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Endogenous Financial Uncertainty and Macroeconomic Volatility: Evidence from the United States

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Abstract

We propose an extended SVAR model to investigate the responses of the macroeconomic volatility to financial uncertainty shocks. The empirical model features the time-varying stochastic volatility-in-mean process where parameters allow for (i) the bilateral simultaneity between the shocks hitting the level and volatility of the endogenous variables, and (ii) the feedback from the endogenous variables to the volatility. Using the U.S. data, our findings show that macroeconomic volatility arises as an endogenous response to a rise in financial uncertainty. Moreover, shutting down the volatility feedback leads financial uncertainty shocks to react more strongly to macroeconomic variables. Consequently, the effects of financial uncertainty on macroeconomic volatility become more severe, especially in the short horizon.

Keywords: Stochastic volatility, Bayesian SVAR, financial uncertainty, macroeconomic volatility
JEL: E44, C51, D80, E60, G10

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1 Introduction

Uncertainty has been considered as the main source of economic fluctuations over the last two decades.[1] Various proxies of uncertainty (either macroeconomic or financial) have been used to understand its role in the dynamic interactions among macroeconomic and financial variables. Major studies of this research strand include, among others, Christiano et al. (2014); Gilchrist et al. (2014); Caggiano et al. (2014); Jo (2014); Jurado et al. (2015); Rossi and Sekhposyan (2015); Baker et al. (2016); Caldara et al. (2016); Berger et al. (2016); Cesa-Bianchi and Rebucci (2017); Bloom et al. (2018); Shin and Zhong (2020); Carriero et al. (2018); Cesa-Bianchi et al. (2019) and Cuaresma et al. (2020). The existing literature primarily relies on the restrictive identification assumptions within the homoscedastic structural VAR model with stochastic volatility-in-mean (SVAR-SVM) to draw conclusions on uncertainty effects. This methodological framework assumes, however, that shocks to the stochastic volatility equations are contemporaneously independent from shocks hitting the level of endogenous macroeconomics variables, which may cause statistical biases regarding the sign and causal direction between uncertainty and macroeconomic variables. The recent work of Ludvigson et al. (2015) explicitly pointed out the potential existence of endogeneity bias in previous studies.

The challenge of the uncertainty literature pertains to the origins of uncertainty and the mechanisms through which uncertainty is transmitted. The existing literature asserts that uncertainty has its roots in economic fundamentals such as productivity, capital investment decisions, and precautionary savings (e.g., Kimball (1989); Bloom (2009); Fernández-Villaverde et al. (2011); Leduc and Liu (2016); Basu and Bundick (2017); Bloom et al. (2018)). Other studies argue that uncertainty could serve both as a cause and as a propagating mechanism through information or financial market frictions (e.g., Van Nieuwerburgh and Veldkamp (2006); Bollerslev et al. (2009); Christiano et al. (2014); Gilchrist et al. (2014); Arellano et al.

[1]See Bloom et al. (2018) for a review of the literature.

(2019)). From this perspective, econometric essays to explore the impacts of uncertainty shocks on the volatility of macroeconomic variables are ultimately unsatisfactory as the commonly-used VAR identification schemes, based on either sign restrictions, long-run restrictions, and instrumental variables estimation, are likely exposed to an unobserved bias caused by omitted variables and non-fundamentals of the errors (Carriero et al., 2018).

Moreover, the specification of volatility using the SVAR approach faces its own challenges due to the fact that the volatility of each variable in the system has its own shock which is independent from the shocks hitting the level of the variables. This implies that unexpected movement in the common component of the volatilities of the vector autoregressive variables impacts the conditional variances, but not the conditional means. This assumption would lead, in turn, to a distorted estimate of endogenous feedback channel (Carriero et al., 2018). Another drawback of the VAR models in the uncertainty literature is that they are characterized by a homoscedastic error structure, which cannot provide a convincing evidence with respect to the time-varying macroeconomic volatility. Thus, the use of heteroskedastic structure with time-varying conditional variance is more adequate because it allows more flexibility in modeling the conditional variance via stochastic volatility.

In line with the above-mentioned literature, the goal of this paper is to assess whether and to what extent financial uncertainty[2] is a source or a consequence of macroeconomic volatility[3]? Answers to these questions will provide important implications not only for stock market investments but also for the regulation of the macroeconomy. For example, if financial uncertainty shocks immediately cause significant macro-financial fluctuations and tend to have prolonged effects on the real economy, macroprudential policy interventions would be a

[2]Financial uncertainty is defined as uncertainty in financial markets. It refers to the situation where information is imperfect or unknown. Various proxies of financial uncertainty are used in the literature. We use different identification schemes through SVAR modeling, namely Cholesky decomposition, sign restrictions and recursive structure.

[3]For the three macroeconomic variables that we consider (GNP growth, GNP deflator inflation and unemployment), the macro-economic volatility is approximated by the standard deviation of these variables.

policy option to reduce the propagation of these shocks to the real economy, thus avoiding systematic risk.

To conduct our empirical investigation, we develop a SVAR model with stochastic volatility-in-mean (SVAR-SVM) where the volatility of system variables is modeled in a similar spirit to the stochastic volatility-in-mean model originally developed by Koopman and Hol Uspensky (2002).[4] Technically, our proposed model contributes to the related literature with respect to three important dimensions. First, it incorporates a correlated stochastic volatility structure to allow financial uncertainty to contemporaneously react to changes in macroeconomic variables. In the meanwhile, both the level and the volatility of endogenous macroeconomic variables are affected by correlated shocks. Second, it enables us to identify the effect of the endogenous volatility feedback through the structure of innovations.[5] A few studies have emphasized the possible endogeneity effects of uncertainty (e.g., Bachmann et al. (2013); Mumtaz and Theodoridis (2018); Carriero et al. (2018); Mumtaz and Theodoridis (2018)). Our methodology differs, however, from this literature in the sense that we model the impact of both the conditional mean and the conditional variance on macroeconomic fundamentals via time-varying stochastic volatility. This specification provides a more realistic appraisal of volatility dynamics compared to those predicted by regime-switching models or GARCH specifications. It is also worth noting that contrary to previous studies that impose constant coefficients in the conditional mean, we allow the conditional mean's coefficients to vary over time in order to take the possibility of dynamic simultaneous feedback effects into account. Finally, our work extends the existing uncertainty literature by using a large time-series data which allows for long-term fluctuations in the macroeconomic volatilities, and thereby, avoids the problem of omitted variable bias.

[4] This type of volatility modeling is alternative to the ARCH-M model and has been proven efficient.

[5] Our identification scheme is obtained by a heteroscedasticity structure in which the shocks of the transition equation (volatility) are able to efficiently unveil the correlation with shocks attributed to the observation equation (level). As a result, it allows the observed data to dynamically impact the volatilities.

