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Financial regimes and uncertainty shocks.

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Abstract

Financial markets are central to the transmission of uncertainty shocks. This paper documents a new aspect of the interaction between the two by showing that uncertainty shocks have radically different macroeconomic implications depending on the state financial markets are in when they occur. Using monthly US data, we estimate a nonlinear VAR where economic uncertainty is proxied by the (unobserved) volatility of the structural shocks, and a regime change occurs whenever credit conditions cross a critical threshold. An exogenous increase in uncertainty has recessionary effects in both good and bad credit regimes, but its impact on output is estimated to be five times larger when the economy is experiencing financial distress. Accounting for this nonlinearity, uncertainty accounts for about 1% of the peak fall in industrial production observed in the 2007–2009 recession.

Keywords: Uncertainty; Stochastic Volatility; Financial Markets; Threshold VAR.

JEL Classification: C32, E32, E44, G01.

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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 2008 (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 both policy and research debates as an important independent source of economic cycles.[2] There is a clear link between the two: since investors price risk, financial markets naturally seize up when economic uncertainty is high. Indeed, while the role of uncertainty has been traditionally explained by appealing to the existence of real frictions (Bernanke 1993; Bloom 2009, 2014), a recent line of research places financial frictions at the centre of the transmission mechanism (Arellano *et al.*, 2012; Christiano *et al.*, 2014; Caldara *et al.*, 2014; Gilchrist *et al.*, 2014), showing that financial markets are the crucial link in the propagation of uncertainty shocks both in the US and elsewhere.

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 should depend on the intensity of the financial frictions in the economy, and thus it could vary significantly over the cycle under the influence of fluctuations in asset prices and lenders' and borrowers' balance sheet conditions. When private sector balance sheets are sound, the economy might behave as if it were financially unconstrained, shutting down the financial channel. Weak balance sheets and 'thin' financial markets, on the contrary, could boost the transmission mechanism and make the economy highly vulnerable to a marginal increase in uncertainty. To investigate this possibility, we estimate a nonlinear VAR using monthly US data covering the period between January 1973 and May 2014 and study how the response of output and prices 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 economy's structural shocks, which is allowed to affect the model's endogenous variables (Mumtaz and Theodoridis, 2012; Mumtaz and Surico, 2013;

[1] The real implications of financial disturbances are studied by Gilchrist and Zakrajšek (2009, 2012), Nolan and Thoenissen (2009), Gertler and Kiyotaki (2010), Gertler and Karadi (2011), Helbling *et al.* (2011), Perri and Quadrini (2011), Jermann and Quadrini (2012), Meeks (2012), Liu *et al.* (2013) 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 (2008) and Blanchard (2009).

Mumtaz and Zanetti, 2013). In this way we bypass the choice of an observed proxy for uncertainty and use an indicator which is closer to its theoretical counterpart and more directly linked to agents' (in)ability to form predictions on the economy's fundamentals. Second, the model allows for the possibility that the transmission of the shocks may change when financial markets are dysfunctional. To this end, we include in the model an indicator of financial market distress (the Chicago Fed's *Financial Condition Index*, which captures the dynamics of a large set of financial prices and quantities), and let the parameters of the VAR shift when the indicator 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 they have an output multiplier which is roughly five 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 1% of the peak fall in output observed in the Great Recession.[3] These results provide new evidence on the pivotal role played by financial markets in propagating (or not) uncertainty shocks. They also point to an important complication that must be taken into account when studying the role and relative importance of financial and uncertainty shocks in causing macroeconomic fluctuations: the two are not easily separable, because uncertainty becomes more relevant if/when the economy has previously been subjected to a sequence of adverse financial shocks. The Great Recession provides a powerful illustration of this issue. Finally they suggest that, even though uncertainty shocks constitute an independent source of economic volatility, it could be sensible for policy makers to focus on monitoring and possibly ameliorating credit conditions rather than worrying about uncertainty *per se*.

[3] In a related paper, Caggiano et al. (2014) study a model where the transmission mechanism is linked to the real rather than the financial cycle, finding on post-WWII US data that uncertainty shocks appear to be more powerful during recessions. We discuss the relation between our work and theirs' at length in sections 2 and 4.

The remainder of the paper is organized as follows. Section 2 reviews the literature and discusses the logic behind, and some evidence of, the interaction between financial markets and uncertainty studied in this paper. Section 3 discusses model, data and estimation. Section 4 illustrates the results. Section 5 examines the robustness of the results to a number of modelling assumptions. Section 6 presents some concluding remarks.

2 Literature

Economic uncertainty is known to be strongly countercyclical (see Bloom (2014) for a recent survey of the evidence). This correlation is typically rationalized as the consequence of the recessionary effect of uncertainty shocks.[4] The traditional view of this transmission mechanism relies on some form of partial irreversibility in investment. Irreversibility generates a *wait-and-see* effect by which firms may optimally choose to postpone investment in the face of a more volatile environment (Bernanke, 1983; Bloom, 2009; Bloom *et al.,* 2012). A more recent strand of research places financial rather than real frictions at the centre of the transmission mechanism (Arellano *et al.*, 2012; Christiano *et al.*, 2014; Gilchrist *et al.*, 2014).[5] If financial contracts are subject to agency or moral hazard problems, a rise in economic uncertainty increases the premium on external finance, leading to an increase in the cost of capital faced by firms (or borrowers more generally) and thus a fall in investment. The 'financial view' of the transmission mechanism has two related implications. The first one is that changes in asset prices and credit aggregates are the crucial link in the transmission of uncertainty shocks to the real economy. The second one is that the strength of the transmission mechanism is tightly linked to the intensity of frictions in financial markets. Using a quantitative model that includes a rich set of real and financial frictions, Gilchrist *et al.* (2014) show that uncertainty has a modest impact on economic activity in a financially frictionless economy. A similar message is delivered by Pinter *et al.* (2013), who find that the impact of uncertainty shocks

[4]We limit our discussion to set-ups where (i) uncertainty, risk and volatility are synonyms (i.e. uncertainty is defined as, and assumed to coincide with, the actual volatility of some economic fundamental, either at the aggregate or at the firm level); and (ii) causation runs from uncertainty to economic activity. Departures from these hypotheses are examined for instance by Ilut and Schneider (2014) and Bachmann and Moscarini (2012).

[5]The real/financial divide sketched here is of course a stark simplification of the views that have been put forward on the topic. Villaverde *et al.* (2011b) develop a small-open-economy model where uncertainty appears in the form of heteroscedastic shocks to the real exogenous borrowing rate and affects real aggregates because of a hedging motive. Basu and Bundick (2012) study uncertainty in a model without either real or financial frictions, showing that nominal frictions and countercyclical markups are important to generate plausible business cycle dynamics after an uncertainty shock.

on output is an increasing function of the fraction of hand-to-mouth consumers in the economy (a proxy of financial market imperfections); and by Carriere-Swallow and Cespedes (2013), whose comparative analysis shows that uncertainty shocks are relatively more powerful in countries with underdeveloped financial markets.

This paper examines the implications of the 'financial view' of the transmission mechanism along a different dimension, asking 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, while 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, which in turn may change significantly over time under the influence, for instance, of fluctuations in real and financial asset prices. When balance sheets are sound and credit abundant, the US economy might resemble the frictionless benchmarks studied as limiting cases by Gilchrist *et al.* (2014) and Pinter *et al.* (2012), where the dynamics associated to uncertainty shocks are relatively subdued. Strained balance sheets, low asset prices and 'thin' financial markets would on the contrary make the economy highly vulnerable to a marginal increase in uncertainty.[6] Models where agents face occasionally binding borrowing or collateral constraints offer a natural way to think about this form of state-dependence (Mendoza and Smith, 2006; Mendoza, 2010; Bianchi and Mendoza 2010; Bianchi, 2011; He and Krishnamurty 2012, 2013; Brunnermeier and Sannikov, 2014). In these economies agents save to avoid being constrained in equilibrium, and strong non-linearities arise when unexpected shocks push them close to the constraint. A number of authors have documented the empirical relevance of this mechanism by showing that credit conditions can significantly alter the transmission of both real and financial shocks (McCallum, 1991; Balke, 2000; Guerrieri and Iacoviello, 2013). Our paper contributes to this literature by showing that credit conditions also exert a critical influence on the transmission of uncertainty shocks.

A number of studies have employed VAR frameworks to study the relation between uncertainty and economic activity (a non-exclusive list would include Bloom 2009; Leduc and Zheng, 2012; Bachmann *et al.* 2013; Carriero *et al.*, 2013; Mumtaz and Surico, 2013; Bulligan and Emiliozzi, 2014). These works do not consider uncertainty and financial shocks jointly. A first attempt in this direction is Popescu and Smets (2010), who use a VAR with a recursive

[6] A cyclicality of this kind is unlikely to arise under the 'real view' of the transmission mechanism, because in that case the underlying frictions are linked to technology and hence very likely to be fixed over time.

identification scheme where uncertainty is ordered before an index of financial market conditions, finding that financial shocks are an important driver of real output whereas the impact of uncertainty shocks is small and short-lived. Gilchrist *et al.* (2014) show that uncertainty and credit spreads are strongly correlated and that the predictive power of uncertainty for output is significantly eroded if credit conditions are separately accounted for. The identification of credit and uncertainty shocks is the focus of Caldara *et al.* (2014). The authors demonstrate that uncertainty shocks affect output if and only if credit spreads are allowed to respond contemporaneously to a change in uncertainty; the impact vanishes if this channel is switched off by the identification strategy, which provides further evidence in support of the 'financial view' of the transmission mechanism. We follow the same line of analysis, but focus on modelling a potential interaction between financial conditions and uncertainty which is ruled out by construction in the linear set ups of Popescu and Smets (2010) and Caldara *et al.* (2014).

