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The macroeconomic impact of economic uncertainty and financial shocks under low and high financial stress

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A B S T R A C T

External financial frictions might increase the severity of economic uncertainty shocks. We analyze the impact of aggregate uncertainty and financial condition shocks using a threshold vector autoregressive (TVAR) model with stochastic volatility during distinct US financial stress regimes. We further examine the international spillover of the US financial shock. Our results show that the peak contraction in euro area industrial production due to uncertainty shocks during a financial crisis is nearly-four times larger than the peak contraction during normal times. The US financial shocks have an influential asymmetric spillover effect on the euro area. Furthermore, the estimates reveal that the European Central Bank (ECB) is more cautious in implementing a monetary policy against uncertainty shocks while adopting hawkish monetary policies against financial shocks. In contrast, the Fed adopts a more hawkish monetary policy during heightened uncertainty, whereas it acts more steadily when financial stress rises in the economy.

1. Introduction

Possible changes in the state of financial conditions can give strong signals regarding future economic activity. As witnessed before the global financial crisis, financial fragility is understood as the extent to which financial frictions can increase the destructive effect of shocks on economic activity (IMF, 2017). For instance, the probable increase in firms' credit spread is addressed as the leading financial frictions. The rise of credit spread decreases the equity payout and debt purchases, thereby reducing the hiring labor and aggregate output (Arellano et al., 2018). On the other hand, the financial sector crises also involve significant international spillover risks that directly concern the global financial community. In the face of these developments, financial frictions and uncertainty shocks have recently come into prominence as an essential source of economic cycles in the literature (for recent surveys, see Bloom, 2009, 2014, 2017; Klößner & Sekkel, 2014; Balcilar et al., 2016; Gilchrist et al., 2014; Zetlin-Jones & Shourideh, 2017; Caggiano et al., 2020). On the other side, we can argue that once the global financial vulnerabilities are severely elevated, the increasing uncertainties in this

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fragile environment entail substantial downside risks to growth. Moreover, the possible effects of uncertainty shock on the real economy might vary depending on the conditions of the financial markets.[1] Within this perspective, a growing literature investigates the sources of the economic cycle by establishing the link between credit markets and the propagation of uncertainty (Alessandri & Mumtaz, 2019; Arellano et al., 2019; Balcilar et al., 2020a; Bloom, 2009; Christiano et al., 2014; Gilchrist et al., 2014).

If the degree of volatility shocks, which is taken as aggregate uncertainty shocks in our study, on reel economic activity varies mostly through financial market conditions (Stock and Watson, 2012), it is naturally expected that external financial market environments will also affect the magnitude of uncertainty shocks on the financially integrated economies. Nonetheless, most of the literature, focusing on these discussions by splicing credit market disruptions and economic uncertainty, rules out the international dimensions of the economic cycle's determinants. Other strands of literature[2] have examined the international spillovers of uncertainty on some economic indicators across various countries. These research areas have come into prominence especially trade, and financial flows among countries have been integrated increasingly for decades on a global scale. These related studies neglect the financial friction transmission mechanism when analyzing the international uncertainty spillovers in similar veins. Ignoring this link is undoubtedly creates a crucial shortcoming for corresponding literature. To address this deficiency, we estimate a nonlinear model, proposed by Alessandri and Mumtaz (2019), using monthly data covering the period from 1995M1 to 2020M12 and scrutinize the impact of uncertainty and financial condition shocks on the industrial production, consumer price, and short-term interest rate of the Euro Area (EA). Considering the US's role as the main source of uncertainty (IMF, 2013) and its vast trade and capital flows with EA, we use the US as a proxy of global economic and financial conditions for the EA economy. Hence, we can analyze the extent to which aggregate uncertainty and financial frictions impact the euro area's economic cycle during different financial conditions. As such, our paper contributes to the literature on recent research topics regarding both the alternative source of the business cycle and international uncertainty spillover across national economies.

Our empirical results indicate that the impacts of uncertainty and financial condition shocks on the euro area economy differ considerably across different global financial regimes. For instance, the peak contraction in euro output growth against aggregate uncertainty shocks in busts is nearly-four times larger than (-0.12 % versus -0.03 %) the peak contraction during booms. On the other hand, while the US financial condition shock decreases the EA inflation 1.5 times larger during bad times when comparing good times, we do not get any evidence about the existence of an asymmetrical relationship caused by uncertainty shocks. Moreover, our empirical findings show that the European Central Bank (ECB) adopts a more cautious and 'wait-and-see' approach in the face of uncertainty, but the Federal Reserve (Fed) is inclined to implement unconventional monetary policy more aggressively during both financial regimes. However, interestingly, the monetary policy stance of the ECB is more responsive to financial condition shocks regardless of the financial states of the US. Lastly, we find strong evidence in favor of asymmetric effects with regards to the contribution of uncertainty shocks in euro area macroeconomic indicators during distinct US financial conditions.

The rest of the paper is organized as follows. After reviewing the literature in Section 2, we describe the TVAR methodology and model specifications in Section 3. Section 4 covers the model's data, and Section 5 presents the model simulations and discussions. We report some sensitivity analyses in Section 6. Finally, Section 7 concludes the paper.

2. Literature review

Financial market frictions have long been considered to play an essential role in business-cycle fluctuations (Jermann & Quadrini, 2012; Zetlin-Jones & Shourideh, 2017). According to the conventional view, the firms and households cut spending on investment and consumption in times of perturbations that originate directly in the financial sector, thereby suspending consumption and production. For instance, Nolan and Thoenissen (2009) try to recognize and measure the importance of shocks to the financial accelerator mechanism in the US market. Their findings suggest that financial shocks are tightly linked to the US business cycle, and corresponding shocks become more of an issue to understand the US economic cycle after World War II. Furthermore, Jermann and Quadrini (2012) find a meaningful link between tight financial conditions and economic downturns in their study.