Our results, from applying our setup to U.S. financial and macroeconomic data, mainly show that volatilities of financial uncertainty shocks are high at short horizons and become smaller as the horizon increases, suggesting the time-variation in volatility. There is robust evidence to support the fact that higher financial uncertainty shocks raise the volatility of macroeconomic variables with, however, a delayed effect. From a technical perspective, our specification of correlated errors in both observation and transition equations is found to improve the capability of identifying the endogenous movements of uncertainty shocks. Moreover, the inclusion of stochastic volatilities in the mean equation as well as of volatility feedback effects produces more accurate forecasts. Overall, our findings lead to the conclusion that financial uncertainty is endogenous and neglecting the volatility feedback effects of financial uncertainty would very likely imply distorted estimation of the impacts of financial uncertainty shocks on macroeconomic volatility.

The rest of the paper is organized as follows. Section 2 describes the sample data and the main variables we use in this study. Section 3 presents the theoretical framework of our SVAR-SVM model with time-varying parameters. Section 4 reports the results. Section 5 concludes the paper.

2 Data and Variables

To explore the impact of financial uncertainty shocks on the U.S. economy, we collect quarterly data from DataStream and the Federal Reserve Bank of St Louis (FRED) spanning the period from 1990:Q1 to 2018:Q2. The sample period covers several financial crises and prolonged turbulent times, allowing us to consider a number of historical events of high financial volatility for shock identification. The end point of the sample was contingent on the data availability.

Our model is estimated using a set of six endogenous variables $Y_t = (M_t, F_t)'$ that encompass three macroeconomic variables M_t and three financial indicators F_t. The macroeconomic variables include the quarterly real GNP growth (y), the quarterly GNP deflator inflation (P), and the quarterly civilian unemployment rate (U). The financial indicators include the yield spread of BAA corporate bonds over the 10-year Treasury bill rate (S), the house price index (HPI), and the S&P500 index $(S\&P)$. The data on unemployment rate, real GNP growth and GNP deflator inflation are obtained from FRED, while the spread between BAA corporate bond yield and the 10-year Treasury bill rate, house price index and the S&P500 index are obtained from DataStream.

To remove the potential impact of the endogeneity problem at the earliest stage, we set the lag length of the endogenous macroeconomic variables to two. This is consistent with the conjecture employed in VAR models that use quarterly data (Cogley and Sargent, 2005; Primiceri, 2005). Since the exact impact of the lagged volatility of the structural shocks on macroeconomic variables could not be captured easily, we allow it to last within a 3-month period. We also implement linear detrending to take into account the low-frequency movements in the macroeconomic variables.

Table 1: Descriptive statistics

Statistic	Mean	St. Dev.	Min	Max	Skewness	Kurtosis	Jarque-Berra		N
GNP growth (y)	0.5319	0.7614	−2.65	2.09	−1.3202	6.1412	79.991	**	114
GNP deflator (P)	0.6672	0.5075	−0.16	2.72	2.0248	7.2870	165.202	**	114
Unemployment (U)	6.0970	1.4472	3.90	10.53	0.9229	3.7673	18.982	**	114
Yield spread (S)	2.3746	0.7870	1.08	5.82	1.5677	7.2624	133.001	**	114
House price (HPI)	129.22	40.3410	75.30	202.53	0.0184	1.5491	10.005	**	114
S&P 500 index	1173.8	588.9992	317.05	2732.58	0.4946	2.8919	4.704	*	114

Notes: In this table, descriptive statistics for the variables y, P, U and S are obtained from time-series that are multiplied by 100 with the actual observation values. For the Jarque-Berra test, ** and * denote significance at 1% and 10% levels respectively, both indicating the rejection of normality. N denotes the number of quarterly observations.

Descriptive statistics of variables, given in Table 1, show that all series, and particularly the GNP growth (y), the GNP deflator inflation (P) and the $S\&P$ 500 index $(S\&P)$, are characterized by high variability as their standard deviation exceeds 50% of their average.

Moreover, all time series exhibit strong deviations from the normal distribution as their skewness and kurtosis values depart widely from 0 and 3, with the exception of S&P500 index whose distribution only depart slightly from normality. This characteristic is formally validated by the Jarque-Berra test which statistically rejects normality for all time series. High volatility and deviations from normality emphasize the role of uncertainty in the U.S. economic and financial systems.

3 Empirical Model

As stated earlier, we develop a SVAR-SVM model to investigate the responses of macroeconomic volatility to financial uncertainty shocks. This section successively presents its general framework and its empirical specifications that we apply to the US market economy.

3.1 Volatility-in-mean specification

We consider the general class of the stochastic volatility model (called SVM model) in the spirit of the seminar work of Koopman and Hol Uspensky (2002), where the conditional variance of the observable variables enters into the conditional mean equation.

In more formal terms, consider the variance equation of the stochastic volatility model of the following form:

$$\sigma_t^2 = \sigma^{*2} exp(h_t) \tag{1}$$

with σ^* a positive scaling factor measuring the volatility level. We define the volatility process σ_t^2 as the product of the positive scaling factor and the exponential of the stochastic volatility process h_t. We formally assume that $h_t = ln(\sigma_t^2/\sigma^{*2})$ with :

$$h_t = \theta h_{t-1} + \eta_t \tag{2}$$

where θ represent a diagonal matrix implying that each element of h_t follows an autoregressive processes $AR(1)$. In this setup, θ captures the shocks persistent effect and η_t is the error term of stochastic volatility.

Without losing generality, the mean equation can be rewritten as:

$$Y_t = c + \sum_{i=1}^{k} \beta_i y_{t-i} + b\sigma^{*2} exp(h_t) + \sigma_t \epsilon_t, \quad \epsilon_t \overset{iid}{\sim} (0,1) \tag{3}$$

where b represents the risk premium coefficient and captures the volatility-in-mean effect. To simplify the exposition, we specify the variance equation in logarithmic form, that is:

$$\sigma_t = \sigma^* exp(\frac{h_t}{2}) \tag{4}$$

This is a common feature in stochastic volatility models with the aim to implicitly implement non-negativity constraints, and imply that the elements of h_t have log-normal distributions.

As can be seen in Eq. (1),Eq. (2),Eq. (3) and Eq. (4), the mean and its volatility evolve stochastically as:

$$Y_t = c + \sum_{i=1}^{k} \beta_i y_{t-i} + b\sigma^{*2} exp(h_t) + \sigma^* exp(\frac{h_t}{2})\epsilon_t, \quad \epsilon_t \overset{iid}{\sim} (0,1) \tag{5}$$

$$h_t = \theta h_{t-1} + \eta_t, \quad \eta_t \overset{iid}{\sim} (0,1) \tag{6}$$

3.2 The SVAR with stochastic volatility (SVAR-SVM)

We consider the following generalization of the state–space structural vector autoregression (SVAR) with stochastic volatility (SV) which is very close to the SVM formula specified by Koopman and Hol Uspensky (2002), and Lemoine and Mougin (2010).

$$
\begin{cases}
Y_t = c + \sum_{j=1}^{P} \beta_j Y_{t-j} + \sum_{k=1}^{K} b_k \widetilde{h}_{t-k} + \widetilde{\epsilon}_t & (7) \\
\widetilde{h}_t = \alpha + \theta \widetilde{h}_{t-1} + \sum_{j=1}^{K} \delta_j Y_{t-j} + \widetilde{\eta}_t & (8)
\end{cases}
$$

where Y_t denotes $N \times 1$ vector of endogenous variables, while $\widetilde{h}_t$ are $N \times 1$ vector of stochastic volatilities. In the empirical model, one can interpret $\widetilde{\eta}_t$ as the innovation to the volatility and $\widetilde{\epsilon}_t$, the innovation to the level, both are modelled as $\widetilde{\eta}_t = S^{1/2}\eta_t$ and $\widetilde{\epsilon}_t = H_t^{1/2}\epsilon_t$.