The empirical evidence regarding time variation or state dependence in the transmission of uncertainty shocks is relatively scant. Beetsma and Giuliodori (2012) estimate linear VARs using rolling windows and show that the impact of uncertainty shocks on output in the US has decreased over the last five decades. Caggiano *et al.* (2014) use instead a Smooth-Transition VAR where the parameters are allowed to depend on the state of the business cycle. The model is estimated on quarterly post-war data for the US, and it suggests that uncertainty shocks have a stronger impact on unemployment during recessions. Neither of these works models the interdependence between uncertainty and financial conditions. If the 'financial view' of the transmission channel is valid, this interdependence is obviously crucial. To the best of our knowledge, this paper represents the first attempt to describe it explicitly in a nonlinear model. The comparison between our work and Caggiano *et al.* (2014) poses of course an important question: assuming the transmission mechanism does change over time, is the change driven by the state of the real or the financial cycle? The close association typically observed in the data between high uncertainty, credit contractions and slow growth makes this a difficult question to answer, but we provide evidence that the 'financial hypothesis' receives stronger support from the data.

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

(Beetsma and Giuliodori, 2012) or the VIX index (Caggiano *et al.*, 2014), we measure uncertainty as the average volatility of the economy's structural shocks, which in our framework can be estimated directly from the data. This measure is closer to its theoretical counterpart and it is more directly related to the overall predictability of the economic environment. As Jurado *et al.* (2013) argue, economic predictability is the key factor for decision making, and it has no obvious relation with many of the proxies commonly used in the empirical literature.[7] The idea of using a single volatility process in a multivariate model has been introduced by Carriero *et al.* (2012), while volatility-in-mean effects are studied in the context of (otherwise) linear VAR models by Mumtaz and Theodoridis (2012), Mumtaz and Surico (2013) and Mumtaz and Zanetti (2013). The combination of stochastic volatility and regime switches is a novelty of our approach.

3 A VAR with financial regimes and volatility effects

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 endogenous variables (Mumtaz and Theodoridis, 2012; Mumtaz and Surico, 2013; Mumtaz and Zanetti, 2013). The model 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:

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

Here $Z_t = \{Y_t, P_t, R_t, F_t\}$ is a set of four endogenous variables: industrial production growth, consumer price inflation, the three-month Treasury Bill rate and the *Financial Condition Index*, an indicator of financial distress published by the Chicago Fed (the data is described in Section 3.2). Uncertainty is represented by λ_t, which is defined below. We allow for the

[7] We discuss these points further in Section 3, and provide a comparison between our estimate of uncertainty and that by Jurado et al. (2013) in Section 4.

possibility of two distinct regimes, and consider the case where the regime is determined by the level of some lag of the financial indicator F_{t-d} relative to an unobserved threshold Z^*:

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

Both the delay d and the threshold Z^* are unknown parameters. As in standard threshold models, all parameters are allowed to change across regimes. In particular:

$$\begin{aligned} \Omega_{1t} &= A_1^{-1} H_t A_1^{-1\prime} \\ \Omega_{2t} &= A_2^{-1} H_t A_2^{-1\prime}, \end{aligned} \tag{3}$$

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.* (2012), we thus assume that a single, scalar volatility process λ_t drives time variation of the entire variance-covariance matrix of the structural shocks, and we take that process to represent economic uncertainty. We set $P = 13$, a standard choice with monthly data, and $J = 3$, which means that the state of the economy in month t may be affected by levels of uncertainty that prevailed over the current quarter.

The novelty of this set up is its combination of a smoothly-changing volatility process (equation 4) with shifts in regimes associated to periods of financial distress (equations 1–2). This combination allows us to remain close to the theoretical literature on uncertainty, which typically postulates a process of the form of (4) for some of the shocks, while taking into account a state-dependent transmission mechanism consistent with models that incorporate occasionally binding financial constraints. The model nests both a linear VAR with volatility effects and a TAR without volatility effects, both of which provide useful benchmarks for our analysis. 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 financial constraints, and no restriction is placed on how the primitive shocks e_t and η_t play out in different regimes. As equation (4) shows, uncertainty is directly linked to agents' difficulty in forecasting the economy's fundamentals. Intuitively, a volatility/uncertainty shock $\eta_t > 0$ raises λ_t, causing an upward shift in the 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 equation (1), we allow for the possibility that consumption and investment choices, asset prices and monetary policy may adjust endogenously to the new, riskier state of the economy.

We note that the specification of equation (4) implies that uncertainty is associated to the *average* volatility of the structural shocks, in the sense that (i) all structural shocks are implicitly given the same weight in estimating λ_t, and (ii) common and idiosyncratic (i.e. shock-specific) volatilities are treated symmetrically (both can influence λ_t). This formulation is computationally convenient and is consistent with the approach suggested by Jurado *et al.* (2013). As a matter of fact, our estimates of uncertainty turn out to be very similar to theirs', as we show in Section 4. In principle one could take a different stance and think of economic uncertainty specifically as the *common* factor behind changes in the covariance matrix. In that case, one would filter out any idiosyncratic variation in the volatilities and allow for shock-specific loadings in order to estimate λ_t. We consider this alternative in Section 5, and find that the difference are immaterial from our point of view. Irrespective of how λ_t is defined, the volatility-in-mean specification employed in this paper has an important advantage: it permits modeling the economy's first and second moments in a unified, internally-consistent framework. In this model, agents form the expectation $E_t Z_{t+k}$ taking into account both the persistence of λ_t (if $F \neq 0$) and its effect on Z_t (if $\gamma_{ij} \neq 0$ for some i, j), and this expectation is integrated out in the impulse-response analysis. We regard this as a significant conceptual improvement relative to two-steps procedures of the type employed in Jurado *et al.* (2013).[8]

[8] The two steps in Jurado et al. (2013) are the following. First, uncertainty ($\mathcal{U}_t$ in their notation) is calculated from the forecast errors for a set of macro-financial indicators ($\mathcal{Y}_{t+k}$), using a forecasting model and an information set that does not (and by construction cannot) include $\mathcal{U}_t$ itself. Second, the impact of uncertainty shocks is studied in a VAR in $[\mathcal{Y}_t \;\; \mathcal{U}_t]$, where macro-financial variables and uncertainty interact. The problem with this is that while the first step assumes that $\mathcal{U}_t$ does not affect $E_t\mathcal{Y}_{t+k}$, the second investigates precisely this linkage.

3.2 Data

We use monthly data covering the period 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 (FRED) Database. To capture the state of financial markets in the US we use the *Financial Condition Index (FCI),* a real-time indicator of financial distress constructed and maintained by the Chicago Fed and described extensively in Brave and Butters (2011, 2012). 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. Its generality is particularly useful in our application, for two related reasons. The first one is that, since uncertainty shocks can affect firms' through a number of different markets, using a broad indicator is necessary in order to fully capture the financial side of the transmission mechanism. In particular, FCI includes spreads on bank funding, bonds, repo, swap and securitization markets, all of which could in principle influence firms' access to external finance. The index also includes volume and quantity indicators which could be important to capture forms of credit rationing that are not fully reflected in prices. The second related reason is that, given the strong unconditional correlation between economic uncertainty and financial conditions documented in the literature, controlling accurately for the general state of financial markets is important in order to isolate the role played by uncertainty shocks – a point that emerges clearly from both Caldara *et al.* (2014) and Gilchrist *et al.* (2014). A narrow indicator might pick up only some of the variation in aggregate financing conditions; if the part that is left out is correlated with uncertainty, which is likely, this could cause the model to overestimate the importance of the latter. By using FCI we hope instead to quantify the impact of uncertainty 'net' of all financial information available to the agents at any point in time.[9]

3.3 Estimation

This section describes the priors and the algorithm used to estimate the model. Following Banbura *et al.* (2010) we introduce a natural conjugate prior for the VAR parameters $B_i = \{c_i, \beta_i\}$ via dummy observations. In our application, the prior means are chosen as the OLS

[9] A third advantage is that by using FCI we effectively turn our VAR into a factor model that exploits a large information set, thus reducing the risk of uncovering spurious non-linearities caused by the omission of relevant variables. We investigate this issue further in Section 5.

estimates of the coefficients of an AR(1) regression estimated for each endogenous variable using a training sample. As is standard for US data, we set the overall prior tightness $\tau = 0.1$. For the threshold we assume a normal prior, $P(Z^*)\tilde{}N(\bar{Z}, \bar{V})$ where $\bar{Z} = 1/T\sum_{i=1}^{T} Z_t$ and $\bar{V} = 10$. Given the scale of the financial indicator this represents a fairly loose prior. We assume a flat prior on the delay d but limit its values between 1 and 12. The elements of S have an inverse Gamma prior: $P(s_i)\tilde{}IG(S_{0,i}, V_0)$. The degrees of freedom V_0 are set equal to one. The prior scale parameters are set by estimating the following regression: $\bar{\lambda}_{it} = S_{0,i}\bar{\lambda}_t + \varepsilon_t$ where $\bar{\lambda}_t$ is the first principal component of the stochastic volatilities $\bar{\lambda}_{it}$ obtained using a univariate stochastic volatility model for the residuals of each equation of a VAR estimated via OLS using the endogenous variables Z_t. The prior for the off-diagonal elements A_1 and A_2 is $A_0 \sim N\left(\hat{a}^{ols}, V\left(\hat{a}^{ols}\right)\right)$ where $\hat{a}^{ols}$ are the off-diagonal elements of the inverse of the Cholesky decomposition of $\hat{v}^{ols}$, with each row scaled by the corresponding element on the diagonal. These OLS estimates are obtained using the initial VAR model described above. $V\left(\hat{a}^{ols}\right)$ is assumed to be diagonal with the elements set equal to 10 times the absolute value of the corresponding element of $\hat{a}^{ols}$. We set a normal prior for the unconditional mean of the log-volatility, $\mu = \alpha/(1-F)$. This prior is $N(\mu_0, Z_0)$ where $\mu_0 = 0$ and $Z_0 = 10$.The prior for Q is $IG\left(Q_0, V_{Q0}\right)$ where Q_0 is the average of the variances of the transition equations of the initial univariate stochastic volatility estimates and $V_{Q0} = 5$. The prior for F is $N\left(F_0, L_0\right)$ where $F_0 = 0.8$ and $L_0 = 1$.