An extensive literature has explored the link between uncertainty and the economic cycle after the Great Recession since the traditional driving forces on the business cycle are insufficient to explain the prolonged recession experienced by the US and other developed countries. In his pioneer study, Bloom (2009) documents that the uncertainty shock generates a rapid drop and rebound in output and employment due to the firms' fixed investment costs that create a real-option value of waiting under uncertainty. Following this study, lots of academic papers (Baker et al., 2016; Balcilar et al., 2016, 2017; Caggiano et al., 2020; Carriero et al., 2015, 2018; Cesa-Bianchi & Fernandez-Corugedo, 2018; Cheng et al., 2016; Colombo, 2013; Cuaresma et al., 2020; Fernández-Villaverde & Guerrón-Quintana, 2020; Gupta et al., 2020, Jones & Enders, 2016; Jurado et al., 2015, Phan et al., 2021; Li and Qiu, 2021; Phan et al., 2021) have explored the role of uncertainty on various economic indicators such as economic growth, inflation, unemployment, and exchange rates for both single and multiple country examples. Baker et al. (2016) point out that news-based policy uncertainty is significantly associated with larger stock price fluctuations, decreasing investment, and employment in policy-sensitive sectors like

[1] We define two different types of financial conditions. Positive values of the financial condition indices have been related to tighter-than-average financial conditions, while negative values have been related to looser-than-average financial conditions. Accordingly, financially stress times (bad times) represent the US financial condition index that exceeds a particular threshold value, while normal times (good times) represent relates to the case where financial index is below the threshold value.

[2] See some recent papers such as Carrière-Swallow and Céspedes (2013), Yin and Han (2014), Berger et al. (2017), Trung (2019), and Bhattarai et al. (2020) for more information about international uncertainty spillovers.

defense, health care, finance, and infrastructure construction.

Other strands of academic literature[3] concentrate on these two key drivers (uncertainty and financial shocks) of the business cycle together by using different econometric methods, country data, and sample periods. However, most of these studies measure the impact of uncertainty during distinct financial regimes exclusively for a single country. For example, Gilchrist et al. (2014) examine the interaction between uncertainty, credit spreads, and economic activity for the US and find that uncertainty has a limited effect on output in a financially frictionless economy. Christiano et al. (2014), on the other hand, find that the risk shock becomes the most important driving force on the business cycle when they include financial variables in the data for the US economy. Using the penalty function approach, Caldara et al. (2016) analyze the interaction of economic uncertainty and financial conditions and argue that uncertainty shocks have an incredibly negative economic effect during periods that appear to be associated with financial tensions. Alessandri and Mumtaz (2019) quantify the impact of volatility shocks and credit conditions on the US business cycle using the TVAR model with time-varying volatility from January 1973 to May 2014. They find that uncertainty shocks have recessionary effects at all times, but their impact on output grows apace when the economy goes into a financial crisis. Using a similar nonlinear model, Balcilar et al. (2020a) analyze the relationship between economic uncertainty and financial market conditions in South Africa, documenting that the macroeconomic implications of an uncertainty shock differ across distinct financial states.

Another growing strand of the literature examines the impacts of uncertainty shocks on cross-country economies. Previous studies such as Kim (2001), Favero and Giavazzi (2008), Chudik and Fratzscher (2011), Mumtaz and Musso (2019), Cuaresma et al. (2020), Punzi (2020), Balcilar et al. (2020b), and Caggiano and Castelnuovo (2021) provide significant evidence to support the validity of transatlantic spillovers in business cycles and financial markets between domestic countries. Nevertheless, none of these studies explicitly analyses cross-country relations of the connection between uncertainty and financial frictions together. Although the main purpose of these studies is similar to ours, our study differs from them in terms of methodology and the way of dealing with the subject. For instance, Colombo (2013) analyzes the spillover effects from the US on the euro area macroeconomic aggregates by utilizing the linear structural VAR model. Moreover, Netšunajev and Glass (2017) investigate the US and EA labor market reaction to uncertainty shocks using Bayesian Markov-Switching like Caggiano et al. (2014). They conclude that the US labor market tends to react and absorb shocks more quickly than the euro area's labor market. In this scope, our study extends the literature on financial frictions and studies the cross effects of uncertainty shocks in two prominent economic regions, the US and the euro area. Thus, unlike other previous studies, this paper investigates the impact of aggregate uncertainty and financial condition shocks on the euro economy under distinct external financial conditions.

3. Methodology

To examine the aggregate uncertainty shock on euro area's economic activity, we utilize the TVAR model with the uncertainty specification of Alessandri and Mumtaz (2019). This extended model allows first-moment dynamics to be characterized under different financial regimes (financially stressful and calm periods). Thus, the TVAR model can be written as follows:

$$X_t = \left(c_1 + \sum_{j=1}^{P}\beta_{ij}Z_{t-j} + \sum_{j=0}^{J}\gamma_{ij}\ln\lambda_{t-j} + \Omega_{1t}^{1/2}e_t\right)\widetilde{S}_t + \left(c_2 + \sum_{j=1}^{P}\beta_{2j}Z_{t-j} + \sum_{j=0}^{J}\gamma_{2j}\ln\lambda_{t-j} + \Omega_{2t}^{1/2}e_t\right)\left(1 - \widetilde{S}_t\right) \quad (1)$$

where $X_t = (g_t^{US}, \pi_t^{US}, R_t^{US}, f_t^{US}, g_t^{EA}, \pi_t^{EA}, R_t^{EA})'$ is a matrix of endogenous variables and consists of seven variables: log growth rate of US industrial production index (g_t^{US}), US consumer price inflation (π_t^{US}), US shadow-short rate (R_t^{US}), US financial conditions index (f_t^{US}), EA industrial production index (g_t^{EA}), EA consumer price index (π_t^{EA}) and EA shadow-short rate (R_t^{EA}). The two sets of parameters, represented by $\left\{c_i, \beta_{ij}, \lambda_{ij}, \Omega_i\right\}_{i=1,2}$ in Eq. (1), characterize two distinct regimes according to the value of the transition variable $\widetilde{S}_t \in \{0, 1\}$, thereby capturing economic dynamics in distinct US financial conditions. The λ_t represents the aggregate uncertainty and is treated as an unobservable state variable. Additionally, the uncertainty is calculated by the average volatility of structural shocks. On the other side, two economic regimes with potentially different dynamics can be constructed by introducing $\widetilde{S}_t$ as shown in Eq. (1). In our case, the regime is determined by the level of the US financial condition index corresponding to some unobserved threshold z^*:

$$\widetilde{S}_t = 1 \Leftrightarrow f_t^{US} \leq z^*, \text{and}\, \widetilde{S}_t = 0 \Leftrightarrow f_t^{US} \geq z^*$$

where both the delay d and the threshold z^* are unknown parameters. $\widetilde{S}_t = 1$ represents the normal regime when the US financial conditions index falls under an unobserved threshold value z^* determined by the data, while $\widetilde{S}_t = 0$ indicates stress regime. Besides, the time-varying covariance matrix (Ω_{it}) of the residuals (e_t) in Eq. (1) plays a critical role in our analysis and is defined as $\Omega_{it} = A_i^{-1}H_tA_i^{-1'}$. In this definition, the non-zero elements of lower triangular matrices, A_i, evolve as a random walk as described in Primiceri (2005) and the $H_t = \lambda_t S$ where $S = \text{diag}(s_1, .., s_N)$. Finally, the volatility that we define as aggregate uncertainty follows an AR(1) process:

[3] See e.g., Bloom (2009), Christiano et al. (2014), Gilchrist et al. (2014), Arellano et al. (2019), Alessandri and Mumtaz (2019), and Balcilar et al. (2020a, 2020b).

$$\ln\lambda_t = \alpha + F\ln\lambda_{t-1} + \eta_t \tag{2}$$

where η_t is an i.i.d. innovation with $\mathrm{var}(\eta_t) = Q$. The volatility description in Eq. (2) does not differentiate between the common and idiosyncratic components, and λ_t is a convolution of both components. Also, it has been ensured that the contribution of all structural shocks to aggregate volatility has the same weight λ_t. However, this wight is time-varying as it is governed by λ_t. In this context, we can say that if $\eta_t > 0$, λ_t increases and this leads to an upward shift in e_t, reducing the accuracy of economic agents' prediction of X_{t+n}.

Before moving to the explanation of the generalized impulse response function, we would like to briefly touch on how to approximate the posterior distribution of parameters and state variable λ_t by using the Gibbs sampling algorithm.[4] Given a draw of the state variable, the model collapse to a standard TVAR after the simple generalized least squares transformation of the corresponding model for making the errors homoscedastic. It is worth noting that the conditional posterior distribution of the VAR parameters in stress and normal financial regimes, the threshold, and delay are the same as those of a standard TVAR (Alessandri & Mumtaz, 2017). Furthermore, the delay parameter, d, is a multinomial distribution, whilst we draw the threshold value its non-standard posterior by using a Metropolis-Hastings algorithm as described by Chen and Lee (1995). After splitting the whole observation into two regime-specific periods, we can sample the VAR coefficients from the normal distribution. Given a draw for VAR parameters, the threshold, and λ_t, the conditional posterior distribution of A and the variances S can be drawn from normal and the inverse Gamma distribution, respectively. Lastly, we draw state-variable λ_t by utilizing the independence Metropolis algorithm that is introduced by Jacquier et al. (1994).

The TVAR model is estimated using the Gibbs sampling with 50,000 posterior and 50,000 burn-in draws. A training sample of 20 observations is used for the initialization of priors. The lag order of the TVAR is 2, and the delay for the transition variable is 2. To calculate impulse response function, we follow the procedure in Koop et al. (1996) and use Monte Carlo integration to study the potential differences in the propagation of uncertainty shocks on EA economic activity under distinct US financial conditions. In particular, the regime-dependent impulse response functions are defined as:

$$IRF_t^S = E\left(Y_{t+n}\backslash\Psi_t, X_{t-1}^S, \mu\right) - E\left(Y_{t+n}\backslash\Psi_t, X_{t-1}^S\right) \tag{3}$$

where Ψ_t symbolizes all the parameters and hyperparameters of the model, n is the horizon under consideration, $S \in \{0, 1\}$ denotes the regime, and μ is the shock (i.e., increase in uncertainty or volatility, in our study). The first term in Eq. (3) denotes a forecast of the endogenous variables conditioned on one of the structural shocks μ. On the other side, the second term represents the baseline forecast obtained by equating the shock to zero. Thus, we have an excellent opportunity to gauge how uncertainty contributes to the Euro Area's business cycle in different financial conditions via a stochastic simulation of the VAR model.

4. Data

The seven variable dataset we use contain monthly data on the log growth rate of the US industrial production index (US-IP), the US consumer price inflation (US-CPI), the US shadow-short rate (US-SSR), the US financial conditions index (US-FCI), EA industrial production index (EA-IP), EA consumer price index (EA-CPI), and EA shadow-short rate (EA-SSR) over the period from 1995M1 to 2020M12. The CPI, IP, and US financial condition index are taken from Datastream. Moreover, we use Wu and Xia's (2016) and Krippner's (2013) shadow-short rate as a measure of the short-term interest rate of US and EA, respectively, given that at least half of our analysis period encompasses the zero lower bound (ZLB). Industrial production and consumer price indices are transformed into monthly growth ($g_t = \ln(x_t/x_{t-1}) \times 100$), while the other variables are used in levels. In accordance with the main purpose of this study, we prefer to use the US FCI[5] among various financial market indicators[6] to capture the global condition of financial markets including the euro area. The US FCI is a comprehensive, flexible, and highly robust indicator of financial stress, constructed from 105 mixed-frequency indicators of financial activity and made publicly available by the Federal Reserve Bank of Chicago.

Table 1 reports the descriptive statistics. The average industrial production and consumer price index growth of the US and the euro area take positive value, but the US indicators are larger than euro area indicators. Similarly, on average, the shadow-short rates of both countries take a positive value. Interestingly, the standard deviation of both countries' industrial production growth is significantly larger than the standard deviation of the consumer price index. In other words, the fluctuation in industrial production cannot be brought under control as inflation in these advanced economies. The fact that the US FCI is below zero indicates the existence of a loose financial market on average. This can be seen as evidence that the expansionary policy period experienced after the crises lasted longer than the Fed's contractionary policy period due to an overheated economy in the US.

We also examine the corresponding series by Ljung-Box test statistics of first [Q(1)] and the sixth [Q(6)] autocorrelation tests and

[4] The technical details regarding the implementation of algorithm can be found in Alessandri and Mumtaz (2019).

