is introduced via heteroscedastic inno-
 18 vations in the Taylor rule followed by the central bank. Model and simulation are described
 19 in more detail in the online annex to the paper (see section C). We simulate artificial data
 20 from a third-order approximation to the model and then estimate the vol-in-mean VAR on
 21 the simulated data. Conditioning on a volatility shock, the VAR generates responses that
 22 closely match those of the theoretical model: the theoretical IRFs lie within a one standard
 23 deviation confidence band of the VAR responses for all variables throughout a 5 year sim-
 24 ulation horizon. The responses are particularly accurate for aggregate output, which is our

⁸The threshold structure captures the interaction between uncertainty λ_t and financial conditions F_t (and more generally all interactions of the form $S_t F_{t-1}$, 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.

1 main variable of interest.

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

1 (Caldara *et al.*, 2016).

2 4. Data

3 The estimation employs monthly data covering the period from January 1973 to May
4 2014. Industrial production index, consumer price index and the nominal three-month Trea-
5 sury bill rate are taken from the Federal Reserve Bank of St. Louis Database (FRED[®]).
6 The choice of the financial indicator is clearly important given the objective of the exercise,
7 and it is not straightforward. On the one hand, the indicator should capture the dynamics
8 of a large set of financial variables: uncertainty can affect firms' funding through a number
9 of markets at the same time; a broad indicator is likely to be more robust to structural insta-
10 bilities affecting the link between financial and real economy (Stock and Watson, 2003); and
11 controlling accurately for the state of financial markets is important to isolate uncertainty
12 shocks in a credible way (Caldara *et al.*, 2016). On the other hand, the indicator should
13 not be too correlated with the business cycle. Since the analysis relies on our ability to
14 isolate episodes of genuine financial distress in the data, a strong correlation between real
15 and financial cycle would weaken our tests and make our null hypothesis indistinguishable
16 from that examined by Caggiano *et al.* (2014). Insofar as broad indicators are more likely to
17 be subject to endogeneity issues these two objectives are hard to reconcile. We circumvent
18 the problem by using a range of alternative indicators. The first and broadest one is the
19 Financial Condition Index (FCI), a real-time indicator of financial distress constructed and
20 maintained by the Chicago Fed. The index is extracted using dynamic factor analysis from
21 a set of 120 series that describe a broad range of money, debt and equity markets, as well as
22 the leverage of the financial industry (Brave and Butters, 2012). To mitigate endogeneity,
23 we also use a "purged FCI" obtained as the residual from a regression of FCI on the Chicago
24 Fed National Activity Index. The third alternative is the Excess Bond Premium (EBP)
25 constructed by Gilchrist and Zakrajsek (2012), which represents the excess return required

1 by bond investors over and above their compensation for expected defaults. Finally, we also
 2 employ a simple, model-free measure of funding conditions, namely Moody’s spread between
 3 BAA corporate bonds and 10-year Treasury bill rates. Section 6. also examines versions of
 4 the baseline model that include observable proxies of aggregate uncertainty, such as the VIX
 5 index (see e.g. Bloom, 2009) and the government debt-to-GDP ratio (Mumtaz and Surico,
 6 2018).⁹

7 5. Results

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

15 5.1. A financial accelerator for uncertainty shocks

16 The periodization estimated by the Threshold VAR model is illustrated in Figure 1,
 17 which shows the Financial Condition Index and the associated financial regimes. Gray
 18 bands identify periods when the FCI is above the estimated critical threshold Z^* , implying
 19 that the US economy is experiencing financial distress (see equation (2)). We refer to this
 20 as the ‘crisis’ regime. The delay parameter (d) has a median estimate of one month, with
 21 a 95% upper bound of two months only: this suggests that the economy tends to enter the
 22 crisis regime immediately once the threshold is breached. Figure 2 reproduces the estimated
 23 average volatility $\hat{\lambda}_t$ together with the measure of economic uncertainty calculated by Jurado

⁹Mumtaz 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.

1 et al. (2015). Both indicators suggest that economic uncertainty was highest in the USA in
 2 the early 1980s and in 2007-2009. The correlation between the two series is generally very
 3 strong, confirming that the two approaches rely on similar assumptions for the measurement
 4 of uncertainty (see Section 3.). This similarity also suggests that the volatilities of the
 5 (relatively small) set of variables included in the model provide a credible description of
 6 aggregate economic uncertainty, which Jurado *et al.* (2015) estimate using a much larger
 7 dataset (see also Section 6.). Taken together, figures 1 and 2 clearly confirm the stylized
 8 fact that high volatility, financial tensions and low growth are often associated in the recent
 9 history of the USA. Figure 3 plots the response of the US economy to an exogenous increase in
 10 uncertainty, defined as a positive one standard deviation shock to the λ_t process in equation
 11 (4). The responses associated to good and bad financial times, namely to periods of low
 12 and high FCI, are pictured respectively in black and in red. For each regime the figure
 13 reports the median generalized impulse-responses and the associated 68% confidence bands
 14 (see Section 3.1. and Koop et al. (1996) for details). Notice that the volatility dynamics,
 15 shown in the last panel on the right, are identical across regimes because the stochastic
 16 volatility process λ_t is not regime-dependent. In both regimes an increase in uncertainty leads
 17 to a financial tightening (panel 4) and a contraction in output (panel 1). The responses,
 18 however, are much more pronounced in the crisis regime: the contraction is more abrupt
 19 and the peak fall in output is roughly six times larger (-0.17% versus -0.02%). The key
 20 prediction of the ‘financial view’ of the transmission mechanism is thus supported by the
 21 data: uncertainty shocks are relatively inconsequential in normal times but their impact
 22 on credit markets and economic activity is greatly amplified during episodes of financial
 23 distress, when borrowing constraints bind more severely.¹⁰ Panel 2 shows that the response
 24 of inflation also changes dramatically across regimes: prices increase in normal times and

¹⁰We 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).