Now suppose that β_j, b_k are the corresponding $(N \times N)$ coefficient matrices at each point in time. We denote the parameter b_k as the risk premium coefficient that allows us to examine the volatility-in-mean feedback effect while β_j is a regression coefficient measuring the dynamics of endogenous variables in the mean equation. Thus, the above equation $Eq.$ (7) is known as the measurement or observation equation with Y_{t-j} denoting lagged terms of endogenous variables while $\widetilde{h}_t$ is the log volatility and c an $(N \times 1)$ intercepts vector.

$Eq.$ (8) is known as the transition equation or volatility equation for the stochastic volatilities where $\widetilde{h}_t$ refers to the log-volatility of the structural shocks. In order to understand the vector $\widetilde{h}_t$, let log-volatility of the structural shocks be a stacked vector the main diagonal matrix $H_t = diag\left(exp(\widetilde{h}_t)\right)$. Formally, the stochastic volatilities are expressed by the $(N \times 1)$ vector $\widetilde{h}_t = [h_{1,t}, h_{2,t}, .., h_{N,T}]$ where each element of $\widetilde{h}_t$ is assumed to follow VAR model.

We follow Kim et al. (1998); Mumtaz and Zanetti (2013) and Mumtaz and Theodoridis (2019), and allow $\widetilde{h}_t$ to depend on its first lag with θ being the $(N \times N)$ coefficient matrices of the volatility persistence. More precisely, we explicitly treat θ as a non-diagonal matrix with the elements of $\widetilde{h}_t$ enabling us to model the dynamic relationship amongst endogenous variables themselves with α as an $(N \times 1)$ intercept vector.

In the model given in Eq. (7)-Eq. (8), the $(N \times N)$ coefficient matrices δ_j ensure that lagged endogenous variables would influence $\widetilde{h}_t$ and, intuitively, affect the endogenous variables of Y_t. In a reduced form, we define the correlation amongst the disturbances by $\widetilde{\eta}_t = S^{1/2}\eta_t$

and $\widetilde{\epsilon_t} = H_t^{1/2}\epsilon_t$. We retain the form of $Eq.$ (7) – $Eq.$ (8) but assume that the disturbances are correlated as follows:

$$\Psi = \begin{pmatrix} \underbrace{\eta_t}_{N\times 1} \\ \underbrace{\epsilon_t}_{N\times 1} \end{pmatrix} \overset{iid}{\sim} N(0,\Sigma), \underbrace{\Sigma}_{M\times M} = \begin{pmatrix} \Sigma_{\eta_t} & \Sigma'_{\eta_t,\epsilon_t} \\ \Sigma_{\eta_t,\epsilon_t} & \Sigma_{\epsilon_t} \end{pmatrix}$$

where the diagonal elements of Σ involve restrictions equal to 1. The time-varying variance–covariance matrix Ω_t of the system takes the following form:

$$\Omega_t = \begin{pmatrix} S^{1/2} & 0 \\ 0 & H_t^{1/2} \end{pmatrix} \begin{pmatrix} \Sigma_{\eta_t} & \Sigma'_{\eta_t,\epsilon_t} \\ \Sigma_{\eta_t,\epsilon_t} & \Sigma_{\epsilon_t} \end{pmatrix} \begin{pmatrix} S^{1/2} & 0 \\ 0 & H_t^{1/2} \end{pmatrix}'$$

The shocks to the observation equation Eq. (7) have a variance $H_t = diag\left(exp(\widetilde{h}_t)\right)$ so that $\widetilde{h}_t = [h_{1,t}, h_{2,t}, .., h_{N,T}]$. The observation equation of the state-space system is then defined as:

$$Y_t - H_t^{1/2}\mu_{\epsilon_t|\eta_t} = c + \sum_{j=1}^{P}\beta_j Y_{t-j} + \sum_{k=1}^{K} b_k \widetilde{h}_{t-k} + \widetilde{\epsilon_t} \tag{9}$$

$$var(\epsilon_t) = \Omega_t = H_t^{1/2}\Sigma_{\epsilon_t|\eta_t} H_t^{1/2\prime}$$

$$\mu_{\epsilon_t|\eta_t} = \eta_t \Sigma_{\eta_t}^{-1}\Sigma'_{\eta_t|\epsilon_t}$$

$$\Sigma_{\epsilon_t|\eta_t} = \Sigma_{\epsilon_t} - \Sigma_{\eta_t\epsilon_t}\Sigma_{\eta_t}^{-1}\Sigma_{\eta_t\epsilon_t}{}'$$

where $\mu_{\epsilon_t|\eta_t}$ denotes the conditional mean of ϵ_t and $\Sigma_{\epsilon_t|\eta_t}$ is the conditional variance.

The shocks to the transition equation Eq. (8) have a variance $S = diag(\widetilde{s})$ with

$\underbrace{\tilde{s}}_{N\times 1} = [s_1, s_2, ..., s_n]'$. Taking into account the residuals μ_t and Σ, we set the transition equations as follows:

$$\tilde{h}_t - S^{1/2}\mu_{\eta_t|\epsilon_t} = \alpha + \theta\widetilde{h}_{t-1} + \sum_{j=1}^{K}\delta_j Y_{t-j} + \widetilde{\eta}_t \tag{10}$$

$$var\left(\eta_t\right) = S^{1/2}\Sigma_{\eta_t|\epsilon_t}S^{1/2\prime}$$

$$\mu_{\eta_t|\epsilon_t} = \epsilon_t\Sigma_{\epsilon_t}^{-1}\Sigma_{\eta_t|\epsilon_t}$$

$$\Sigma_{\eta_t|\epsilon_t} = \Sigma_{\eta_t} - \Sigma_{\eta_t\epsilon_t}{}'\Sigma_{\eta_t}^{-1}\Sigma_{\eta_t\mu_t}{}'$$

Several features differentiate our model from the SVARs typically used in the uncertainty literature. *First*, the contemporaneous value and the lagged values of $\widetilde{h}_t$ are allowed to affect Y_t through volatility shocks process. As such, our specification fits naturally well into the theoretical framework and becomes more attractive in modelling volatility dynamics because the structure of the stochastic volatility is technically able not only to identify financial uncertainty shocks, but also to interpret the direct impact of innovations to the volatility of these structural shocks $\widetilde{h}_{t-k}$ on the level of the endogenous variables Y_t. In practical terms, the specification of model allows us to place an economic interpretation on the shocks as it allows the model to tackle the analysis of the impact of volatility while maintaining the flexibility of the state space framework.