The MCMC algorithm for the estimation is based on drawing from the following conditional posterior distributions:

1. $G(Z^*\backslash\Xi)$. Following Chen and Lee (1995) we use a random walk metropolis step to draw Z^*. We draw a candidate value Z^*_{new} from $Z^*_{new} = Z^*_{old} + \Psi^{1/2}\epsilon$, $\epsilon\tilde{}N(0,1)$. The acceptance probability is given by $\frac{f(Z_t\backslash Z^*_{new},\Xi)}{f\left(Z_t\backslash Z^*_{old},\Xi\right)}$ where $f\left(.\right)$ denotes the posterior density and Ξ represents all other parameters in the model. We choose the scaling factor Ψ to ensure that the acceptance rate remains between 20% and 40%. The posterior density is given by $L\left(Z_t\backslash\Xi\right) \times P\left(Z^*\right)$ where the likelihood function is the product of the log likelihoods in the two regimes. The calculation of the likelihood is described in the appendix to Carriero *et al.* (2012).

2. $G(d\backslash\Xi)$. Chen and Lee (1995) show that the conditional posterior for d is a multinomial distribution with probability $\frac{L(Z_t\backslash d,\Xi)}{\sum_{d=1}^{12} L(Z_t\backslash d,\Xi)}$ where $L\left(.\right)$ denotes the likelihood function.

3. $G(B_i \backslash \Xi)$.Given a draw of λ_t, the left and the right hand side variables of the VAR: y_t and x_t can be transformed to remove the heteroscedasticity in the following manner

$$\tilde{y}_t = \frac{y_t}{\lambda_t^{1/2}}, \tilde{x}_t = \frac{x_t}{\lambda_t^{1/2}}$$

Then the conditional posterior distribution for the VAR coefficients in each regime is standard and given by

$$N(B_i^*, \bar{\Omega}_i \otimes (X_i^{*\prime} X_i^*)^{-1})$$

where $B_i^* = (X_i^{*\prime} X_i^*)^{-1} (X_i^{*\prime} Y_i^*)$, $\bar{\Omega}_i = A_i^{-1} S A_i^{-1\prime}$ and Y_i^* and X_i^* denote the transformed data in regime i appended with the dummy observations.

4. $G(A_i \backslash \Xi)$. Given a draw for the VAR parameters and the threshold the model in each regime can be written as $A_i' (v_{it}) = e_{it}$ where $v_{it} = Z_{it} - c_i + \sum_{j=1}^{P} \beta_{ij} Z_{it-j} + \sum_{j=0}^{J} \gamma_{ij} \ln \lambda_{t-j}$ and $VAR(e_t) = H_t$. This is a system of linear equations with a known form of heteroscedasticity. The conditional distributions for a linear regression apply to each equation of this system after a simple GLS transformation to make the errors homoscedastic. The jth equation of this system is given as $v_{jt} = -\alpha v_{-jt} + e_{jt}$ where the subscript j denotes the jth column while $-j$ denotes columns 1 to $j-1$. Note that the variance of e_{jt} is time-varying and given by $\lambda_t s_j$. A GLS transformation involves dividing both sides of the equation by $\sqrt{\lambda_t s_j}$ to produce $v_{jt}^* = -\alpha v_{-jt}^* + e_{jt}^*$ where * denotes the transformed variables and $var\left(e_{jt}^*\right) = 1$. The conditional posterior for α is normal with mean and variance given by M^* and V^* :

$$\begin{aligned}
M^* &= \left(V\left(\hat{a}^{ols}\right)^{-1} + v_{-jt}^{*\prime} v_{-jt}^*\right)^{-1} \left(V\left(\hat{a}^{ols}\right)^{-1} \hat{a}^{ols} + v_{-jt}^{*\prime} v_{jt}^*\right) \\
V^* &= \left(V\left(\hat{a}^{ols}\right)^{-1} + v_{-jt}^{*\prime} v_{-jt}^*\right)^{-1}
\end{aligned}$$

5. $G(S \backslash \Xi)$. Given a draw for the VAR parameters and the threshold the model in can be written as $(A_1' (v_{1t})) \tilde{S} + (A_2' (v_{2t})) (1 - \tilde{S}) = e_t$. The j^{th} equation of this system is given by $v_{jt} = (-\alpha_1 v_{-jt}) \tilde{S} + (-\alpha_1 v_{-jt}) (1 - \tilde{S}) + e_{jt}$ where the variance of e_{jt} is time-varying and given by $\lambda_t s_j$. Given a draw for λ_t this equation can be re-written as $\bar{v}_{jt} = (-\alpha_1 \bar{v}_{-jt}) \tilde{S} + (-\alpha_1 \bar{v}_{-jt}) (1 - \tilde{S}) + \bar{e}_{jt}$ where $\bar{v}_{jt} = \frac{v_{jt}}{\lambda_t^{1/2}}$ and the variance of $\bar{e}_{jt}$ is s_j. The conditional posterior is for this variance is inverse Gamma with scale parameter

$\bar{e}'_{jt}\bar{e}_{jt} + S_{0,j}$ and degrees of freedom $V_0 + T$.

6. Elements of λ_t. Conditional on the VAR coefficients, the regime variable $\tilde{S}$ and the parameters of the transition equation, the model has a multivariate non-linear state-space representation. Carlin *et al.* (1992) show that the conditional distribution of the state variables in a general state-space model can be written as the product of three terms:

$$\tilde{h}_t \backslash Z_t, \Xi \propto f\left(\tilde{h}_t \backslash \tilde{h}_{t-1}\right) \times f\left(\tilde{h}_{t+1} \backslash \tilde{h}_t\right) \times f\left(Z_t \backslash \tilde{h}_t, \Xi\right) \tag{5}$$

where Ξ denotes all other parameters and $\tilde{h}_t = \ln \lambda_t$. In the context of stochastic volatility models, Jacquier *et al.* (1994) show that this density is a product of log normal densities for λ_t and λ_{t+1} and a normal density for Z_t.Carlin *et al.* (1992) derive the general form of the mean and variance of the underlying normal density for $f\left(\tilde{h}_t \backslash \tilde{h}_{t-1}, \tilde{h}_{t+1}, \Xi\right) \propto f\left(\tilde{h}_t \backslash \tilde{h}_{t-1}\right) \times f\left(\tilde{h}_{t+1} \backslash \tilde{h}_t\right)$ and show that this is given as

$$f\left(\tilde{h}_t \backslash \tilde{h}_{t-1}, \tilde{h}_{t+1}, \Xi\right) \sim N\left(B_{2t}b_{2t}, B_{2t}\right) \tag{6}$$

where $B_{2t}^{-1} = Q^{-1} + F'Q^{-1}F$ and $b_{2t} = \tilde{h}_{t-1}F'Q^{-1} + \tilde{h}_{t+1}Q^{-1}F$. Note that due to the non-linearity of the observation equation of the model an analytical expression for the complete conditional $\tilde{h}_t \backslash Z_t, \Xi$ is unavailable and a metropolis step is required. Following Jacquier *et al.* (1994) we draw from 5 using a date-by-date independence metropolis step using the density in 6 as the candidate generating density. This choice implies that the acceptance probability is given by the ratio of the conditional likelihood $f\left(Z_t \backslash \tilde{h}_t, \Xi\right)$ at the old and the new draw. To implement the algorithm we begin with an initial estimate of $\tilde{h} = \ln \bar{\lambda}_t$ We set the matrix $\tilde{h}^{old}$ equal to the initial volatility estimate. Then at each date the following two steps are implemented:

(a) Draw a candidate for the volatility $\tilde{h}_t^{new}$ using the density 5 where $b_{2t} = \tilde{h}_{t-1}^{new}F'Q^{-1} + \tilde{h}_{t+1}^{old}Q^{-1}F$ and $B_{2t}^{-1} = Q^{-1} + F'Q^{-1}F$

(b) Update $\tilde{h}_t^{old} = \tilde{h}_t^{new}$ with acceptance probability $\frac{f\left(Z_t \backslash \tilde{h}_t^{new}, \Xi\right)}{f\left(Z_t \backslash \tilde{h}_t^{old}, \Xi\right)}$ where $f\left(Z_t \backslash \tilde{h}_t, \Xi\right)$ is the likelihood of the VAR for observation t and defined as $|\Omega_t|^{-0.5} - 0.5 \exp\left(\tilde{e}_t \Omega_t^{-1} \tilde{e}'_t\right)$ where $\tilde{e}_t = Z_t - [(c_1 + \sum_{j=1}^{P} \beta_{1j} Z_{t-j} + \sum_{j=0}^{J} \gamma_{1j} \tilde{h}_{t-j} + \Omega_{1t}^{1/2} e_t)\tilde{S}_t + (c_2 + \sum_{j=1}^{P} \beta_{2j} Z_{t-j} +$

$\sum_{j=0}^{J}\gamma_{2j}\tilde{h}_{t-j}+\Omega_{2t}^{1/2}e_t)(1-\tilde{S}_t)]$ and $\Omega_{it}=A_i^{-1}\left(\exp(\tilde{h}_t)S\right)A_i^{-1\prime}$.

Repeating these steps for the entire time series delivers a draw of the stochastic volatilities.[10]

7. $G(\alpha, F\backslash\Xi)$.We re-write the transition equation in deviations from the mean

$$\tilde{h}_t-\mu=F\left(\tilde{h}_{t-1}-\mu\right)+\eta_t \tag{7}$$

where the elements of the mean vector μ_i are defined as $\frac{\alpha_i}{1-F_i}$. Conditional on a draw for $\tilde{h}_t$ and μ the transition equation 7 is a simply a linear regression and the standard normal and inverse Gamma conditional posteriors apply. Consider $\tilde{h}_t^*=F\tilde{h}_{t-1}^*+\eta_t, VAR\left(\eta_t\right)=Q$and $\tilde{h}_t^*=\tilde{h}_t-\mu, \tilde{h}_{t-1}^*=\tilde{h}_{t-1}-\mu$. The conditional posterior of F is $N\left(\theta^*, L^*\right)$ where

$$\begin{aligned}
\theta^* &= \left(L_0^{-1}+\frac{1}{Q}\tilde{h}_{t-1}^{*\prime}\tilde{h}_{t-1}^*\right)^{-1}\left(L_0^{-1}F_0+\frac{1}{Q}\tilde{h}_{t-1}^{*\prime}\tilde{h}_t^*\right)\\
L^* &= \left(L_0^{-1}+\frac{1}{Q}\tilde{h}_{t-1}^{*\prime}\tilde{h}_{t-1}^*\right)^{-1}
\end{aligned}$$

The conditional posterior of Q is inverse Gamma with scale parameter $\eta_t'\eta_t+Q_0$ and degrees of freedom $T+V_{Q0}$.