1 fall in a crisis.¹¹ The literature offers mixed evidence on the relation between uncertainty
 2 and inflation. Uncertainty shocks are deflationary for instance in Basu and Bundick (2017),
 3 Christiano *et al.* (2014), and Leduc and Liu (2014), where they act as aggregate demand
 4 shocks, but they are inflationary in Fernandez-Villaverde *et al.* (2015) and Mumtaz and
 5 Theodoridis (2015), where uncertainty on future demand and marginal costs introduces a
 6 precautionary upward bias in the firms' pricing decisions. Our result suggests that this
 7 precautionary mechanism prevails in good times but is dominated by the standard channel
 8 in bad times, when aggregate demand is more sensitive to uncertainty because of binding
 9 borrowing constraints. Finally, notice that, although the short-term interest rate does not
 10 respond significantly to the shock (panel 3), its qualitative behavior can be easily rationalized
 11 in the light of this discussion. In a crisis both output and prices fall, so monetary policy can
 12 work countercyclically and interest rates tend to drop (the distribution of the responses lies
 13 mostly below the zero line). In normal times instead the shock generates stagflation and the
 14 responses are symmetrically distributed around zero. Truncating the sample to December
 15 2008, so to exclude the 'zero lower bound' period, does not affect any of these results.

16 We next replicate the analysis using three alternative indicators to identify financial
 17 regimes in US history: a "purged" FCI obtained as the residual from a regression of FCI
 18 on economic activity, the Excess Bond Premium by Gilchrist and Zakrajsek (2012), and the
 19 spread between Moody's BAA corporate bond yield and the 10-year T-Bill rate (see Section
 20 4).¹² The results are summarized in Figure 4. This is similar to Figure 3, except that the
 21 regimes are displayed on two separate rows and financial variables are omitted to improve
 22 clarity. To further facilitate the comparison across models we simulate in all cases an increase
 23 in volatility of approximately 0.5 units, which corresponds to one standard deviation in the

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

¹²In 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 equation (2). Hence, the information sets are very similar across models. What changes is the mechanism that determines the endogenous switches across regimes.

1 benchmark model. As column 4 shows, the dynamics of the volatility process λ_t are very
 2 similar across models. All specifications produce output and inflation responses that are
 3 in line with those of the benchmark model. The fall in industrial production (column 1)
 4 is larger in the crisis regime irrespective of which indicator is used to identify the regimes.
 5 In absolute terms, purged FCI and EBP generate smaller crisis-times responses than FCI,
 6 suggesting that some of the amplification effects in our baseline analysis might be associated
 7 to recessions rather than financial tensions. However, the asymmetry between good and bad
 8 times is clear and sizable for these indicators too. In the EBP-based model, for instance, the
 9 trough in output is approximately five times larger in the bad regime. The sign asymmetry
 10 in the inflation response (column 2) is equally robust: in all models consumer prices rise in
 11 good times (row 1) and fall marginally in bad times (row 2).¹³ The TAR models assume
 12 that the transitions across financial regimes are abrupt, which is broadly consistent with the
 13 onset of the periods of financial distress in our sample. The results do not change if we use a
 14 ‘smooth’ transition mechanism, modeling the regimes through a logistic function that allows
 15 for gradual changes in credit conditions. The estimated regimes turn out to be very similar
 16 to those obtained from the benchmark TAR model and the responses of output and inflation
 17 are again strongly asymmetric (see section D of the online annex for details).

18 5.2. Large shocks and the Great Recession

19 Given the nonlinear nature of the model, the implications of a change in uncertainty
 20 might in principle also depend on sign and size of the shock. Figure 5 compares the response
 21 of industrial production to (i) ‘small’ and ‘large’ perturbations, defined respectively as one
 22 and five standard deviation shocks, and (ii) positive and negative perturbations, i.e. rises and
 23 falls in the volatility of the US economy.¹⁴ All responses are obtained from the benchmark

¹³Part 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 downweigh the financial tightening of the early 1980s, emphasizing instead the 2001-2002 period.