Second, to shed light on the time-variation of uncertainty, our structure of stochastic volatility finds its root in the formulation used in time-varying VAR models (see, e.g. Cogley and Sargent (2005); Primiceri (2005); Gambetti et al. (2008); Canova and Gambetti (2009, 2010)). Compared to the earlier models, we allow for time-varying volatility impacts in both the mean and the variance of variables. More importantly, the log-volatility of structural shocks, $\widetilde{h}_{t-k}$, are time-varying and included in the measurement equation as regressors, which provides more precise estimates for typical macroeconomic applications because it helps avoid the risk of losing information about prior sensitivity. Indeed, measuring uncertainty under level specification proved to be sensitive to the scaling of the variables and far more computationally unstable (Mumtaz and Zanetti, 2013; Mumtaz and Theodoridis, 2015). *Third*, our model contains an important advantage over the univariate stochastic volatility of mean model or the standard Bayesian VAR with stochastic volatility. More precisely, many scholars, such as Clark and Ravazzolo (2012) among others, have dealt with an independent auto-regressive or random walk process for each log-variance, while here we build on the fact that the elements of $\widetilde{h}_t$ may co-move together. In short, our assumption is useful and flexible enough to capture possible changes in volatility of shocks to macroeconomic and financial variables. This is a feature that is missing from previous papers that consider stochastic volatility-in-mean models.

Fourth, there is a very limited number of studies which have been dealt with volatility shocks through Bayesian methods. Related earlier SVAR-based studies are given by Mumtaz and Zanetti (2013) and Mumtaz and Theodoridis (2015) which uses in particular changes in the volatility of the variables for identifying uncertainty shocks. Certainly, estimation and Bayesian inference in such models are not yet fully developed. The issue here has to do the usually maintained uncorrelated assumption between shocks to the volatility equation, η_t, and the ones to the observation equation, ϵ_t . Our framework goes one step further by allowing for correlated shocks, which implies the non-zero co-variance between level shocks and volatility shocks. When considering such correlation, the structural shocks can be identified in a second step and, without loss of generality, SVAR techniques can simply distinguish between uncertainty and level shocks rather than imposing a strict exogeneity a priori. Accordingly, the above generalised stochastic volatility in mean framework described in Eq. (9)-Eq. (10)

enables to track the dynamic effects of volatility of structural shocks on the volatility of macroeconomic variables.

It is also worth mentioning that the presence of the terms $\sum_{k=1}^{K} b_k \widetilde{h}_{t-k}$ and $\sum_{j=1}^{K} \delta_j Y_{t-j}$ allows to reflect the dynamic lead–lag dependence between the level and volatility of the endogenous variables, rather than to rely on lagged changes generated from the data in the transition equation (see Mumtaz and Theodoridis (2015); Chan (2017)). Our model specification makes the level (volatility) shocks evolving over time with lead-lag impact on volatility (level). Hence, this research can also be thought of a novel method to quantify endogenous uncertainty effect with the multivariate extension of the stochastic volatility-in-mean model proposed by Koopman and Hol Uspensky (2002) and applied by Lemoine and Mougin (2010). Note also that our model imposes additional structure to the stochastic volatility models with leverage as in Asai and McAleer (2009); Jacquier et al. (2004); Omori et al. (2007); Pitt et al. (2014).

3.3 Identification of the policy shocks

To capture the financial uncertainty shocks, we consider three identification schemes.

- *Cholesky decomposition*:

  To statistically identify the stochastic volatilities, we impose a normalization on the innovation of the covariance matrix Ω_t. This can be conceivably attained by a Cholesky factorization of the covariance matrix as follows: $\Omega_t = A_{0,t}' A_{0,t}$.

  While such a normalization does not fully describe the macroeconomic behavior, an appropriate ordering of the endogenous variables in the vector Y_t would grant an economic interpretation to the orthogonalized shocks (see Primiceri (2005) and Canova and Gambetti (2009)). Therefore, we assume the ordering of financial indicators before the macroeconomic variables. Accordingly, the variables are ordered as follows :

1) Yield spread of BAA corporate bonds over the 10-year Treasury bill rate S; 2) House price index (HPI); 3) The S&P 500 index $(S\&P)$; 4) Quarterly real GNP growth (y); 5) Quarterly GNP deflator inflation (P); and 6) unemployment rate (U). The structure of the variance matrix of shocks, H_t, is given by the following diagonal form:

$$H_t = \begin{pmatrix} exp(h_{1t}) & 0 & \dots & 0 \\ 0 & exp(h_{2t}) & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & exp(h_{3t}) \end{pmatrix}$$

where h_{1t} is the shock to the credit spread (S), h_{2t} is the shock to house price index (HPI) and h_{3t} is the shock to the S&P 500 index $(S\&P)$.

- *Sign restrictions*:

To define the shock of interest, we would typically impose a restriction scheme on the appropriate elements of the A_0 matrix. In particular, we allow for contemporaneous sign restrictions on the shocks where the structural shocks are modelled as $u_t = A_{0,t}^{-1}\epsilon_t$. This structure implies that $A_{0,t}$ represents the contemporaneous response of the endogenous variables to structural shocks ϵ_t. Accordingly, we require that shocks to h_{1t}, h_{2t} and h_{3t} meet the following conditions:

i) Financial uncertainty shocks to h_{1t} have a positive correlation with house price index (HPI) and the $S\&P500$ index (SP), while shocks to h_{2t} and h_{3t} have a negative impact on GNP deflator inflation (P) and civilian unemployment rate (U). We assume that uncertainty shocks to h_{1t} display a correlation that is bigger in magnitude.

ii) Financial uncertainty shocks to h_{1t}, h_{2t} and h_{3t} are restrained to be at least two standards deviations larger than their mean during the financial crisis.

These assumptions allow us to explore an important number of events of high financial volatility for shock identification.

- *Recursive structure*:

  The recursive identification schemes assume that shocks to h_{1t} have no contemporaneous impact on macroeconomic variables but they can affect the house price index (HPI), and the S&P 500 index (S&P). In order to identify the U.S. financial uncertainty shocks, the recursive structure needed in identifying the structural parameters takes the following form:

  $\tilde{A} = A^{-1}$:

$$\tilde{A} = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ \tilde{a}_{21} & 1 & 0 & 0 & 0 & 0 \\ \tilde{a}_{31} & \tilde{a}_{32} & 1 & 0 & 0 & 0 \\ \tilde{a}_{41} & \tilde{a}_{42} & \tilde{a}_{43} & 1 & 0 & 0 \\ \tilde{a}_{51} & \tilde{a}_{52} & \tilde{a}_{53} & \tilde{a}_{54} & 1 & 0 \\ \tilde{a}_{61} & \tilde{a}_{62} & \tilde{a}_{63} & \tilde{a}_{64} & \tilde{a}_{65} & 1 \end{pmatrix}$$

  More technically, the underlying structure of $\tilde{A}$ implies that an increase in the BAA corporate bond yield relative to the 10-year Treasury bill rate (S) leads to a contemporaneous increase in house price index (HPI), and the $S\&P500$ index $(S\&P)$.