[5] Under the assumption that the US is the dominant driver of the world economy and finance, it is acceptable to use US FCI as a proxy for the euro area's external financial conditions. In addition, the fact that the US and the EA are financially integrated with each other is a consistent argument with this study regarding how the impact of uncertainty shocks differentiate across euro area during distinct tightness of financial market conditions. For details of the considerations and discussions in the selection of financial indicators, see Caggiano et al. (2014).

[6] Empirical literature offers four broad methods for measuring the tightness of financial markets. These approaches might depend on investment-saving curves (Goodhart & Hofmann, 2001), large macroeconomic models (for example, Beaton et al., 2009), impulse response functions based on vector autoregression models (for instance, Swiston, 2008), and principal components analysis and more sophisticated variants, such as dynamic factor models (IMF, 2017).

Table 1
Descriptive statistics.

	US IPI Growth	US CPI Inflation	US Shadow Short Rate	US FCI	EA IPI Growth	EA Inflation CPI Inflation	EA Shadow Short Rate
Mean	0.001	0.002	1.979	−0.39	0.001	0.001	1.077
SD.	0.011	0.003	2.651	0.505	0.019	0.002	2.449
Min	−0.136	−0.018	−2.986	−0.86	−0.206	−0.005	−3.92
Max	0.06	0.014	6.647	2.724	0.12	0.007	5.35
Skewness	−5.731	−1.439	0.06	3.383	−3.741	−0.472	−0.271
Kurtosis	73.507	10.918	−1.236	14.152	52.788	1.24	−1.32
JB	72680.489***	1678.623***	19.625***	3234.895***	37336.828***	32.452***	26.066***
Q(1)	24.837***	55.004***	309.048***	291.316***	5.235**	23.236***	306.257***
Q(6)	34.209***	59.393***	1753.978***	1273.841***	23.622***	46.436***	1706.693***
ARCH(1)	4.209**	46.573***	302.619***	264.822***	104.352***	7.007***	293.655***
ARCH(6)	13.419**	50.914***	299.385***	282.098***	107.536***	13.126**	294.179***

Note: Descriptive statistics for growth rates of industrial production index (IP), inflation based on consumer price index (CPI), interest rates represented by shadow-short rates (SSR; Krippner (2013) for EA ad Wu and Xia (2016) for the US) for the US and euro area (EA) and the financial conditions index (FCI) of the US are reported in the table. The data is at monthly frequency and covers the period 1995:M1-2020:M12 with 312 observations. In addition, to mean, standard deviation (SD), minimum value (Min), maximum value (max), skewness, excess Kurtosis, Jarque-Bera normality test (JB), the table reports first [Q(1)] and sixth [Q(6)] order serial correlation test, and also first [ARCH(1)] and sixth [ARCH(6)] order autoregressive conditional heteroskedasticity test.

the autoregressive conditional heteroskedasticity of all series employing the first [ARCH(1)] and sixth [ARCH (6)] order Lagrange multiplier (LM) test to get more robust outcomes with regards to the normality test. The test statistics report shows that normality assumptions and the null of no ARCH effects are robustly rejected for all series. Fig. 1 also shows the time-series of the corresponding series over the analysis period. The consumer price index of US and EA is on an upward trend, while the highly volatile shadow-short rates show a continuous decline trend from the beginning of the observation period to the end of 2020. The industrial production index, on the other side, has a mildly upward trend for both countries, but it shows a severe decrease during the economic crisis.

Fig. 2 plots the US FCI (right axis and dashed line in red color) together with our estimated economic uncertainty measured by the median log stochastic volatility. Gray bands denoting the financial crises identified by the TVAR model is consistent with the contraction period such as economic downturns in the late 1990s and the beginning of the 2000s, such as the dot-com bubble, the financial crisis of 2007 to 2008, the Great Recession of 2008 to 2012, the Brexit and the European sovereign debt crisis, as well as the recent and ongoing global economic shutdown due to Covid-19. As shown in the figure, there is a considerable co-movement between these series, underscoring the close connection between changes in financial conditions and swings in economic uncertainty throughout a business cycle. To sum up, this result reveals the necessity of analysis that explicitly incorporates the nexus between aggregate economic uncertainty and the US financial conditions. On the other hand, it is worth mentioning that the ups and downs of aggregate uncertainty far from being rare during non-recessionary times pointed out by the financial stress index. Hence, we can deduce that the periods of high financial stress may carry different information on the effects of uncertainty shocks on the macroeconomic environment than expansions, as stressed by Caggiano et al. (2014) and Gilchrist et al. (2014).

5. Empirical results

5.1. Impact of overall uncertainty shocks on the EA economy

Fig. 3 plots the nonlinear impulse responses of euro area economic activity to uncertainty shock in good (black lines) and bad financial times (red lines). Regarding the economic activity, we concentrate on industrial production for real economic activity indicators and inflation and shadow-short rates owing to their policy-relevance. Before making several comments on other empirical results, it should be noted that the response of volatility to uncertainty shock are the same across regimes since the stochastic volatility process λ_t are not regime dependent.

Firstly, the response of euro area industrial production is asymmetric, particularly for the initial few periods, although the confidence bands overlap after 12 months and the responses are insignificant. The peak contraction in output growth in busts is nearly-four times larger than (−0.12 % versus −0.03 %) the peak contraction during booms. This can be seen as robust evidence underpinning the ‘financial view’ of the transmission mechanism that asserts financial frictions multiply the detrimental impact of uncertainty shocks on real and financial markets. Another striking point is that industrial production initially drops, rebounds, and then gradually falls when the financial friction is looser. Firms’ initial pause and subsequent catch-up in the reallocation across economic units may justify this evidence, which is valid for only normal times, not in a financial stress period. However, we do not find evidence of the *overshooting*, which Bloom (2009) documented in his pioneering study, for euro area economic activity.