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

1 specification of the TAR model that includes the FCI. The left column shows that normal-
2 time responses are essentially linear in the sign and size of the shock. Furthermore, the
3 comparison between left and right column reveals that financial crises amplify the shock
4 irrespective of its size and direction. In the crisis regime, however, large shocks give place to
5 an interesting sign asymmetry: a drop in volatility causes a smaller change in output than a
6 rise in volatility of equal size (see bottom right panel). A similar form of asymmetry between
7 positive and negative uncertainty shocks is documented by Foerster (2014). According to
8 the model this asymmetry is the product of two factors: the strong impact that volatility
9 has on financial markets, and the state-contingent nature of the linkage between financial
10 markets and the real economy. In bad times, an increase in volatility keeps the economy
11 in a state where financial markets are tight and the ‘volatility multiplier’ is large. A fall in
12 volatility, on the other hand, generates a relaxation in financial conditions that can push the
13 economy back into the good regime, where borrowing constraints bind less and the ‘volatility
14 multiplier’ is lower. The upshot is that volatility matters more on the way up than on the
15 way down.

16 To quantify the overall role of uncertainty in the business cycle we resort to a forecast
17 error variance (FEV) decomposition. Figure 6 shows the contribution of volatility shocks
18 to the FEVs of all endogenous variables in the benchmark specification. The shocks are a
19 powerful driver of financial conditions in both regimes (column 4). For output and inflation,
20 not surprisingly, they are more relevant in bad times (columns 2 and 3). The fraction
21 of output variance accounted for by volatility shocks is twice as big in the crisis regime,
22 approximately 8% versus 4%. These estimates are broadly consistent with those of Caldara
23 *et al.* (2016), who find that uncertainty accounts for about 10% of the FEV for industrial
24 production and employment. They are instead far smaller than those reported by Caggiano
25 *et al.* (2014), according to whom uncertainty explains 23% of the FEV of US unemployment
26 in a linear VAR and as much as 62% of it in a smooth-transition VAR conditioning on

1 recessions. Although this discrepancy might partly depend on data and sampling issues,
2 the nexus between uncertainty and financial markets is likely to be one of its causes. Since
3 uncertainty and credit conditions co-move very strongly, the baseline model of Caggiano
4 *et al.* (2014), which does not include financial variables, might mix credit and uncertainty
5 shocks and thus overestimate the economic relevance of the latter.¹⁵

6 We conclude this section with a counterfactual exercise that provides a model-based
7 narrative on the historical role of uncertainty shocks in the US. The counterfactual world
8 we consider is one where uncertainty shocks do not occur (i.e. $\eta_t = 0$ in equation (4)), so
9 the volatilities of all level shocks in the economy are constant at their sample means. This
10 "constant uncertainty" world is simulated using both the baseline Threshold VAR and an
11 otherwise identical VAR without threshold effects. For each model we first simulate the data
12 under the counterfactual and then calculate the difference between actual and simulated
13 series. This difference is a direct gauge of the role played by uncertainty shocks in the two
14 frameworks; or, equivalently, of the loss of fit caused in each model by the counterfactual
15 assumption that volatility remained constant over time. The results are illustrated in Figure
16 7. The Threshold VAR (*Threshold*) and the volatility-in-mean VAR without threshold effects
17 (*No Threshold*) are represented respectively by red and black lines. The top left panel reports
18 the results for Industrial Production. The negative values observed in the early 1980s and
19 between 2007 and 2009 indicate that in both models shutting down volatility shocks causes
20 an underestimation of the observed drop in output. However, this effect is much larger in
21 the threshold model: in the Great Recession period, the gap amounts to only 0.2% for the
22 VAR and over 1% for the TAR. The bottom left panel focuses on financial market dynamics.
23 Without volatility shocks, the TAR entirely misses the spikes in FCI that occurred in the
24 early 1980s and in 2008. The results are qualitatively similar for the VAR (FCI is again too

¹⁵Caggiano *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.* (2014), Gilchrist *et al.* (2014) and in this paper.

1 low in those periods), but the discrepancies are far less significant from a quantitative point
2 of view. In short, ignoring financial thresholds leads to a partial and heavily downward-
3 biased picture of the contribution of uncertainty shocks to financial and real cycles in the
4 USA.

5 5.3. *Is it really about financial markets?*

6 Caggiano *et al.* (2014) find that the impact of uncertainty on economic activity in
7 post-war US history has been higher in periods of low growth and high unemployment.
8 According to Mumtaz and Theodoridis (2017), uncertainty shocks have generally become
9 less powerful over the last decades, possibly under the influence of a flatter Phillips curve and
10 a more aggressive monetary policy stance. This raises a question: why does the transmission
11 of uncertainty change over time, and how does the ‘financial view’ hold up against these
12 alternative explanations? This issue is investigated below by comparing the Threshold VAR
13 to a range of alternative time-varying models of the transmission mechanism. The model
14 comparison is based on the Deviance Information Criterion (DIC) of Spiegelhalter *et al.*
15 (2002). DIC is calculated using the mean likelihood of a model and a penalty correction that
16 penalizes the model’s complexity, measured by the number of effective parameters. As such,
17 it is particularly suited to situations where the models under scrutiny are highly nonlinear,
18 or differ significantly in terms of complexity, as in this case. To assess the overall importance
19 of the nonlinearities in the data, we first compare the benchmark TAR model used in the
20 previous section (*Benchmark*) to three simpler specifications. In the first one we retain
21 the double-regime structure but rule out a direct impact of uncertainty on the endogenous
22 variables by setting $\gamma_{ij} = 0$ in equation 1 (*No Uncertainty*). This restriction delivers a model
23 that accounts for the nonlinearities stemming from credit or collateral constraints but does
24 not assign any role to uncertainty. In the second one, symmetrically, we allow for uncertainty
25 effects but remove the threshold structure, obtaining a volatility-in-mean VAR à la Mumtaz