4 Empirical results

We now use our empirical model to examine the responses of macroeconomic variables to the uncertainty associated with the shocks affecting three financial indicators including the yield spread of BAA corporate bonds over the 10-year Treasury bill rate (S), h_{1t}, the house price index (HPI) h_{2t}, and the S&P 500 index $(S\&P)$, h_{3t} under the identification schemes described in the previous section. We begin with reporting the estimated volatility of the financial structural shocks, then present the results of impulse response functions and forecast error variance decomposition.

4.1 Estimated volatility of the financial structural shocks

Figure 1 plots the estimated volatility of the structural shocks associated with the three financial indicators (i.e., financial uncertainty), together with the 90% credible confidence intervals.[6] As can be seen, the results are quite similar across the three shock identification schemes we discussed in the previous section, in terms of both size and fluctuation patterns. The financial uncertainty related to the yield spread shock h_t is larger than the uncertainty from the house and equity prices, but it exhibits a more pronounced decline. There is evidence of time variation in these estimated financial uncertainties because they show high values at horizons of one and two quarters, and become much smaller as the horizon increases. More importantly, their long-lasting patterns of change suggest a potential of sizable and delayed transmission of financial uncertainty shocks on the macroeconomy till the end of the sample.

It is worth noting that when assessing their distance to the mean, the general contours of the estimated volatility series are found to be fairly similar across the three identification schemes. This evidence has important methodological implications as it proves that our key results neither depend on the prior setting in the baseline calibration nor on the degree of fatness of shocks' distributions. Also, the large fluctuations in financial uncertainty emphasize the importance of having the volatility term h_t in the mean equation. These results are highly consistent with those documented by Clark (2011), in that the magnitude and the evolution of uncertainty shocks do not depend on the identification scheme.

Table 2 reports the estimated posterior moments and pseudo-standard errors of the

[6] Credible confidence interval is an interval of posterior probability distribution within which an unobserved parameter value falls with given particular probability.