Given a draw for F, equation 7 can be expressed as $\bar{\Delta}\tilde{h}_t=C\mu+\eta_t$ where $\bar{\Delta}\tilde{h}_t=\tilde{h}_t-F\tilde{h}_{t-1}$ and $C=1-F$. The conditional posterior of μ is $N\left(\mu^*, Z^*\right)$ where

$$\begin{aligned}
\mu^* &= \left(Z_0^{-1}+\frac{1}{Q}C'C\right)^{-1}\left(Z_0^{-1}\mu_0+\frac{1}{Q}C'\bar{\Delta}\tilde{h}_t\right)\\
Z^* &= \left(Z_0^{-1}+\frac{1}{Q}C'C\right)^{-1}
\end{aligned}$$

Note that α can be recovered as $\mu\left(1-\theta\right)$.

4 Results

Figure 1 shows the Financial Condition Index and the associated regimes. Gray bands identify periods when the index is above the estimated critical threshold Z^*, implying that

[10] In order to take endpoints into account, the algorithm is modified slightly for the initial condition and the last observation. Details of these changes can be found in Jacquier et al. (1994).

the US economy is experiencing financial distress. We refer to this as the 'crisis' regime, or regime 2. Figure 2 reproduces our estimate of $\hat{\lambda}_t$ together with the measure of economic uncertainty calculated by Jurado *et al.* (2013). The correlation between the two series is very strong. This result is not too surprising given that the key assumptions behind our approach to the measurement of uncertainty are essentially the same, as explained in Section 3. It also suggests that the common volatility of the (relatively small) set of variables included in our model provides a credible description of overall economic uncertainty, which Jurado *et al.* (2013) estimate using a much larger dataset. Taken together, figures 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. The figures also provide a powerful illustration of the reason why controlling for the price and availability of credit is so important in this context: any model that studies the correlation between uncertainty and output without conditioning on credit conditions is bound to exaggerate the impact of uncertainty on output. According to both our estimates and Jurado *et al.* (2013), economic uncertainty was highest in the early 1980s and in 2007-2009. Both periods coincided with peaks in the financial distress index (as figure 1 shows, they are estimated to be occurrences of the crisis regime), and both were associated to contractions in real output. A different pattern emerges however in the early 1990s and early 2000s recession. In those periods economic activity was stagnant but financial conditions were mild and uncertainty relatively low, particularly according to our measure. This partial decoupling of real and financial cycle is useful because it may provide information on whether the nature of the transmission mechanism for uncertainty depends on the state of the real or the financial cycle – we return to this point in Section 5.

Figure 3 plots the response of the system to both positive and negative one-standard-deviation uncertainty shocks.[11] The two rows show the responses corresponding respectively to normal periods and crises. As the last column of the figure shows, the dynamics of our measure of uncertainty λ_t are identical in the two regimes (the stochastic volatility process is not regime-dependent, see equation (4)). In both regimes, an increase in uncertainty leads to a financial tightening (column 4) and a contraction in output (column 1). The two responses however are much more pronounced in the crisis regime. In particular, the fall in output is

[11] The impulse responses are obtained using monte carlo integration as described in Koop, Pesaran and Potter (1995). In particular, the responses are calculated as $IRF_t^S = E\left(Y_{t+k} \backslash \Psi_t, Y_{t-1}^s, \mu\right) - E\left(Y_{t+k} \backslash \Psi_t, Y_{t-1}^s\right)$, where Ψ_t denotes all the parameters and hyperparameters of the model, k is the horizon under consideration, $S = 0, 1$ denotes the regime and μ denotes the shock. All expectations are calculated by simulation.

roughly six times larger: –0.17% *versus* –0.025%. The key prediction of the 'financial view' of the transmission mechanism is thus supported by the data: uncertainty shocks are relatively inconsequential under good market conditions, when agents are financially unconstrained, but their impact on both credit markets and economic activity is greatly amplified during episodes of financial distress, when borrowing constraints bind more severely.

As the second column of figure 3 shows, the response of inflation also changes dramatically across regimes. In normal times prices increase after an increase in uncertainty, whereas in a crisis they fall.[12] The literature offers mixed evidence on the relation between uncertainty and inflation. Uncertainty shocks are deflationary for instance in the models of Christiano *et al.* (2014) and Leduc and Zheng (2014), where they act as aggregate demand shocks, but they are inflationary in Villaverde *et al.* (2011a) and Mumtaz and Theodoridis (2012). In the latter cases, high uncertainty on future demand and marginal costs makes it costly for firms to underprice their products, and this introduces a (precautionary) upward bias in their pricing decisions. One interpretation for our result is that this precautionary mechanism prevails in good times but is dominated by the standard demand channel in bad times, when binding borrowing constraints make aggregate demand relatively more sensitive to economic uncertainty. Such a shift in the relative strength of the two factors could be reinforced by the mechanism studied by Vavra (2014). Using an S-s pricing model, Vavra (2014) shows that when firm-level volatility is high firms are more likely to be pushed outside their range of pricing inaction by the shocks that hit them, so that price adjustments are more frequent (and nominal rigidities overall less relevant) compared to periods of low volatility. Hence, it is possible that the precautionary motive is more feeble in a crisis because firms know that prices will change more frequently and are less worried about the risk of committing to a predetermined price level for too long.[13] We leave a more formal examination of these speculations to future research. The response of the interest rate appears highly uncertain, but the difference between regimes is qualitatively intuitive in the light of the discussion above.

[12] As figure 3 shows, inflation 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 5).

[13] This conjecture relies on two premises. The first one is that the crisis regime tends to be associated to periods of high aggregate uncertainty as well as heightened financial tensions. This is a fairly uncontroversial implication of the strong link between uncertainty and financial markets documented in the literature and confirmed by figures 1-2. The second one is that aggregate and firm-level uncertainty are also correlated (see *e.g.* Bloom, 2014). This means that most of our 'crises' also coincide with periods of high firm-level uncertainty, which makes the mechanism studied by Vavra (2014) potentially relevant in interpreting our results.

In a crisis both output and prices fall after an increase in uncertainty, so monetary policy can work countercyclically and interest rates drop, in the sense that most of the distribution of R_t lies below the zero line. In normal times instead the shock generates stagflation, and monetary policy appears to respond mainly to the increase in inflation: most of the distribution of R_t lies above the zero line. The confidence bands, however, are very large in both regimes. This suggests that historically there has been no systematic reaction by the Fed to variations in uncertainty.[14]

The responses are symmetric for small and medium-size volatility shocks, but sign asymmetry appears for larger shocks. Figure 4 displays the response of the system to a five standard deviation shock. The responses remain broadly symmetric in normal times (row 1), but are clearly asymmetric in the crisis regime (row 2). In a crisis, a fall in volatility leads to a smaller variation in output and prices than an equivalent increase in volatility. A similar form of asymmetry between positive and negative uncertainty shocks is documented by Foerster (2014). According to our model, this asymmetry is an implication of (i) the strong link that connects volatility and financial markets and (ii) the state-contingent nature of the frictions that affect the latter. An increase in volatility in bad times essentially keeps the economy in a state where financial markets are tense and the 'volatility multiplier' is large. A fall in volatility, on the other hand, generates a decline in financial distress which may push the economy back into a regime where borrowing constraints bind less and the multiplier is lower because output is less sensitive to both uncertainty and credit conditions.

Figure 5 shows the contribution of volatility shocks to the forecast error variances (FEV) of all endogenous variables. The fraction of output variance accounted for by volatility shocks is twice as big in the crisis regime: approximately 8% versus 4%. These results are broadly consistent with those of Caldara *et al.* (2014), who find that uncertainty accounts for about 10% of the FEV for industrial production and employment.[15] These figures 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-

[14] This is of course another issue on which controlling for credit conditions can be important: if uncertainty and credit shocks were accidentally mixed, the picture could look radically different.

[15] In our model financial markets respond simultaneously to variations in uncertainty. Hence, our results should be compared to those obtained by Caldara *et al.* (2014) under the identification scheme which does not orthogonalise uncertainty shocks with respect to bond premia. In other words, the relevant benchmark for us is what the authors label "uncertainty shocks" (rather than the "non-financial uncertainty shocks", which are obtained under an alternative, more restrictive identification scheme).

transition VAR conditioning on recessions. This discrepancy might of course depend to some extent on data and sampling issues. However, we submit that the key factor behind it relates to the treatment of the nexus between uncertainty and financial markets. As we noted above, since credit conditions and uncertainty are strongly correlated, the role of uncertainty is likely to be overestimated if the former are not adequately controlled for – a point also made by Caldara *et al.* (2014) and Gilchrist *et al.* (2014). The baseline model of Caggiano *et al.* (2014) does not include any financial variables. In one of the robustness tests, the authors find indeed that the impact of uncertainty on employment is halved if the S&P500 index is included in the model, but none of the specifications examined in the paper includes credit spreads, which are instead a key ingredient both in the empirical analyses of Caldara *et al.* (2014) and Gilchrist *et al.* (2014) and in our work. The Financial Condition Index employed in our baseline specification includes spreads on a range of debt contracts (see Section 3.2); furthermore, our results are broadly unchanged if FCI is replaced by a plain BAA corporate bond spread (see Section 5). This leads to the conclusion that, roughly speaking, using credit spreads is both necessary and sufficient in order to isolate the role of uncertainty. It is necessary because leaving out the spreads biases the role of uncertainty upwards. It is also sufficient in the sense that replacing the spreads with broader, more complex financial condition proxies does not alter the key estimates in a significant way.[16]

We conclude this section with a counterfactual exercise aimed at providing a model-based narrative on the historical role of uncertainty shocks in the US, particularly over the Great Recession. The counterfactual world we consider is one where volatility shocks are switched off (by setting $\eta_t = 0$ in equation (4)), so that λ_t – and thus the volatilities of all structural shocks in the economy – are constant at their sample means. The results are illustrated in figure 6. The full model (*Benchmark*, red line) is compared to a VAR which retains the volatility-in-mean component but ignores the nonlinearity associated to financial market conditions (*No Threshold*, black line). For each model and variable we plot the difference between the actual data and the series generated by the models under the counterfactual assumption. This provides a gauge of the extent to which excluding the shock causes a discrepancy between models and reality. The main variable of interest, industrial production, is displayed in the

[16] The difference between the Caldara et al (2014) estimate (10%) and our own (4% to 8% depending on the regime) is quantitatively less interesting, but again consistent with this interpretation: the broader the set of financial controls, the smaller the role assigned to uncertainty shocks.

top left panel. The early-1980s and 2007-2009 periods are associated to negative values, which means that excluding volatility shocks leads to an underestimation of the actual contraction in output for both models. This effect, however, is much smaller for the no-threshold model. For the Great Recession period, switching off the volatility shock causes a gap of only 0.2% in the no-threshold model and of over 1% in the benchmark model. The bottom left panel of figure 6 shows the counterfactual from a financial market perspective. We know from the impulse-response analysis that credit prices and quantities (as summarized by the FCI) are themselves more sensitive to uncertainty in crisis conditions. In line with this finding, the counterfactual shows that the threshold model falls short of replicating the FCI spikes of the 1980s and 2008-9 if volatility shocks are switched off. In the no-threshold model, excluding the shocks has implications that are qualitatively similar (FCI is too low in recessions) but quantitatively far less significant. The message delivered by figure 6 is that accounting for the amplification effects caused by financial distress is essential in order to effectively gauge the significance of uncertainty in influencing both financial markets and real economic activity.