1 and Theodoridis (2015) (*No Threshold*) . In the third experiment we combine these two
 2 restrictions obtaining a linear VAR without uncertainty (*No Threshold & No Uncertainty*).
 3 We then consider two alternative ways of modelling the nonlinearity. The first one (*IP-based*
 4 *Threshold*) is a version of the benchmark TAR where the regimes are identified using annual
 5 growth in industrial production instead rather than financial conditions (i.e. we replace
 6 F_t with $\Delta^{12}IP_t$ in equation 2). This mimics the model of Caggiano et al. (2014), where
 7 the regimes are linked to the state of the business cycle. The second alternative (*TVP*
 8 *VAR*) is a VAR where all parameters are treated as random walks, reproducing the smooth
 9 structural change modeled by Muntaz and Theodoridis (2017). The results are reported in
 10 Table 1. The restrictions that shut down the uncertainty channel (*No Uncertainty*), remove
 11 the differences across regimes (*No Threshold*) or turn the model into a linear VAR (*No*
 12 *Threshold & No Uncertainty*) all lead to a significant increase – i.e. a worsening – of the
 13 DIC relative to the benchmark model. This corroborates the empirical relevance of both
 14 volatility shocks and financial regimes in the data. Furthermore, *Benchmark* has a lower
 15 DIC than *IP-based Threshold*. This means that, in our sample, breaks associated to periods
 16 of financial distress capture structural change relatively better than a boom-recession type
 17 of periodization. Finally, *Benchmark* also dominates *TVP VAR*: financial regimes thus fit
 18 the data better than smoothly-changing parameters. In fact, *TVP VAR* turns out to have
 19 the highest DIC of all models included in Table 1, which suggests that its high complexity
 20 pays off relatively poorly in terms of explaining the patterns in the data.¹⁶

21 Discriminating between financial thresholds, real thresholds and smooth, persistent forms
 22 of structural change is intrinsically difficult. Since financial conditions are strongly counter-
 23 cyclical, recessions and episodes of financial distress tend to overlap, blurring the line between
 24 ‘financial’ and ‘real’ cycles. Furthermore, financial conditions improved steadily during the

¹⁶The 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.

1 Great Moderation period (see e.g. Figure 1): this implies that the time-varying parameter
2 VAR of Mumtaz and Theodoridis (2017) might also partly pick up a weaker transmission of
3 uncertainty shocks through financial markets. A clean separation between these possibilities
4 would thus require an encompassing structural model. From a purely statistical stand-
5 point, however, the finance-driven interpretation of the amplification mechanism receives
6 more support from the data. Furthermore, financial frictions and occasionally binding credit
7 constraints are now widely recognized as a quantitatively important amplification mecha-
8 nism for standard business cycle shocks (see e.g. Hubrich and Tetlow, 2015). Our analysis
9 demonstrates that this mechanism also applies to volatility shocks.

10 6. Sensitivity analysis

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

20 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 Figure 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:

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

1

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

2 In the observation equation (5) X_{it} is a panel of 111 macroeconomic variables taken
3 from Stock and Watson (2004) that incorporate information about real activity, inflation
4 and the yield curve and include variables such as production and employment in various
5 sectors, consumer prices, producer and commodity prices and government bond yields (a
6 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
7 summarize the information in X_{it} and B_i denote the associated factor loadings. The model
8 treats the financial conditions index F_t as an observed factor. The transition equation of
9 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
10 benchmark model above. The dynamics of λ_t are described in equation 4. In summary, this

1 extended model incorporates additional information through the factors \tilde{F}_t while retaining
 2 the threshold dynamics and stochastic volatility of the benchmark model.¹⁷ We fix $K = 3$
 3 and use the same lag specification as in the benchmark case. This value for K ensures that
 4 the number of regime-specific parameters to be estimated in the transition equation remains
 5 feasible given the number of observations in each regime. The results from this model
 6 are reported in row 3 of Figure 8.¹⁸ As in the benchmark model, industrial production falls
 7 significantly more during crises, while the response of inflation is negative in the crisis regime
 8 and mildly positive in normal times. The volatility estimate obtained from this model (panel
 9 3) is very similar to the benchmark estimate.

10 6.2. Volatility: measurement, timing and exogeneity.

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

22 Modelling aggregate uncertainty as the *average* volatility of the shocks hitting the US
 23 economy is intuitive and computationally convenient (see Section 3.2.). In principle, however,

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

¹⁸The 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 Figure 8 we rescale the responses to match the average difference in the scale of λ_t estimated using the FAVAR and the benchmark model.

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

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

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

21 where $i=1,2$ denotes the two financial regimes and $\Sigma_{i,\eta_t e_t}$ parameterizes the covariance be-
 22 tween level and volatility shocks in regime i . The distinguishing feature of this setup is that

¹⁹While 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 $\ln e_{it}$.