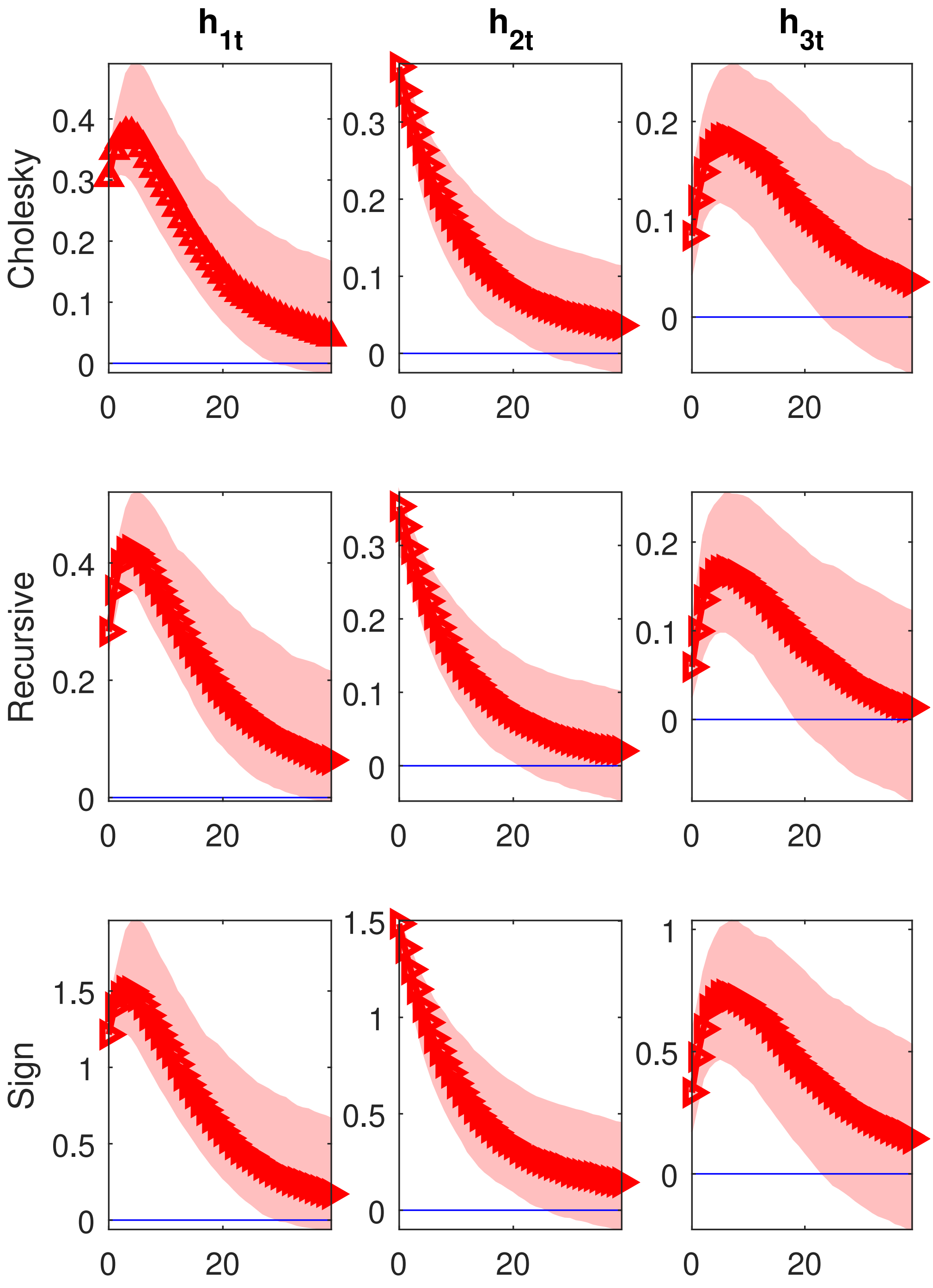

Fig. 1: Estimated Standard Deviation of the Structural Shocks h_t

Table 2: Estimated posterior moments

$Parameter$	Posterior mean	Standard error	90% credible interval	$Parameter$	Posterior mean	Standard error	90% credible interval
Growth				**Deflator**			
c	0.518	0.248	(0.063, 0.653)	c	0.163	0.418	(0.147, 1.242)
β	0.480	0.004	(0.522, 0.384)	β	0.570	0.002	(0.590, 0.494)
b	0.025	0.054	(0.019, 0.051)	b	0.025	0.002	(0.046, 0.044)
α	0.954	0.019	(0.914, 0.019)	α	0.951	0.012	(0.928, 0.965)
θ	0.94	0.006	(0.861, 0.952)	θ	0.85	0.004	(0.074, 0.003)
δ	0.018	0.005	(0.421, 0.971)	δ	0.25	0.002	(0.632, 0.844)
Unemployment				**Yield spread**			
c	0.172	0.227	(0.213, 0.248)	c	0.164	0.350	(0.176, 0.234)
β	0.567	0.003	(0.592, 0.535)	β	0.665	0.002	(0.690, 0.622)
b	0.019	0.001	(0.017, 0.264)	b	0.015	0.001	(0.016, 0.210)
α	0.456	0.015	(0.827, 0.981)	α	0.751	0.014	(0.865, 0.975)
θ	0.72	0.004	(0.623, 0.835)	θ	0.644	0.003	(0.525, 0.792)
δ	0.015	0.003	(0.417, 0.625)	δ	0.051	0.004	(0.465, 0.677)
House prices index				**S&P 500 index**			
c	0.145	0.277	(0.253, 0.448)	c	0.192	0.350	(0.236, 0.394)
β	0.660	0.004	(0.532, 0.772)	β	0.615	0.004	(0.750, 0.701)
b	0.026	0.019	(0.035, 0.043)	b	0.015	0.001	(0.018, 0.020)
α	0.456	0.012	(0.724, 0.831)	α	0.360	0.011	(0.268, 0.543)
θ	0.715	0.003	(0.825, 0.885)	θ	0.750	0.002	(0.788, 0.798)
δ	0.014	0.002	(0.453, 0.843)	δ	0.465	0.003	(0.449, 0.434)

Note: Parameter c is the intercept in the observation equation (first equation below), while α is the intercept of the log-stochastic volatility in the transition equation (second equation below).

$$\begin{cases} Y_t = c + \sum_{j=1}^{P} \beta_j Y_{t-j} + \sum_{k=1}^{K} b_k \widetilde{h}_{t-k} + \widetilde{\epsilon}_t \\ \widetilde{h}_t = \alpha + \theta \widetilde{h}_{t-1} + \sum_{j=1}^{K} \delta_j Y_{t-j} + \widetilde{\eta}_t \end{cases}$$

Parameter β represents the dynamics of endogenous variables in the observation equation while b measures volatility-in-mean feedback. θ captures the volatility persistence while δ captures the lagged effects from the data in the transition equation. The results are based on 150,000 iterations (with 50,000 burns).

volatility models' parameters. The results reveal that the sign of the posterior means is in line with what macroeconomic reasoning would suggest. Indeed, the coefficients associated with the lagged endogenous variables δ and β are positive and statistically significant. Their posterior mean together with 90% confidence intervals show relatively more pronounced estimate, implying that the one-quarter ahead fluctuations in macroeconomic variables cause significant changes in the current volatility. Moreover, the volatility feedback parameter, b_k, is significant and positive, suggesting the importance of the impact of financial uncertainty on macroeconomic volatility throughout the sample.

In what follows, we analyze time-varying dynamics in the volatility of shock process. For tractability, we consider the posterior evidence regarding the volatility of the structural shocks, h_t and volatility feedback, b_k through our sampling interval.

In Figure 2, we have plotted the evolution of parameters and the associated 90% credible intervals. We have several important findings. As can be seen from the left panel of Figure 2, peaks in volatility are observed during the first and third terciles of our sample. At the same time, we see that the evolution of h_t closely tracks with that of volatility feedback, b_k, throughout the first period.

Clearly, this pattern is viewed as a compelling evidence that an increase in volatility coupled with a large h_t value may trigger an increasing volatility feedback effect. More importantly, the most striking feature among these evolution is that volatility and its feedback have a high degree of comovement for a short period.

As this volatility tends to change on a long time horizon, there are not many extreme h_t values, and also volatility feedback, b_k, behave quite differently. One can look at Figure 2 for a visual impression in co-movements where we observe a divergence between the two patterns. At this point, volatility tends to relax much faster with very limited feedback in future volatility. It is also visible from right panel in Figure 2 that the volatility feedback had been steadily decreasing until the end of the period.

However, one must also keep in mind that this is not attributable to the highly persistent overall conditional volatility, We believe that this could be a consequence of the fact that the shocks of observation equation in Eq. (7) are correlated with the shocks of the transition equation in Eq. (8).

It should additionally be noted that the estimates associated with the parameters of h_t process are particularly useful for explaining a larger fraction of volatility. As a matter of fact, the coefficient of second moment shocks θ_t are similar for all series, and the relative standard deviations are highly persistent in terms of their magnitudes and fluctuations, with the posterior mean of θ_t estimated to be about $0.84 - 0.95$ and having a 90% credible confidence interval of $[0.928, 0.995]$. Our results are consistent with those of Shin and Zhong (2020) in that it emphasizes the centrality of second moment structural shocks in identifying the real effects of uncertainty shocks.

It is interesting to note that our results are particularly relevant and novel when viewed in the context volatility-in-mean effect. In particular, we provide an additional stylized fact showing that setting both first and second moment responses to identify our structural financial uncertainty shocks ensures the existence of endogenous financial transmission. In other words, endogenous financial uncertainty is not coincidental but structural in nature. This provides an empirical implication that the transmission effect of uncertainty shocks to the U.S macroeconomic volatility is robust at long horizons.

In short, the assumption of correlated error in both the observation and transition equations improves the capability of clarifying the endogenous movements of uncertainty shocks. Additionally, allowing for a direct impact of volatility in the transition equation is quite robust and flexible in modeling uncertainty shocks.

4.2 Macroeconomic responses to structural shocks of financial variables

In this section, we analyze the implications of correlated errors in stochastic volatility models through the use of impulse response functions and forecast error variance decompositions.

4.2.1 Generalized Impulse response functions (GIRF)

We start by performing a Monte Carlo integration to compute the generalized impulse response functions (GIRF) as described in Koop et al. (1996). For this purpose, we specify the GIRF as:

$$GIRF = E\left(Y_{t+k}\middle|\widetilde{h}_t, Z, Y_t, \eta_{t,j} = \upsilon, e_{t,j} = \nu\right) - E\left(Y_{t+k}\middle|\widetilde{h}_t, Z, Y_t\right)$$

Let Z denote the set of parameters of SVAR model, where k is the horizon, and $\eta_{t,j}$ is the shock to the volatility equation, while, $e_{t,j}$ is shock to the observation equation. To be precise, the first term in equation above involves the forecast of the endogenous variables conditioned on one of possible structural shocks υ, ν while the second term can be treated as a baseline forecast i.e. conditioned on scenario usually associated with shock equals zero.

Intuitively, the "generalized" impulse-responses are calculated as the difference between two conditional expectations. In particular, we simulate the model under an innovation υ to the volatility shock and ν to the level shock.

In Figure 3, we present the impulse responses of each macroeconomic variable at a different horizon using the estimated parameters. For comparability across episodes, the interpretation of the shocks follows the appropriate identification schemes. In addition, for each identified volatility, the responses have been normalized to reflect a common size $\sqrt{\sigma^2_{\eta\epsilon}}$ of the uncertainty shock. According to Figure 3, the estimated responses supports the view that higher financial uncertainty shocks raise the volatility of macroeconomic variables (i.e. unemployment, GNP and inflation). More specifically, we notice that the impulse response estimates to financial uncertainty h_t shock exhibit fairly persistent rise in volatility for conditional output (Y).