Secondly, the effect of financial friction in the case of uncertainty shocks on euro area inflation dynamics remains roughly

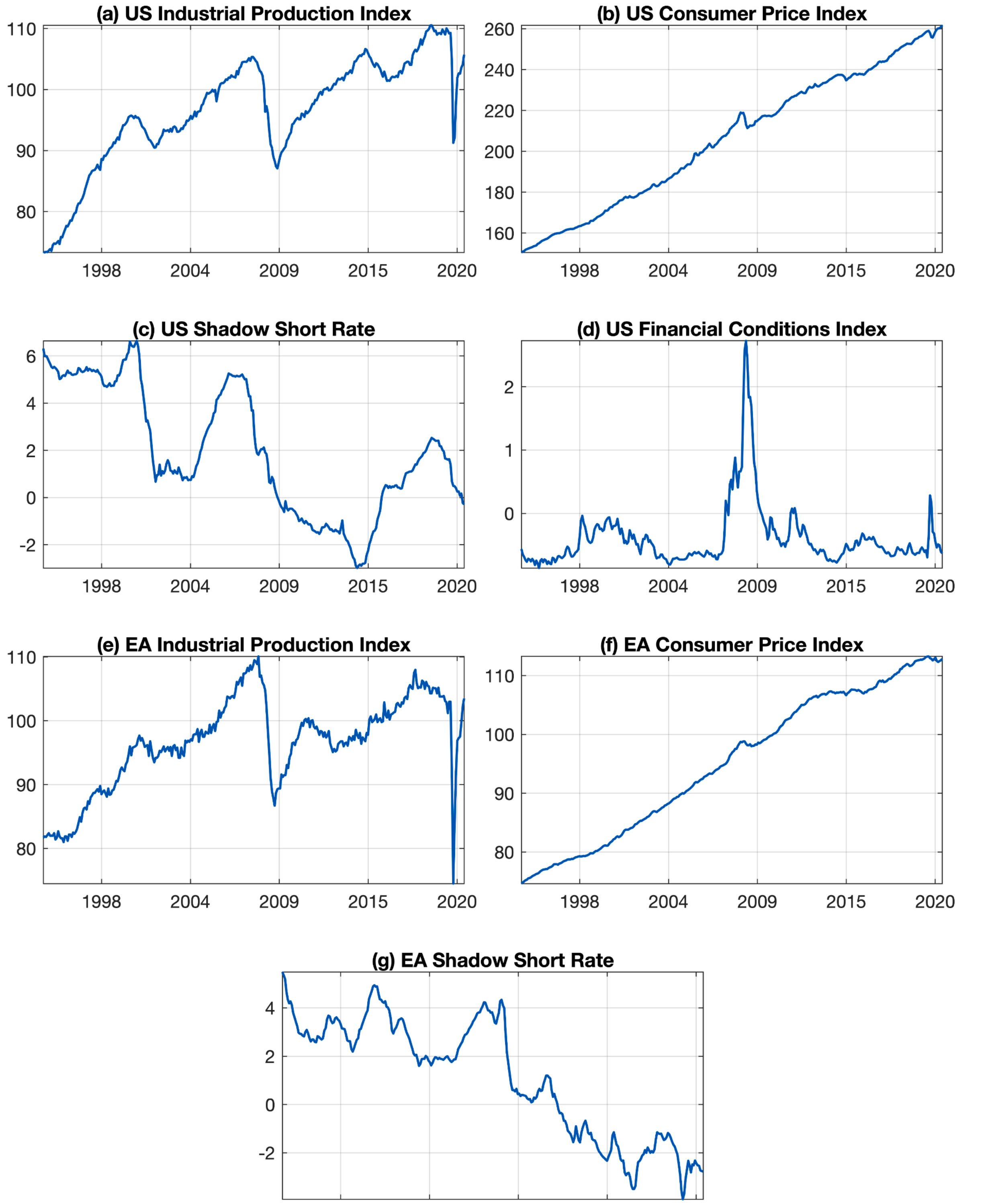

Fig. 1. Time series plots of the data in levels. Note: The figure plots the levels of industrial production index (IP), consumer price index (CPI), shadow-short rates (Krippner (2013) for EA ad Wu and Xia (2016) for the US) for the US and euro area (EA) and the financial conditions index (FCI) of the US for the period 1995:M1-2020:M12.

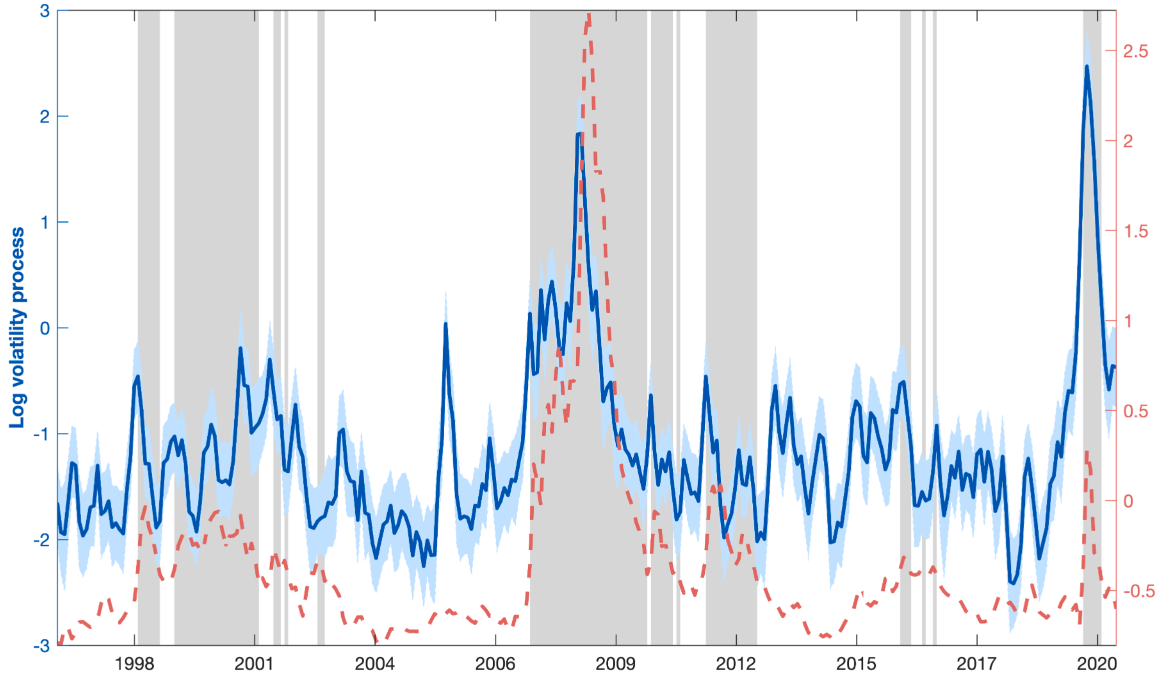

Fig. 2. The US financial regimes and estimated economic uncertainty. Note: The figure displays the US financial regimes index (US FCI, right axis and dashed line in red color) and the estimated economic uncertainty measured by the median log stochastic volatility (left axis and solid line in blue color) over the period 1996:M11-2020:M12. The log volatility is estimated by the threshold VAR model (TVAR) explained in Section 2. The first 20 observations from the beginning are used to initialize the priors. The estimated threshold value is −0.3873. Periods with the values of FCI above −0.3873 are identified as the financial distress or crises regime periods. The light blue band around the log volatility designates the 68% confidence band. The gray shaded regions mark the financial crises regime periods identified by the TVAR model. (For the interpretation of the color references in this figure, the reader may refer to the web version of this article.). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