1 first- and second-moment shocks are correlated and uncertainty can respond endogenously
 2 to changes in macroeconomic fundamentals. It follows that uncertainty shocks cannot be
 3 distinguished from level shocks without further assumptions. To that end, we use narrative
 4 sign restrictions in the spirit of Ludvigson et al. (2017). We assume that uncertainty shocks
 5 (i) raise volatility, (ii) have a (weakly) negative impact on output, and (iii) are negatively
 6 correlated to unexpected changes in the US stock price index. We further assume that (iv)
 7 large uncertainty shocks (two standard deviations or above) took place in October 1987 and
 8 at least once during the Great Recession.²⁰ The responses are depicted in the last row of
 9 Figure 8. The confidence bands are generally wider in this case, owing to the increase in the
 10 complexity of the model and the switch to set identification. However, the crisis regime is
 11 again associated to a larger drop in output and a flip in the sign of the inflation response.
 12 After 12 months, the cumulative drop in output is approximately 0.2% in normal times and
 13 0.5% in bad times, and the fall in inflation in bad times is 0.5% (see section H of the annex
 14 for details).

15 7. Conclusions

16 Financial frictions are known to play an important role in the transmission of uncertainty
 17 shocks. This paper documents a new aspect of the interaction between the two by showing
 18 that an exogenous increase in economic uncertainty can have radically different macroeco-
 19 nomic implications depending on the conditions that prevail in financial markets when the
 20 shock materializes. Using monthly US data covering the period from January 1973 to May
 21 2014, we estimate a nonlinear VAR where uncertainty is captured by the average volatility
 22 of the economy's structural shocks, and a regime change occurs whenever financial markets
 23 are in distress. The regime associated to high financial distress identifies periods in US his-
 24 tory where financial constraints were relatively more severe because balance sheets in the

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

1 private sector were strained, such as the early 1980s and 2008-2009. The estimates show
2 that, although exogenous increases in uncertainty have recessionary effects at all times, their
3 impact on output is roughly six times larger during a ‘financial crisis’. Accounting for this
4 nonlinearity, uncertainty shocks explain one percentage point of the peak fall in industrial
5 production observed in the Great Recession. These results provide further support for the
6 financial view of the transmission mechanism of uncertainty shocks (Christiano *et al.*, 2014;
7 Gilchrist *et al.*, 2014). They also point to a complication that must be taken into account
8 when examining the role of uncertainty and credit conditions in the business cycle: the two
9 are not easily separable, because uncertainty becomes more relevant if and when the econ-
10 omy has previously been hit by adverse financial shocks. Finally, the results suggest that,
11 although uncertainty shocks can cause significant macro-financial fluctuations, policy mak-
12 ers could limit their propagation by preserving the resilience of the financial sector through
13 appropriate macroprudential policy interventions.

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<i>Model</i>	<i>DIC</i>
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

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.

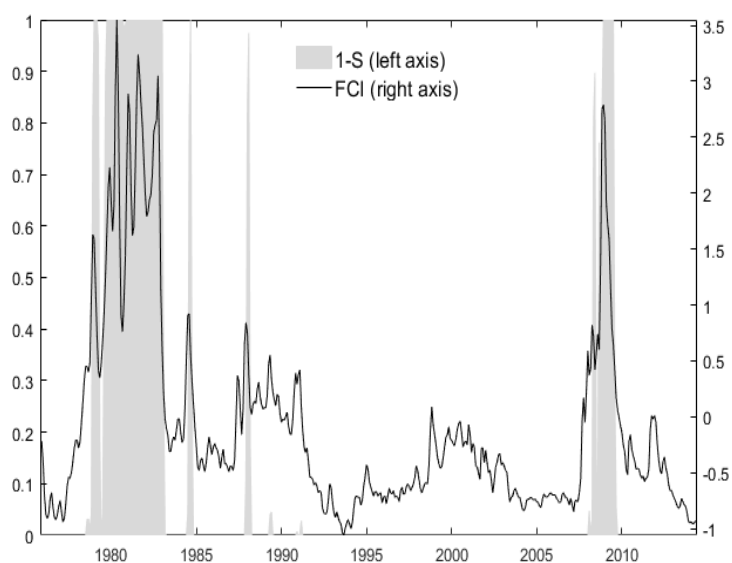


Figure 1: Financial regimes. FCI is the Chicago Fed *Financial Condition Index*. Gray bands identify the subperiods when the US economy is estimated to be in a ‘financial crisis’, defined as a state where the index exceeds the critical threshold in the TAR model of Section 3..