5 Sensitivity analysis

In this section we show that our key results are robust to various changes in the specification of the benchmark model. In particular, the results survive (i) the addition of extra variables to the system; (ii) the use of a corporate bond spread rather than FCI to identify financial regimes; (iii) changes in the timing assumptions embedded in the model; (iv) the introduction of a factor structure for the volatilities of the structural shocks; (v) the replacement of the financial threshold with a smooth-transition mechanism where the parameters change gradually depending on the financial condition indicator. We describe each of these exercises in turn. In the final subsection, we provide further supporting evidence for our key results by examining (a) simpler models that exclude some of the non-linearities embedded in our Threshold VAR, and (b) an analogous model where the change in the transmission mechanism is driven by the real cycle (i.e. by industrial production) rather than the financial cycle.

5.1 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 relatively weak on the real side. In the first sensitivity analysis, we expand the set of non-financial variables included in the model in order to correct for any missing variable bias and account for the possibility of non-fundamentalness of shocks (Forni and Gambetti, 2014). This is done by extending the benchmark model and estimating a Factor Augmented TVAR with stochastic volatility. The extended model is defined as follows

$$\begin{pmatrix} X_{it} \\ F_t \end{pmatrix} = \begin{pmatrix} B_i & 0 \\ 0 & 1 \end{pmatrix} \begin{pmatrix} \tilde{F}_t \\ F_t \end{pmatrix} + v_{it}, v_{it} \tilde{} N(0, R_i) \tag{8}$$

$$\begin{aligned} \tilde{Z}_t \ &= \ \left(c_1 + \sum_{j=1}^{P} \beta_{1j} \tilde{Z}_{t-j} + \sum_{j=0}^{J} \gamma_{1j} \ln \lambda_{t-j} + \Omega_{1t}^{1/2} e_t \right) \tilde{S}_t \\ &+ \left(c_2 + \sum_{j=1}^{P} \beta_{2j} \tilde{Z}_{t-j} + \sum_{j=0}^{J} \gamma_{2j} \ln \lambda_{t-j} + \Omega_{2t}^{1/2} e_t \right) (1 - \tilde{S}_t) \end{aligned} \tag{9}$$

In the observation equation (8) 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. $\tilde{F}_t = \{\tilde{f}_{1t}, \tilde{f}_{2t}, ...\tilde{f}_{Kt}\}$ 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 $\tilde{Z}_t = \{\tilde{f}_{1t}, \tilde{f}_{2t}, ...\tilde{f}_{Kt}, F_t\}$ with stochastic volatility in mean as in the benchmark model above. The dynamics of λ_t are described in equation 4. Therefore, in summary, this extended model incorporates additional information through the factors $\tilde{F}_t$ while retaining the threshold dynamics and stochastic volatility as in the benchmark model. Estimation of the model requires three additional steps in the Gibbs algorithm in order to draw from the conditional posterior distribution of $\tilde{F}_t, B_i$ and R. These are described in the appendix. We fix $K = 3$ and the lag specification is the same 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 top panel of figure 7 shows the regime specific impulse responses of Y_t and P_t from Factor Augmented TVAR to a 1 standard deviation volatility shock.[17] It is immediately clear that the regime 2 response of industrial production is substantially larger. As in the benchmark model, the regime 2 response of inflation is strongly negative. Finally, the third panel of the top row shows that the estimated volatility from this model is very similar to the benchmark model.

5.2 Alternative threshold variable

As noted above, the Financial Conditions Index provides a wide measure of financial conditions. As shown in the second row of figure 7, the results hold if the threshold is defined over a narrower indicator of credit conditions, namely the BAA corporate bond yield spread (over the 10 year government bond yield). In particular, we estimate a version of the model where the spread is included as an additional endogenous variable and is also used to determine the regime switches. The second row of the figure shows that in the regime characterized by a high level of the spread (regime 2), the response of industrial production to an uncertainty shock is much larger than in times when credit is relatively cheaper (regime 1). The response of inflation shows the same pattern as in the benchmark case. The final panel shows that the estimated volatility is also similar to the benchmark case.

5.3 Timing of the volatility impact

The benchmark model incorporates the possibility that uncertainty shocks have a contemporaneous impact on all variables. We find that the impulse responses are not sensitive to this assumption. In particular, we estimate a version of the benchmark model that restricts the contemporaneous impact of λ_t on industrial production and inflation to be zero (but still allows the financial variables to be affected contemporaneously). The results from this version of the model are shown in the fourth row of figure 7 and match the benchmark results closely.

[17] The variables in X_{it} are standardised. The resulting 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 7 we re-scale the impulse responses to match the average difference in the scale of λ_t estimated using the FAVAR and the benchmark model.

5.4 Common factor in volatility

The volatility specification in equation (4) does not explicitly identify a common factor. As argued in Section 3, in our application it is sensible to focus on the average volatility of the shocks rather than the common volatility in a strict sense. Nevertheless, when we explicitly specify a factor structure, the impulse-response functions to uncertainty shocks do not change. In particular, we estimate a version of the benchmark model where the specification of the error covariance matrix changes as follows:

$$H_t = diag(h_{it} s_i)$$

where

$$\ln h_{it} = b_i \ln \lambda_t + \ln e_{it} \tag{10}$$

The factor loadings are denoted by b_i. The common factor $\ln \lambda_t$ follows the transition equation defined in equation (4), while e_{it} is assumed to be white noise. Equation (10) decomposes the log volatility of each shock h_{it} into a common and an idiosyncratic component. This means that λ_t is now estimated stripping out the idiosyncratic component and allowing for shock-specific loadings b_i. As in the benchmark model, $\ln \lambda_t$ is allowed to affect the endogenous variables. While this model can be easily estimated using a slight modification of the MCMC algorithm described above, 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 $\ln e_{it}$. The last row of figure 7 shows the estimated response to a one standard deviation shock to λ_t. The pattern of the responses is very similar to the benchmark case, with the crisis regime being associated to a much larger response of industrial production and a change in the sign of the inflation response. The last panel of the figure shows that the common component is highly correlated with the volatility estimate obtained from the benchmark model.

5.5 Smooth transition

The benchmark model assumes that a threshold determines the transitions across states. The implied regime changes are thus abrupt – a feature that seems to be consistent with the onset of the periods of financial stress in our sample period. However, to account for the possibility that the transitions across regimes are smooth we estimate a version of the model that employes a logistic function to model changes in regimes. In particular, the regime process is defined as

$$\tilde{S}_t = 1 - \left[1 + \exp\left(-\gamma\left(F_{t-d} - Z^*\right)\right)\right]^{-1} \tag{11}$$

where $\gamma > 0$ determines the smoothness of the function. As $\gamma \to \infty$ the specification collapses to the threshold model considered in the benchmark case.[18] The estimated transition function $1 - \tilde{S}_t$ is plotted in figure 8. The regimes are similar to those obtained in the benchmark case and the transitions appear to be quite abrupt, which confirms that a threshold specification is a good description of the data. The impulse-responses from this model are shown in the third row of figure 7. To summarize the results, we define normal times (i.e. regime 1) as periods when $\tilde{S}_t > 0.5$, classify all remaining periods as bad times (i.e. regime 2), and show the average responses corresponding to these two cases. The key result is clearly supported by the model: the fall in industrial production is much larger in bad times (regime 2). For inflation, the responses are qualitatively similar to those of the benchmark model, although the differences between regimes are less pronounced.

5.6 Further evidence on financial regimes

The model used in this paper is complex and highly nonlinear. As a reality check on its plausibility, we compare it to a set of simpler alternatives using the Deviance Information Criterion (DIC) of Spiegelhalter *et al.* (2002).[19] We consider five different specifications of the model. The benchmark is again represented by the model described in Section 3. As an alternative, we first rule out a direct impact of uncertainty on the endogenous variables, setting $\gamma_{ij} = 0$, while retaining the double-regime structure (*No Uncertainty*). This delivers a model that accounts for the nonlinearity stemming from the existence of credit or collateral constraints (and documented elsewhere in the literature, see Section 2), but does not assign any role to uncertainty. Then, symmetrically, we consider a model that allows for a link be-

[18] The estimation of this model can be carried out with minimal changes to the Gibbs algorithm described above. In particular, a Metropolis step is used to draw γ from its conditional posterior. See Lopes and Salazar (2006) for details.