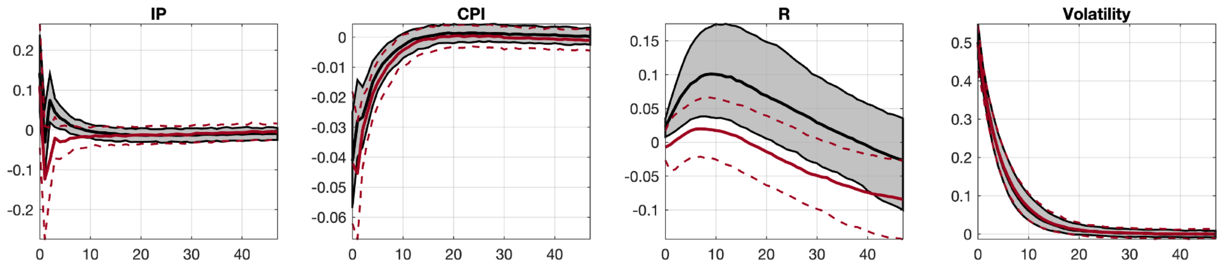

Fig. 3. Impact of volatility shocks on the EA. Note: The figure presents the median impulse responses and 68% confidence bands of the EA macroeconomic variables for a one standard deviation increase in the overall economic volatility in normal and crises periods. The black lines indicate the impact of a one standard deviation increase in the aggregate volatility shocks on the EA economic activity in normal times, while the red line shows the impact of the same shock during episodes of financial distress where the FCI of US exceeds the estimated threshold of −0.3873. Specifically, impulse responses of the IP growth rate, CPI inflation, and shadow-short rate of the EA as well as the overall economic volatility is given in the figure. Horizontal axes are time in months measured from 0 (contemporaneous effect) to 47. The 2-regime TVAR model is estimated using the Gibbs sampling with 50,000 posterior and 50,000 burn-in draws. A training sample of 20 observations is used for the initialization of priors. The estimation period is 1996:M11-2020:M12. The lag order of the TVAR is selected as 2 by the Schwarz's Bayesian information criterion and the delay for the transition variable is 2. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

unchanged.[7] Uncertainty shocks are deflationary in the euro area during both regimes of the US financial, supporting the findings of Christiano et al. (2014), Leduc and Liu (2016), and Basu and Bundick (2017) in the literature. In other words, the uncertainty shock act like an adverse aggregate demand shock (standard channel) during both regimes.

Finally, we discuss the impact of the total uncertainty shock on the euro area policy rate according to different situations of the US financial environment. In a financially stressful regime, the distribution of interest rate response to uncertainty shock lies mostly below zero during the observation horizon, coinciding with Allessendri and Mumtaz's (2019) empirical finding. However, the corresponding shock generates a leap in industrial production and decline in inflation during normal conditions; hence monetary policy can work countercyclically, and shadow interest rates tend to rise.

To quantify the contribution of uncertainty shocks for the dynamics of the variables of interest, we estimate the forecast error variance (FEV) during bad and good times (Fig. 4). Several considerations are in order. First, the percentage of output variance accounted for by volatility shocks in good times is more significant than those in bad times, approximately 6 % versus 4 %. Second, the aggregate uncertainty accounts for inflation in the high-stress regime, while its contribution exceeds 10 % in the low-stress regime. And finally, uncertainty shocks contribute nearly ten times as much to the variance of the short shadow rate during the normal times according to contribution in stressful time after roughly-seven months. The aggregate uncertainty shocks are a remarkable driver of the shadow rate of EA, but its contribution attenuates over time. On the other hand, the explanatory power of volatility on the variance of EA shadow interest rate fluctuates around 5 % during stressful times. Overall, we find strong evidence in favor of asymmetric effects with regards to the contribution of uncertainty shocks in related EA economic indicators during different US financial conditions.

5.2. Impact of overall uncertainty shocks on the US economy

This subsection presents the impulse response function (IRF) and FEV analysis results for the US shown in Fig. 5 and Fig. 6, respectively. These reports are crucial to compare the impact of uncertainty on EA economic activity as well as results of other related studies for the US. First of all, similar to EA, the US industry is more affected by aggregate uncertainty during financial stress times than normal times. Parallel to this result, the peak fall in US inflation is two times larger in the crisis regime than in the normal regime. This result indeed contradicts the outcomes of Alessandri and Mumtaz (2019),[8] who find that the uncertainty shocks cause an inflationary effect on the US economy during normal times. Moreover, one of the most noticeable findings is that the dynamics of interest rate response are entirely different in EA and the US. Put differently, the US short shadow rate reacts suddenly when both industrial production and inflation fall in a crisis regime; however, the EA shadow-short rate increases first, then decreases to below zero, implying monetary policy in the US and the euro area take different paths. Regardless of financial conditions, the ECB adopts a more cautious and "wait-and-see" approach in the face of uncertainty, but the Fed incline to implement unconventional monetary policy more aggressively. Our empirical finding, thus, is in line with the monetary policy stance of ECB and Fed.[9] Finally, as shown in Panel 4 of Fig. 5, the impact of adverse uncertainty shocks deteriorates the US credit markets to a large extent during episodes of financial distress. Besides, Fig. 6 reports the estimated FEV analysis for the US market and suggests a milder contribution of uncertainty shocks on industrial production, inflation, and credit markets during normal regimes than stress regimes. However, this situation is reversed for the shadow-short rate.