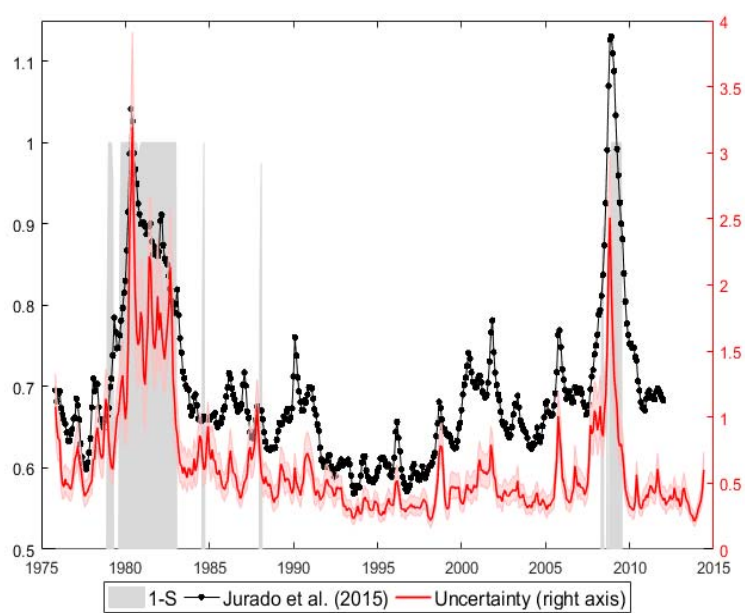


Figure 2: Financial regimes and economic uncertainty. Gray bands denote the financial crises identified by the TAR model discussed in Section 3.. The black line is the uncertainty estimate of Jurado *et al.* (2015). The red line is uncertainty measured as the average volatility of the structural shocks in the US economy according to the TAR model (median estimate and 68% confidence band).

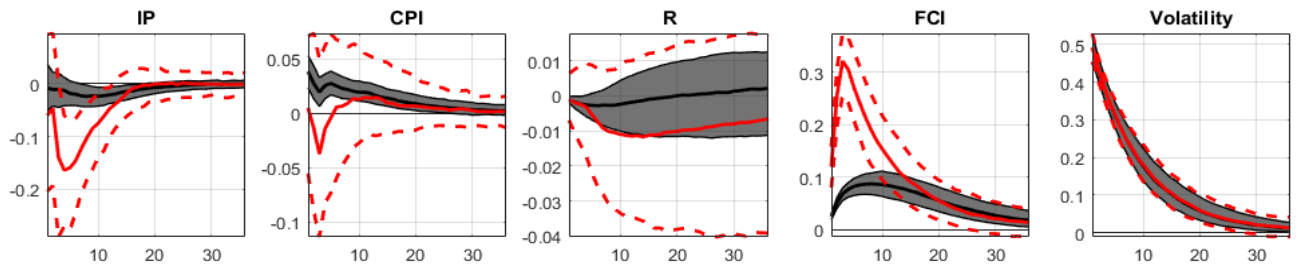


Figure 3: Impact of volatility shocks in good and bad times. The black lines show the impact of a one standard deviation increase in the volatility of the US economy in normal times. The red line shows the impact of the same shock during episodes of financial distress, defined as periods when the Financial Condition Index (FCI) exceeds an endogenously-determined critical threshold (see equation (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.

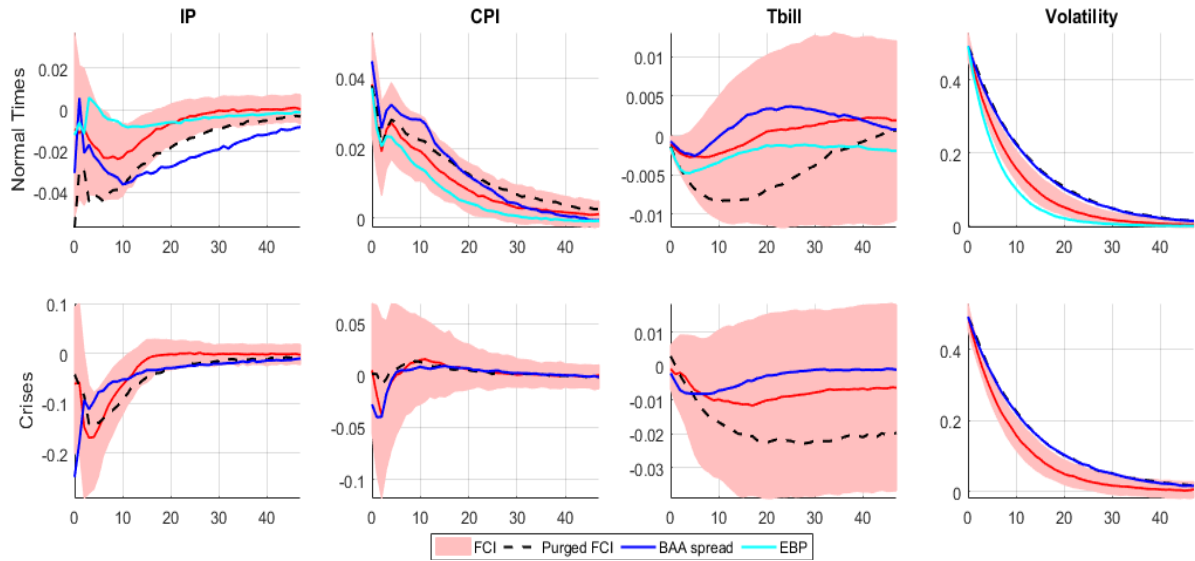


Figure 4: Impact of volatility shocks under alternative financial conditions indicators. The figure shows the response of industrial production growth, consumer price inflation and 3-month T-Bill rate (columns 1 to 3) to a one standard deviation increase in the average volatility of the US economy (column 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 figure 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.