Accordingly, volatility can roughly be described as increasing by 50% over the first part of the sample. On the other hand, the response of GNP deflator inflation (P) and unemployment (U) differ more significantly. As expected, macroeconomic volatilities are subject to relative changes over time where financial uncertainty shocks seem to be a plausible reason for this variation within the first 10 quarters. However, the impact of these shocks on macroeconomic volatilities exhibits a temporary effect and becomes close to zero in the long-term (see Figure 2). Generally speaking, the responses are qualitatively in line with those reported by Carriero et al. (2018).

4.2.2 Variance decomposition

So far, from the analysis of impulse response function, we have found that endogenous financial uncertainty shocks may have hump-shaped pattern effects on the macroeconomic variables of the SVAR model.

To further elicit the sources of volatility of macroeconomic variables, we conduct a forecast error variance decomposition. Over the entire sample, we compute a variance decomposition based on the contributions of the volatility shock and level shock to the forecast error variance (FEV) of the endogenous variables. Table 3 reports the median estimates for the FEV decomposition over different sub-periods using the method described by Uhlig (2004). According to these estimates, the volatility shock is almost evenly important at short horizons $(2Q - 4Q)$. Our finding indicates that the contribution of the volatility shock accounts for 35% of the fluctuations in the quarterly real GNP growth (Y) and inflation (P), which is consistent with the findings of Christiano et al. (2014) but somewhat different from those of Caggiano et al. (2014) in terms of significance levels and the coefficient signs. However,

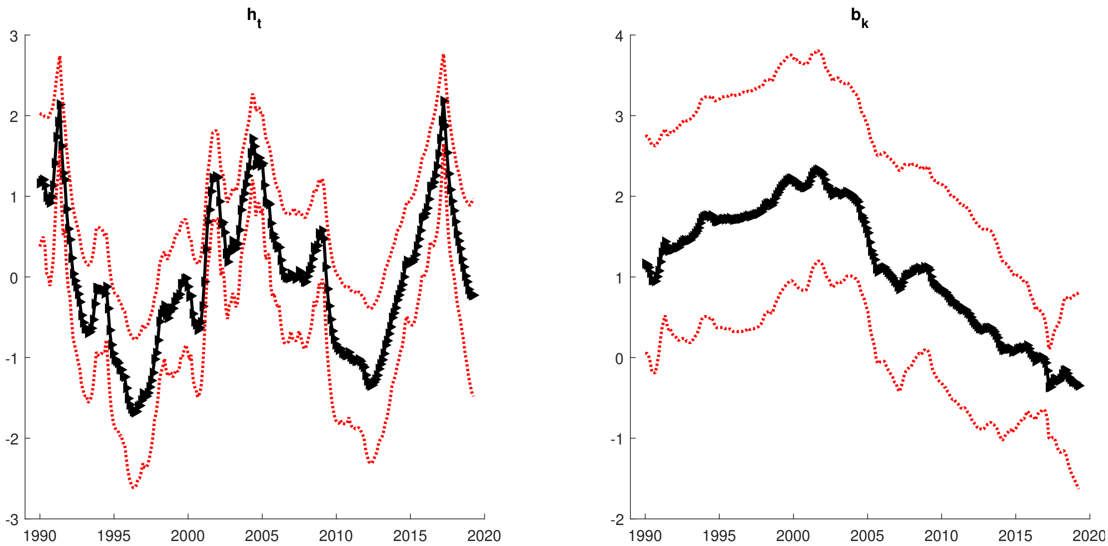

Fig. 2: Evolution of volatility h_t and volatility in mean feedback b_k

Note: The black lines represent the estimated posterior means and the dotted red lines denote the 90% credible confidence .

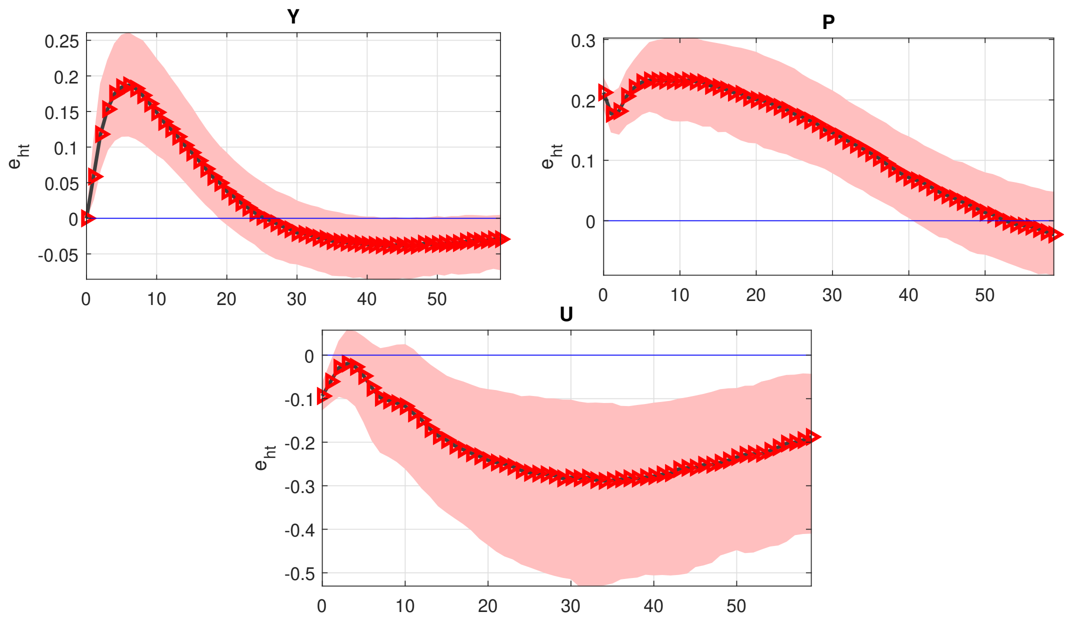

Fig. 3: Impulse response of macroeconomic variables to a financial uncertainty shock

the effects on unemployment are quite modest for most of the sample; and this contribution appears to be significant, and quantitatively more robust than what has been brought forward by Bachmann et al. (2013) and Jurado et al. (2015).

The most striking fact about stochastic volatility that we have found so far is that introducing correlated error feature into SVAR model makes the variance of the structural shocks time-varying. This indicates that in terms of the structural shocks, the contribution to the forecast error variance in subsequent periods is also time-varying. We can see from the Table 3 that the overall contribution is relatively important on impact and it weakens over time. Additionally, we observe at the 8- and 12-quarter horizons, both level and volatility shocks account for about 8-10% of the fall in the forecast error variance of the long-run uncertainty expectations. These results are in line with the second order "variance" phenomenon found by Carriero et al. (2018) rather than the first order "level" shock displayed by Bloom (2009) and Mumtaz and Theodoridis (2018).