5.3. Impact of financial conditions shocks on the EA economy

To compare the impact of uncertainty and financial frictions on the EA economy, we also drive the IRF of corresponding macroeconomic indicators to US financial condition shocks during periods of tense and loose financial regimes. In doing so, we have a great opportunity to see whether the US financial friction is a significant source of EA business cycles or not. As illustrated in Fig. 7, the tightening of the US financial conditions causes a more pronounced decline in both output growth and inflation in the euro area during the crisis regime. These empirical findings provide evidence to support the existence of a severe asymmetry between both regimes. Our finding regarding EA industrial production is in line with the empirical results of Caldara et al. (2016), who find that financial conditions have an asymmetric and large prolonged impact on the US industrial production. Furthermore, the response of the shadow-short rate of EA to US financial condition shocks is more significant during crises regime than in the normal regime, implying the ECB takes action to conduct more loose monetary policy in the period of financial stress up to roughly-two years. In particular, this

[7] The aggregate uncertainty shocks cause inflation to decrease a bit higher during bad times compared to good times, but this difference is statistically negligible.

[8] Alessandri and Mumtaz (2019) use the nominal three-month Treasury bill rate as a proxy of the monetary policy, and they need to truncate the sample to exclude the 'zero lower bound' period not to affect their results. Instead, we use the shadow-short rate to encompass both conventional and unconventional monetary policy implementation periods. Also, some papers (i.e., Basu & Bundick, 2012; Caggiano et al., 2014) argued that the uncertainty shocks might have a more pronounced effect during the presence of zero lower bound, underpinning our choice of the shadow-short rate as a proxy of the policy rate.

[9] The ECB tries to ensure only price stability in the economy, whereas the Fed attempts to achieve both price stability and maximum employment (dual mandate), affecting the central banks' policy stance. That stance can be described as the contribution made by monetary policy to economic, financial, and monetary developments. The fact that the possibility of different nations in the euro area to purchase sovereign debts was not envisaged in the Maastricht Treaty in the 1992 is another issue that makes it difficult for the ECB to implement unconventional monetary policy in economic crises.

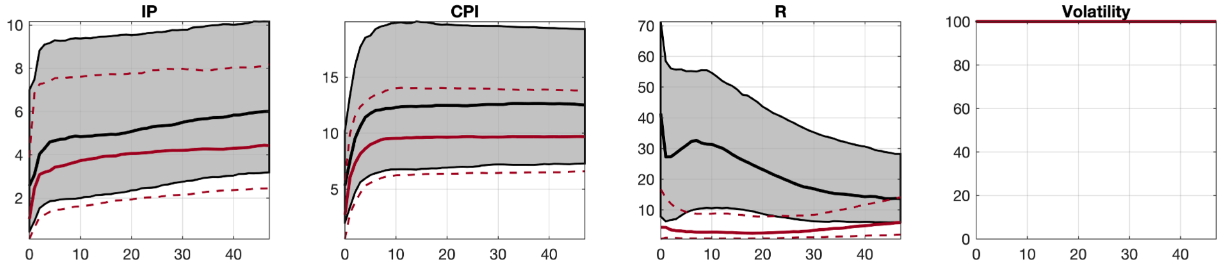

Fig. 4. Forecast error variance decomposition for the effect of volatility shocks on the euro area. Note: The solid line in each panel shows the fraction of median forecast error variance explained by volatility shocks for one of the variables of EA (first to third columns) and volatility shock itself (fourth column). The gray shaded region and red dotted lines mark 68 % confidence bands for median forecast error variance in normal and financial distress times, respectively. Horizontal axes represent time in months measured from 0 (contemporaneous effect) to 47 months. The black line (with gray shaded areas) corresponds to calm periods and the red line (with red dotted lines) corresponds to financial crises where the FCI of US exceeds the estimated threshold of −0.3873. The TVAR model with two regimes is estimated using the Gibbs sampling with 50,000 posterior and 50,000 burn-in draws. A sample size of 20 is used for initial training to initialize priors. The data for the period 1996:M11-2020:M12 is used for the estimation. The lag order of the TVAR is 2, which is selected by the Schwarz's Bayesian information criterion, and the threshold delay is also 2. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

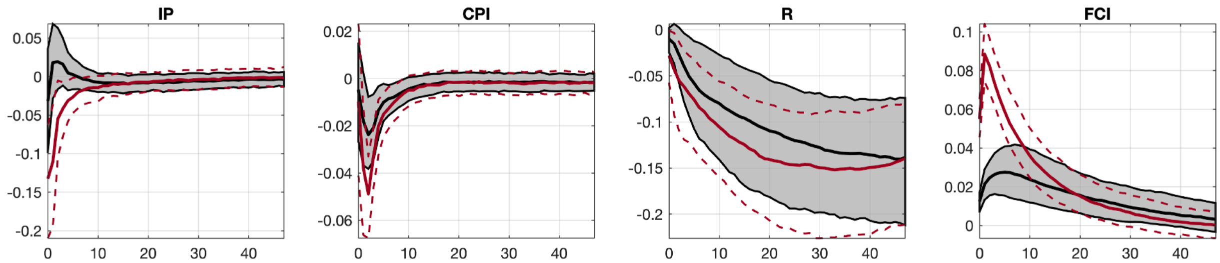

Fig. 5. Impact of volatility shocks on the US. Note: The figure presents the median impulse responses and 68% confidence bands of the US macroeconomic variables for a one standard deviation increase in the overall economic volatility in normal (black lines) and crises periods (red lines). See note to Fig. 3 for further details. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