[19] DIC is calculated using the mean likelihood of the model and a penalty correction that penalizes model complexity, measured by the number of effective parameters. Low values indicate good models.

tween uncertainty and macro-financial aggregates but ignores the possibility of changes in the transmission mechanism, i.e. a volatility-in-mean VAR à la Mumtaz and Theodoridis (2012) (*No Threshold*). In a third experiment we combine the two restrictions above (*No Threshold & No Uncertainty*), obtaining a linear VAR without uncertainty. Finally we consider a specification with the same structure as the benchmark, but where the regimes are driven by industrial production rather than the financial condition index (*IP-based Threshold*). In this latter case, we try to exploit the close-but-not-perfect correlation between volatility, credit conditions and growth in the data to compare our characterization of the transmission mechanism to the "real" alternative studied by Caggiano *et al.* (2014), who focus on recessions rather than periods of financial tension. The results are reported in Table 1. Note first that both the *No Uncertainty* and the *No Threshold* restriction worsen DIC relative to the benchmark. The effect is compounded if they are imposed jointly (*No Threshold & No Uncertainty*). The data is thus suggestive of both volatility effects and multiple regimes. Secondly, the *IP-based Threshold* model has the highest (i.e. worst) DIC of all. Its performance is significantly worse than the benchmark's, which implies that financial conditions are a better candidate than industrial production to identify changes in the shock transmission mechanism. The model is also worse than the two specifications without regimes (*No Threshold, No Threshold & No Uncertainty*). This suggests that the increase in complexity associated to the regime-switching mechanism does not payoff if output is used in the transition equation. The impulse-responses generated by this model (which we do not report for brevity) do provide evidence of an asymmetry that is consistent with Caggiano *et al.* (2014), whereby uncertainty shocks have a larger impact on output in low-growth environments. Nevertheless, the balance of evidence is clearly more consistent with the hypothesis that structural changes are driven by financial conditions rather than the real business cycle.

6 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 may 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 uncertainty is proxied by the average (unobserved) volatility of the economy's structural shocks, and a regime change occurs whenever financial markets experience a high level of 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 the 2007-2009 crisis. We find that exogenous increases in uncertainty have a recessionary effect in both normal and distressed financial market conditions, but their impact on output is five times larger when financial markets do not function smoothly. Accounting for this nonlinearity, the shocks explain 1% of the peak fall in industrial production observed in the 2007–2009 recession. These results provide further support for the 'financial view' of the transmission mechanism of uncertainty shocks (Christiano *et al.,* 2014; Caldara *et al.,* 2014; Gilchrist *et al.,* 2014). They also point to a complication that must be taken into account when examining the relative importance of credit and uncertainty shocks in causing macroeconomic fluctuations: the two are not easily separable, because uncertainty becomes more relevant if and when the economy has previously been subjected to a sequence of adverse financial shocks. The Great Recession provides a powerful illustration of this issue. Our results suggest that, even though uncertainty shocks constitute an independent source of economic volatility, policy makers could focus on monitoring financial markets and preventing financial disruptions rather than worrying about uncertainty *per se*.

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	Model	*DIC*
	Benchmark	-5700.4
i.	No Uncertainty	-5680.2
ii.	No Threshold	-5687.5
iii.	No Threshold & No Uncertainty	-5669.7
iv.	IP-based Threshold	-5638.3

Table 1: Deviance Information Criterion. The table reports the Deviance Information Criterion of Spiegelhalter *et al.* (2002) for five different specifications of the model. Benchmark is the full model described in Section 3. Model (i) rules out a direct impact of uncertainty (while retaining the two-regime structure). Model (ii) assumes a single regime (while allowing for the impact of uncertainty on the rest of the system). Model (iii) combines the two restrictions. Model (iv) has the same structure as the benchmark, but assumes that switches between regimes are driven by industrial production rather than the financial condition index.

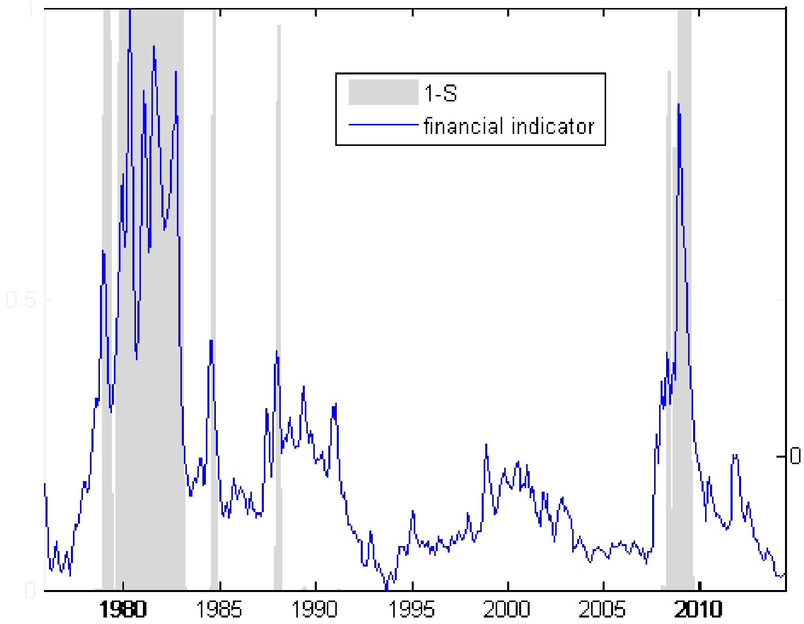

Figure 1: Financial regimes. The *Financial Indicator* is an index of financial market distress based on a dynamic factor model. Grey bands identify the subperiods when the US economy is estimated to be in a 'crisis', defined as a state where the index exceeds the critical threshold defined in equation (2).

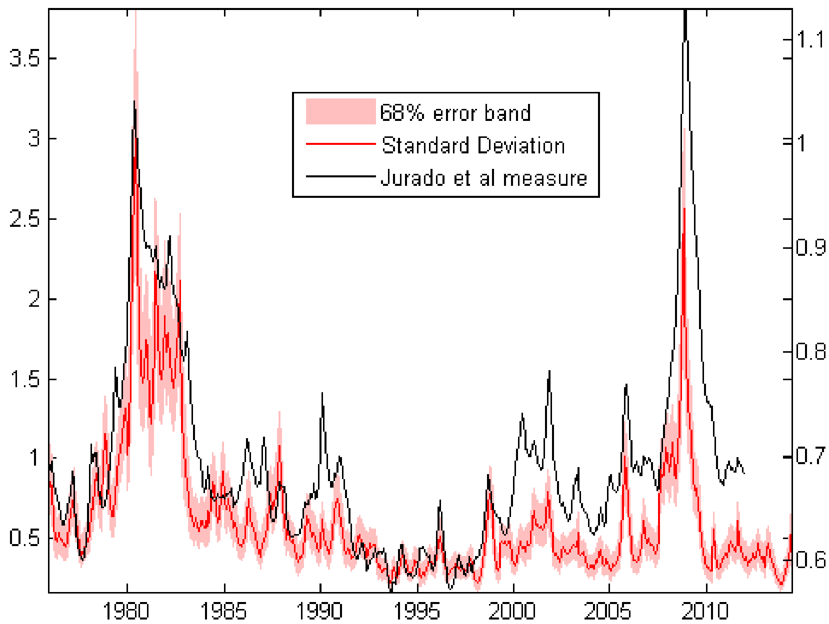

Figure 2: Economic uncertainty. The red line is the median estimate of the average volatility of the structural shocks hitting the US economy (λ_t , see Section 3). The black line is the uncertainty estimate proposed by Jurado *et al.* (2013).

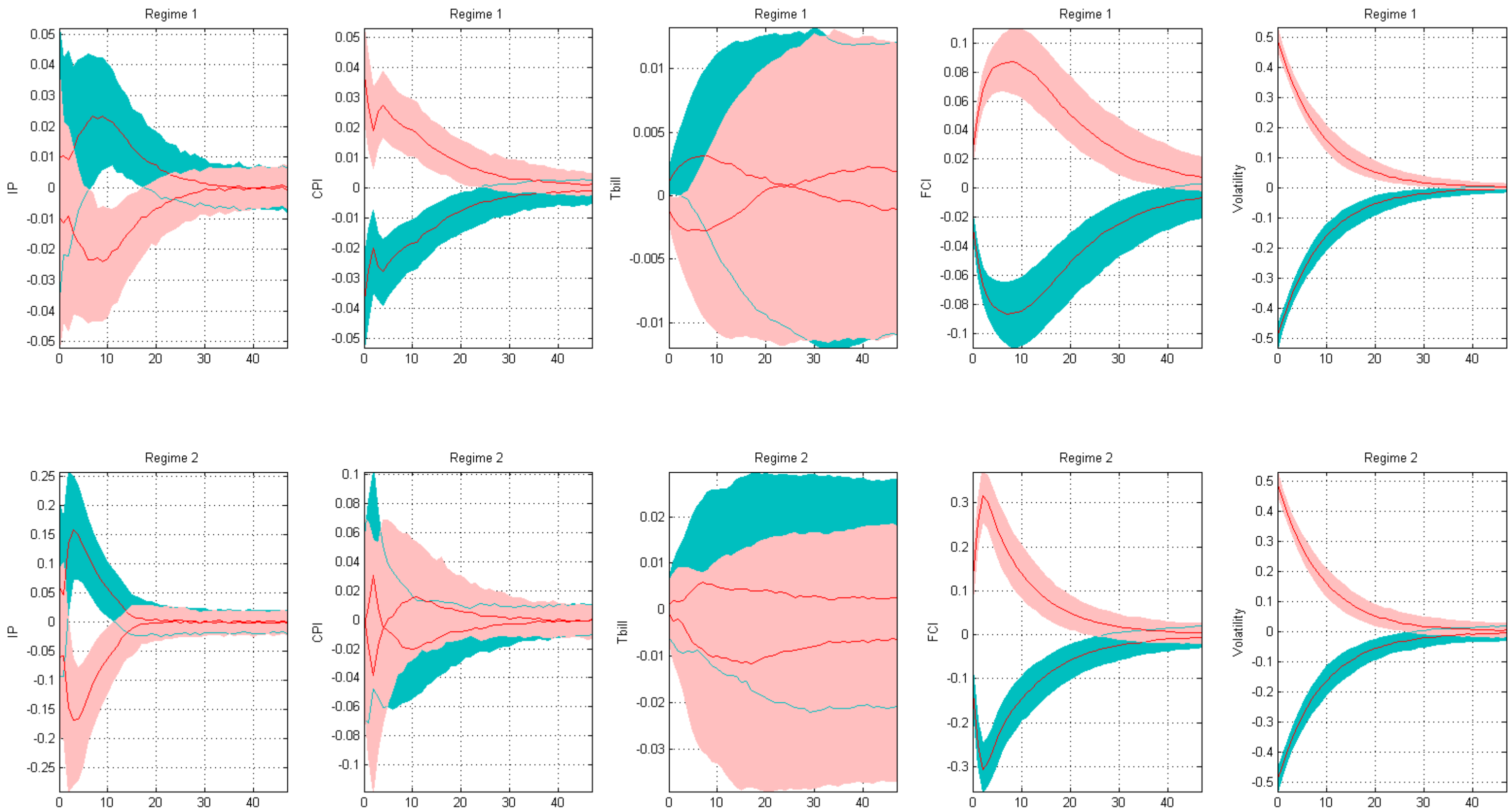

Figure 3: Impact of a one standard deviation volatility shock. Red (resp. green) bands show the response of the US economy to a positive (resp. negative) one standard deviation volatility shock according to the Threshold VAR of section 3. The first row shows the responses associated to calm periods while the second row shows the responses associated 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 time, measured in months.