Overall, our results are not in all cases consistent with the findings of Caldara et al. (2016) and Gilchrist et al. (2014). However, theoretically speaking, this is not surprising as this partial inconsistency illustrates the differences in the methodologies. Compared to set of alternative models such as a small-scale VAR, our model with stochastic volatility-in-mean formulation is more reliable in detecting endogenous uncertainty shocks.

4.3 Volatility-in-mean feedback effects

To get a better understanding of how introducing endogenous volatility feedback effects drastically changes the volatility dynamics under the different identification schemes. We consider the effects of erroneously imposing the restriction $(b_k = 0)$ to the feedback coefficient b_k (see Eq. (7)) but we also take the correlation between the shocks to the level and volatility into account.

In the spirit of the study of Clark (2011) and Clark and Ravazzolo (2012), we evaluate

Table 3: Contribution to volatility and levels of endogenous variables

Variable	Horizon	Decomposition of volatility shocks	Decomposition of level shocks
GNP growth (y)	2 Q	34.819	22.206
		(23.5,28.40)	*(23.2,24.2)*
	4 Q	23.901	18.167
		(15.52,18.65)	*(11.37,12.51)*
	8 Q	17.684	14.316
		(10.48,12.58)	*(8.57,9.52)*
	12 Q	9.654	6.18
		(2.08,2.48)	*(1.07,2.42)*
Unemployment (U)	2 Q	8.874	6.245
		(9.52,12.44)	*(8.32,9.62)*
	4 Q	10.658	9.265
		(7.08,8.46)	*(6.82,7.22)*
	8 Q	8.840	6.235
		(6.32,7.02)	*(5.72,6.02)*
	12 Q	4.902	3.245
		(2.74,4.40)	*(1.40,3.10)*
Inflation (P)	2 Q	34.736	29.425
		(13.64,14.20)	*(12.12,13.14)*
	4 Q	27.405	26.278
		(13.02,12.65)	*(11.02,11.40)*
	8 Q	22.632	20.279
		(1.79,11.89)	*(1.62,11.72)*
	12 Q	17.893	15.719
		(10.24,0.40)	*(10.12,0.19)*

Notes: This table reports the changes in forecast error variances by level shocks and volatility shocks using the VAR model with time-varying stochastic volatility the accuracy of point real-time forecast (defined as posterior medians) within a Monte Carlo simulation framework and root mean square errors $(RMSEs)$ between unrestricted model and a model with the feedback effects b_k restricted to be zero, (i.e., $b_k = 0$).

In Table 4, we present the results of the benchmark model and the restricted model. Here again, the results more formally quantify our findings. The posterior distributions exhibit diverging patterns but improve the point forecast over time relative to the unrestricted model. In particular, it can be observed that most of the improvement in forecast is found at short horizon $(1Q - 2Q)$. This confirms the evidence that achieving more accurate SVAR forecasts can be done not only by including stochastic volatilities in the mean equation but also including the feedback effects as well. Nevertheless, we do find some evidence of endogeneity, the coefficients are broadly different from zero $(b_k \neq 0)$ and particularly recover the true value of data with precise estimates which do not completely die out even at the 8-quarter ahead horizons. There are indeed some differences between the two models. Specifically, we find that imposing a restriction would lead to unbiased and inefficient estimates. With this caveat in mind, available evidence renders some support to the claim that ignoring the possibility of endogenous volatility feedback effects would complicate the task of generating informative disclosures of historical movements in volatility.

Intuitively, the evidence from estimation results predicts that if financial uncertainty was treated as exogenous, then the resulting posterior distributions would be considerably distorted and would fail to recover the true values of the coefficients that affect not only the conditional mean of Y_t but also the underlying conditional variance as well.

To sum up, these results indicate that shutting down the volatility feedback effects of financial uncertainty would very likely lead to distorted estimation of the effects of financial uncertainty shocks on macroeconomic volatility, and it would create a confusion between its contemporaneous and lagged effects. In other words, this pattern shows that financial uncertainty might be endogenous.

Table 4: Monte Carlo results: Comparison between imposing $b_k = 0$ vs $b_k \neq 0$

Parameter	$1Q$[a]		$2Q$[b]		$4Q$[c]		$6Q$[d]		$8Q$[e]		$10Q$[f]	
	Mean	**RMSE**	**Mean**	**RMSE**	**Mean**	**RMSE**	**Mean**	**RMSE**	**Mean**	**RMSE**	**Mean**	**RMSE**
$b_k = 0$												
β	0.098	0.009	0.245	0.009	0.013	0.089	0.003	0.078	0.007	0.114	0.006	0.028
σ	0.004	0.014	0.077	0.015	0.065	0.002	0.074	0.000	0.325	0.082	0.916	0.262
θ	0.185	0.045	0.069	0.078	0.005	0.046	0.078	0.055	0.194	0.0070	0.928	0.081
δ	0.165	0.036	0.078	0.004	0.063	0.015	0.045	0.077	0.243	0.049	0.097	0.087
$b_k \neq 0$												
β	0.002	0.889	0.764	0.445	0.057	0.447	0.008	0.070	0.940	0.027	0.936	0.029
σ	0.001	0.446	0.003	0.096	0.065	0.047	0.005	0.054	0.101	0.011	0.100	0.012
θ	0.004	0.410	0.004	0.080	0.045	0.004	0.014	0.036	0.040	0.007	0.050	0.005
δ	0.005	0.780	0.002	0.070	0.052	0.046	0.051	0.065	0.002	0.042	0.004	0.042

Data generating process DGP [a] DGP=0.1 [b] DGP=0.22 [c] DGP= 0.25 [d] DGP= 0.21 [e] DGP= 0.22 [f] DGP= 0.20

5 Conclusion

In this paper, we have attempted to answer a crucial question: Is financial uncertainty an exogenous source of macroeconomic volatility or an endogenous response to economic fundamentals? In this regard, we develop a time-varying stochastic volatility-in-mean model where shocks to the transition and observation equations are correlated. We apply our model to the U.S. macroeconomic and financial variables.

Our results point towards the conclusion that endogenous financial uncertainty shocks do matter for macroeconomic volatility. Ultimately, the results indicate that more severe increase in endogenous volatility shocks may cause more negative impact on macroeconomic volatility (i.e., an increase in the magnitude of volatility). Results are robust to a number of identification schemes of uncertainty shocks. It is also found that shutting down the feedback channel raises the volatility shocks and leads uncertainty shocks to react more strongly to macroeconomic variables (i.e. unemployment, GNP and inflation), in turn, causing macroeconomic volatility effects to be more severe, especially in the short horizon. The empirical results carried out from this paper are helpful in shedding further important implications for the policymakers. In particular, uncertainty shocks are found to cause immediate and significant macro-financial fluctuations and tend to have prolonged effects on the real economy. Our results therefore support the immediate adoption of macro-prudential policy interventions geared toward limiting the propagation of these shocks to the real economy.

For further research on this topic, it is recommended to extend the analysis by checking on whether or not the stochastic volatility model with the time-varying parameter variants also fit other macroeconomic or financial time series better.

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