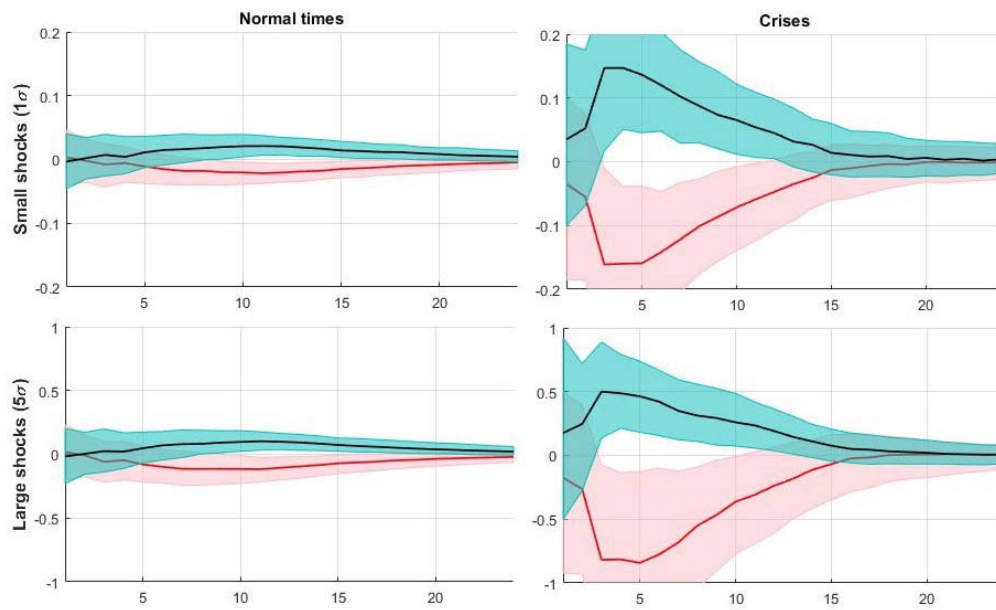


Figure 5: Sign asymmetries. The first row shows the response of US industrial production to a one standard deviation volatility shock in normal times (left column) and in financial crises (right column). Green and red shades represent the 68% confidence bands associated respectively to decreases and 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.

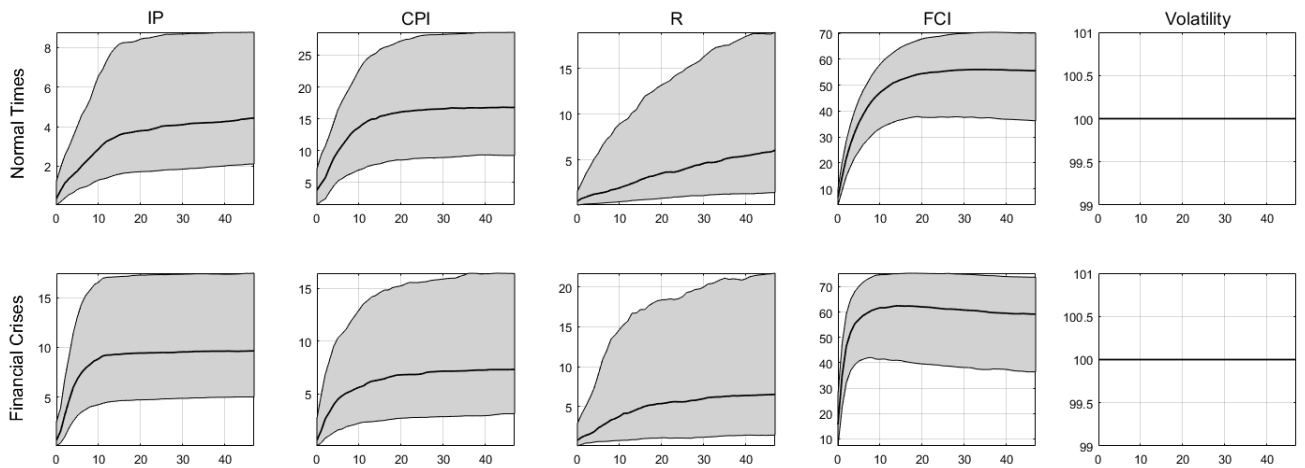


Figure 6: Forecast error variance decomposition. Each panel shows the fraction of forecast error variance explained by volatility shocks for one of the variables included in the Threshold VAR of section 3.. The first row corresponds to calm periods and the second row corresponds to financial crises,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