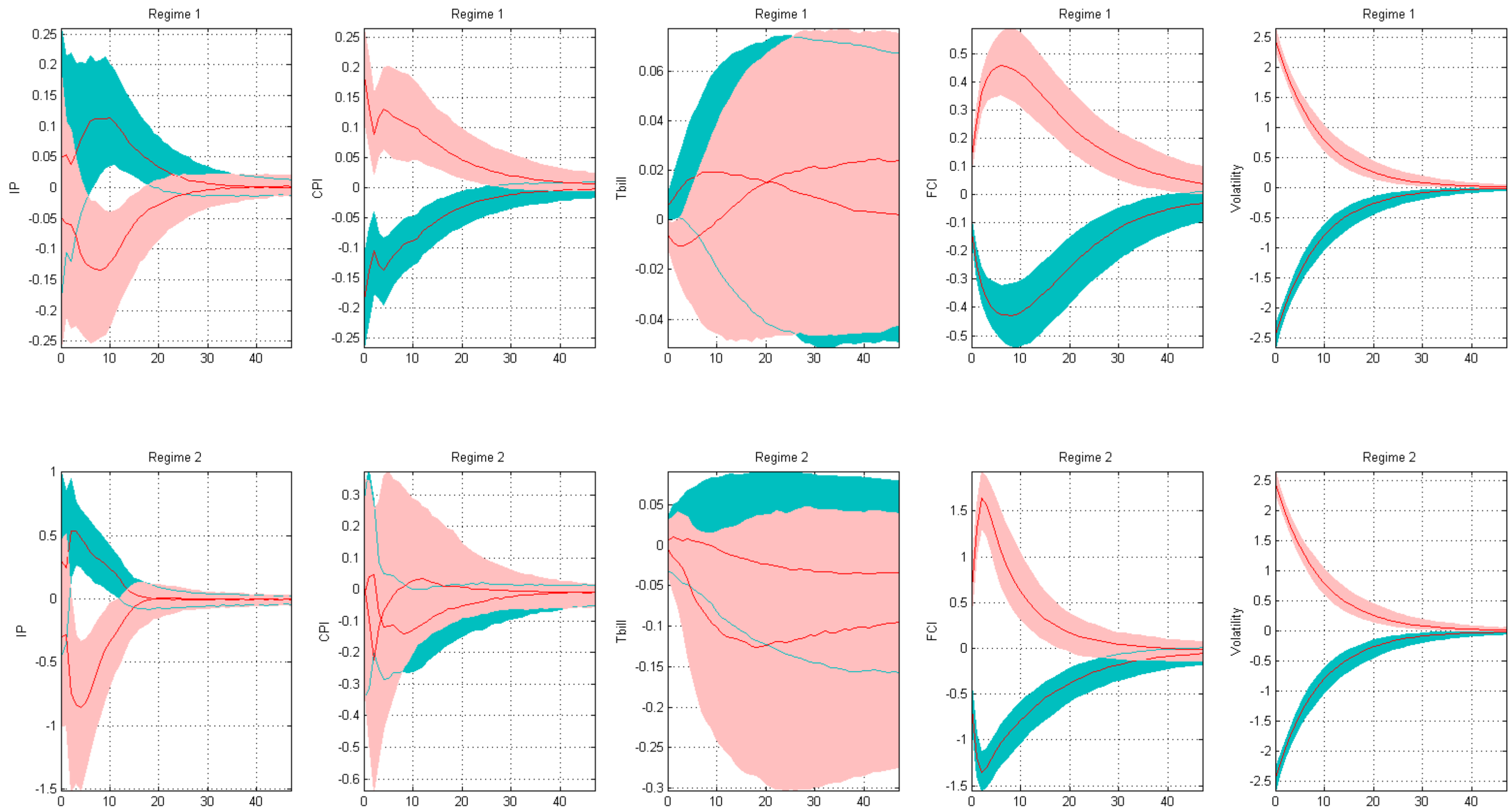

Figure 4: Impact of a five standard deviation volatility shock. See notes to figure 3.

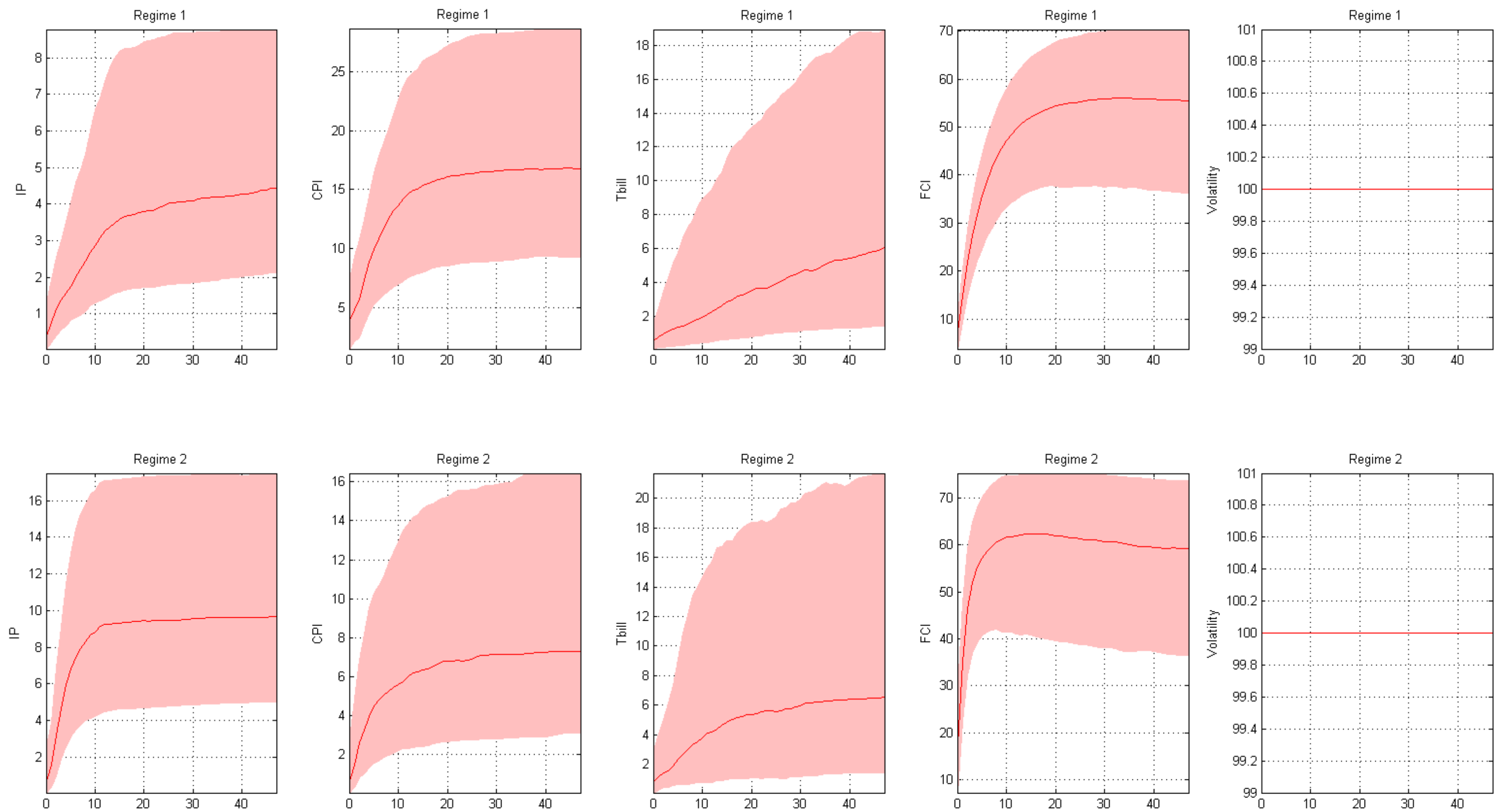

Figure 5: Forecast error variance decomposition. Each panel shows the fraction of forecast error variance explained by the volatility shock for one of the variables included in the Threshold VAR of section 3. The first row corresponds to calm periods, while the second row corresponds to financial crises, defined as periods when the financial distress indicator FCI exceeds an endogenously-determined critical threshold (defined in equation (2)). The horizontal axis is the forecast horizon measured in months.

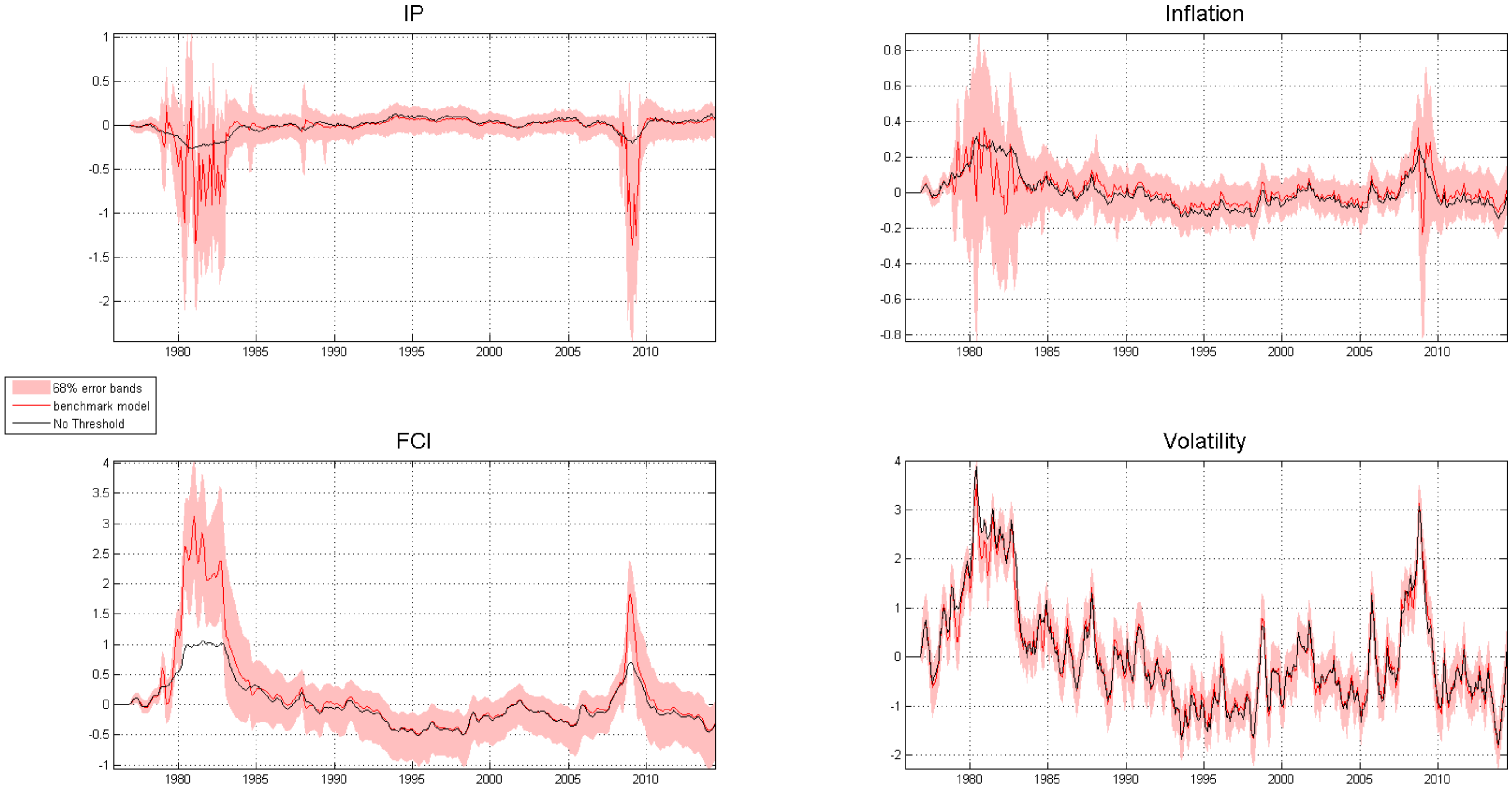

Figure 6: Counterfactual scenario. The figure shows the difference between the actual data and the series generated by two models under the assumption of no volatility shocks ($\eta_t = 0$ in equation (4)). The black lines are generated using a linear VAR. The red lines and the associated 68% confidence bands are generated using a Threshold VAR that separates periods of calm and tense financial market conditions.

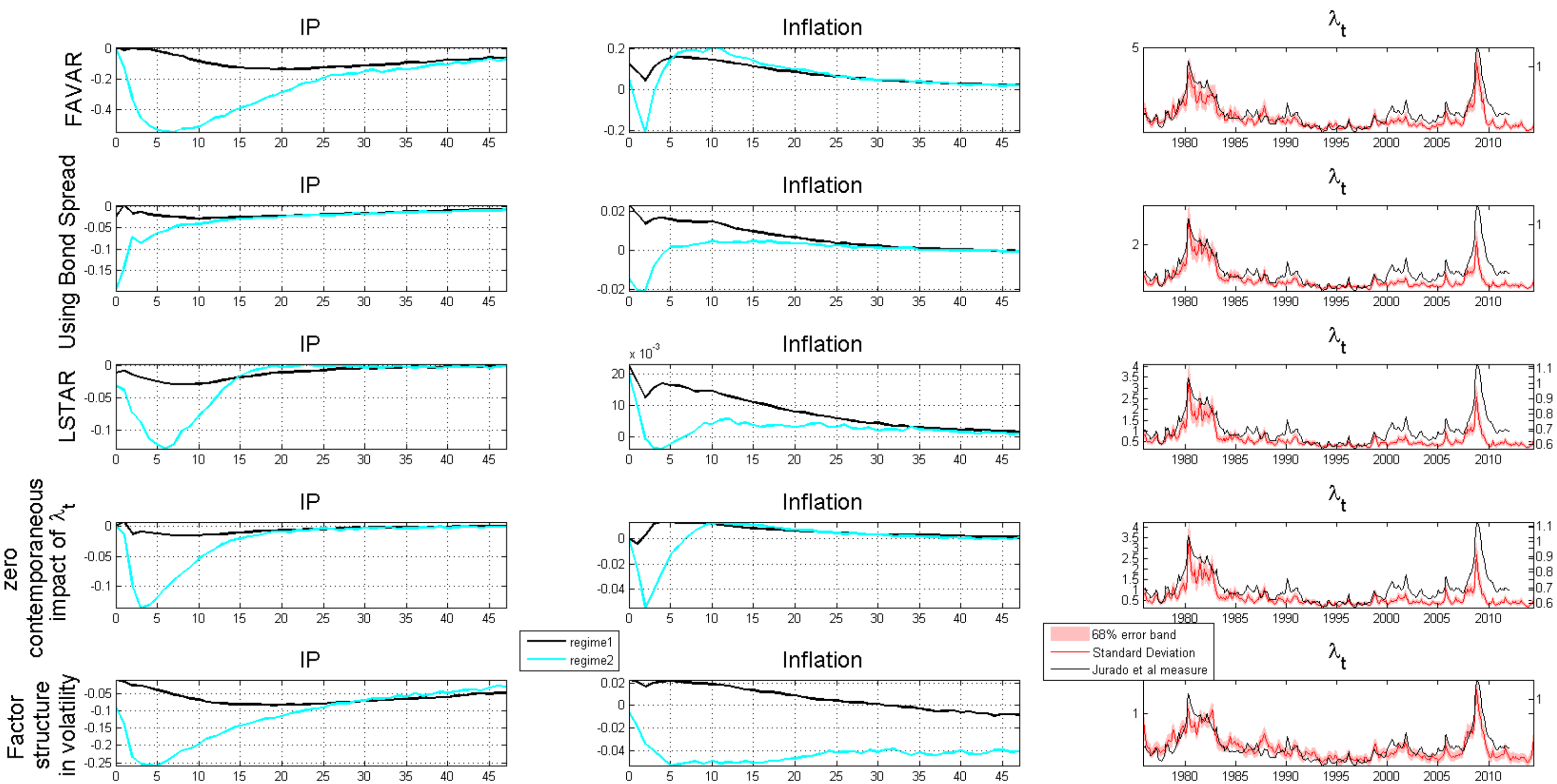

Figure 7: Robustness analysis. The figure shows the volatility series (column 3) and the responses of industrial production and inflation to a positive one-standard-deviation volatility shock (columns 1-2) estimated using five alternatives to the benchmark TAR model: a FAVAR, a TAR with corporate bond spreads, a smooth-transition VAR, a TAR with lagged volatility, and a TAR where volatilities are modelled using a factor structure. See section 5 for details.

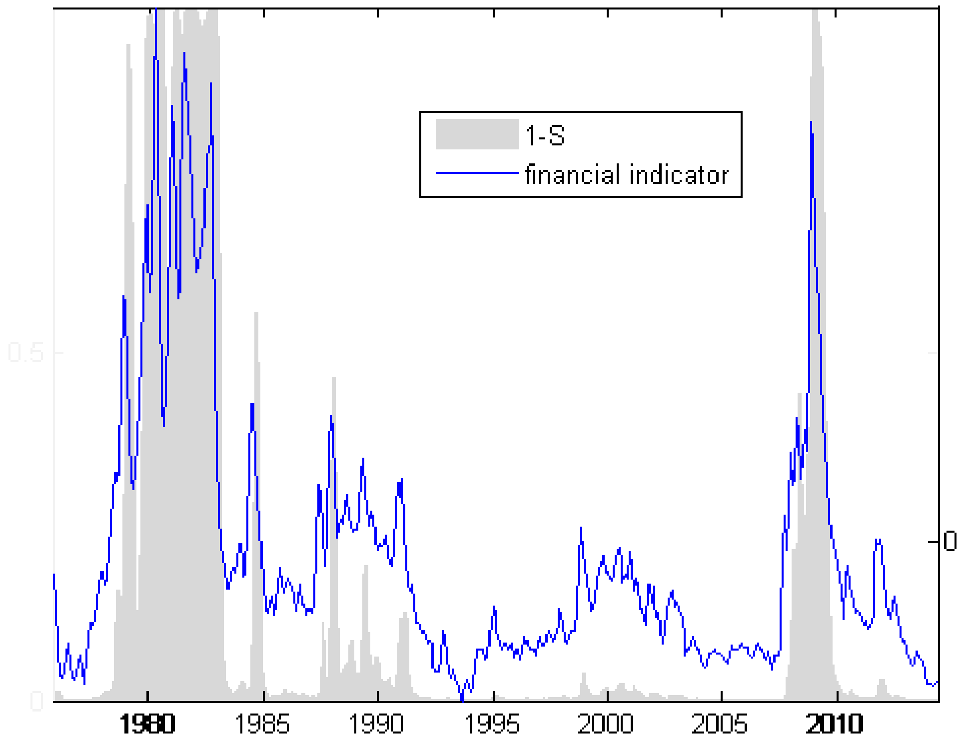

Figure 8: STAR transition function. The *Financial Indicator* is an index of financial market distress based on a dynamic factor model. The grey area shows the transition function from a Smooth Transition VAR model where the transition across regimes is driven by the financial indicator. See section 5 for details.