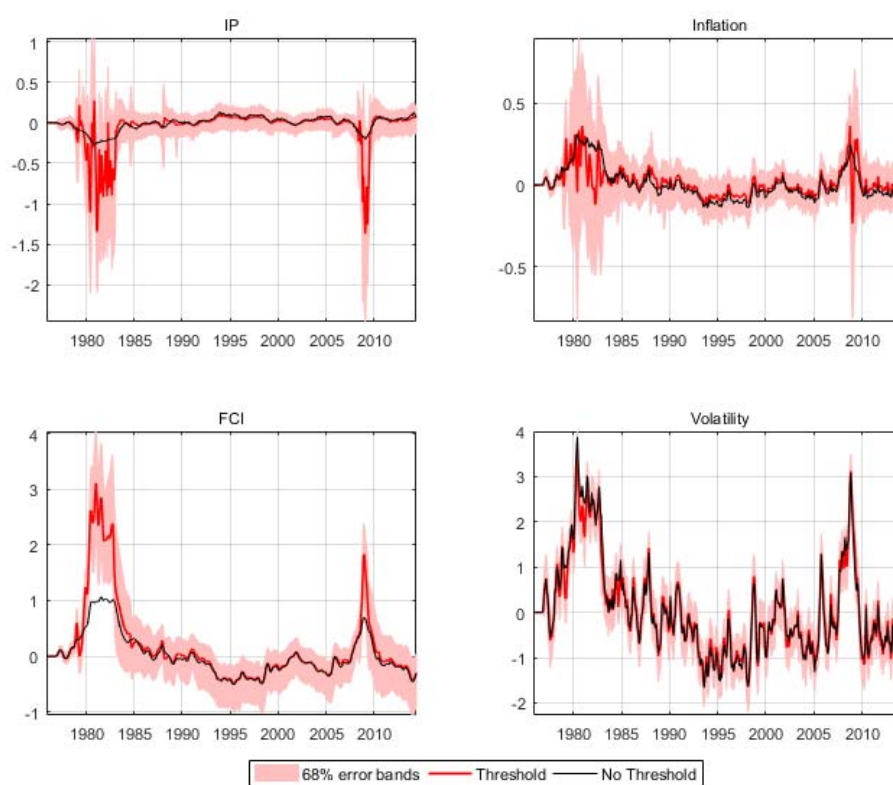


Figure 7: A counterfactual without uncertainty shocks. For each variable, the figure shows the difference between actual data and model-generated series under the assumption of no volatility shocks ($\eta_t = 0$ in equation (4)). The black lines are based on a linear VAR. The red lines and the associated 68% confidence bands are based on a Threshold VAR that separates periods of calm and distressed financial conditions.

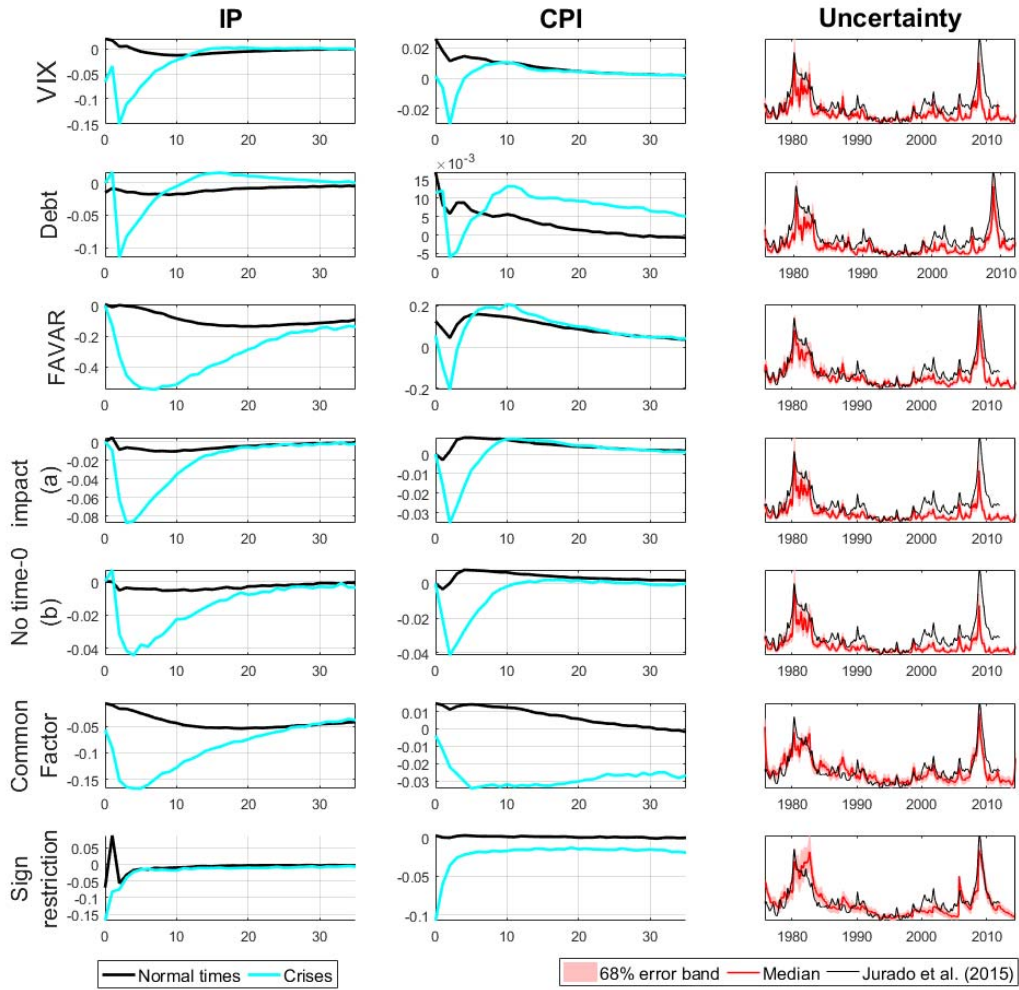


Figure 8: Robustness analysis. Each row refers to an alternative specification of the benchmark TAR model studied in Section 5.1.. For each specification the figure shows the estimated average volatility series (column 3) and the responses of industrial production and inflation to a one-standard-deviation 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.