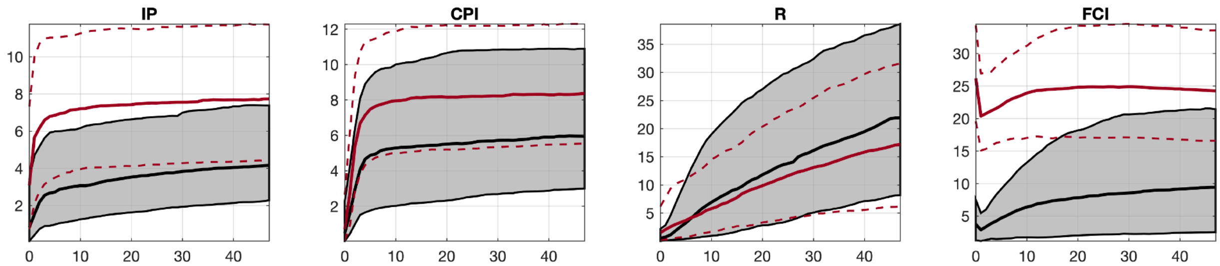

Fig. 6. Forecast error variance decomposition for the effect of volatility shocks on the US. Note: Each panel of the figure presents the fraction of median forecast error variance explained by volatility shocks in calm periods (black lines) and financial distress periods (red lines) for one of the variables of the US. Shaded regions represent 68% confidence bands. Horizontal axes are in months from 0 to 47. See note to Fig. 4 for further details. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

finding is consistent with Kollmann (2013), who finds that financial shock emanating from banks, exacerbated in times of recession, matters more for EA macro variables than for the US real activity.

5.4. *Impact of financial conditions shocks on the US economy*

Fig. 8 reports the effect of financial conditions shocks on the US economy. Similar to the results for the euro area in the previous section, we provide evidence that the impact of financial shocks on the US market has an asymmetric effect according to the state of financial tightening. The asymmetry between good and bad times is clear and sizable for these empirical results. In the high financial stress regime, for instance, the impact of FCI on US industrial production and inflation is approximately-two times larger than the low financial stress regime. When taken into account the previous empirical findings (see sections 5.1 and 5.2) regarding the EA, the

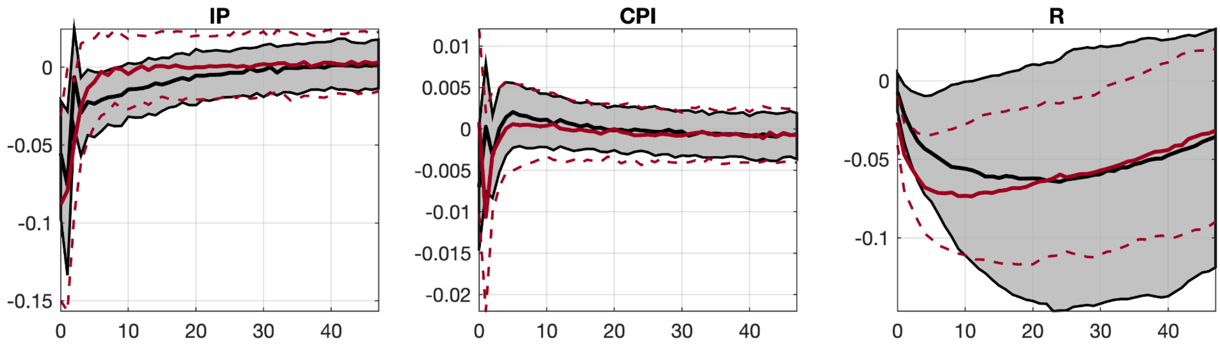

Fig. 7. Impact of financial conditions shocks on the EA. Note: The figure presents the median impulse responses and 68% confidence bands of the EA macroeconomic variables for a one standard deviation increase in the US financial conditions index in normal (black lines) and crises periods (red lines). See note to Fig. 3 for further details. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

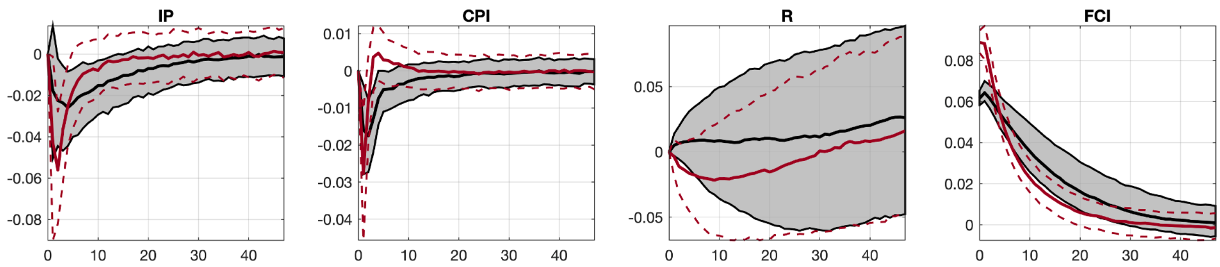

Fig. 8. Impact of financial conditions shocks on the US. Note: The figure presents the median impulse responses and 68% confidence bands of the US macroeconomic variables for a one standard deviation increase in the US financial conditions index in normal (black lines) and crises periods (red lines). See note to Fig. 3 for further details. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

responses of the policy rate to financial conditions shocks reflect the main difference in our analysis. That is to say, the Fed consent to loosen monetary policy in the face of financial condition shocks just in case of serious disturbance in the credit market. However, this is not relevant for the EA market (see Fig. 7). The expansionary monetary policy is undertaken by the ECB irrespective of the financial conditions in the market. However, as we mentioned above, the Fed displays a much more aggressive attitude to the uncertainty shocks than the ECB. Hence, we can conclude that while the Fed is more sensitive to uncertainty shocks, the ECB is more susceptible to financial condition shocks.

5.5. Sign and regime asymmetry

Unlike linear counterparts, the nonlinear models taking into account distinct states can successfully capture the asymmetric effects between observed variables. Besides, the sign of the shocks (positive or negative shocks) might create asymmetries, and a similar form of asymmetry between positive and negative shocks is investigated by several papers such as Alessandri and Mumtaz (2019) and Balcilar et al. (2020a) in the literature. Following them, Fig. 9 and Fig. 10 plot impulse responses of industrial production to both uncertainty and financial condition shocks, respectively, for EA and the US during distinct financial conditions. First of all, we can say that the financial disturbances strengthen the uncertainty shock and financial conditions shock irrespective of its sign for both EA and the US. Furthermore, we find that a fall in uncertainty causes a smaller change in output than a rise in the uncertainty of equal size during crises regime in the euro area (see left panel of Fig. 9). On the other hand, comparing with financial tightening shock, a relaxation in financial conditions has a larger effect on output during both regimes in the euro area (see left panel of Fig. 10). Lastly, we do not find clear evidence regarding the existence of the sign asymmetry for the US.

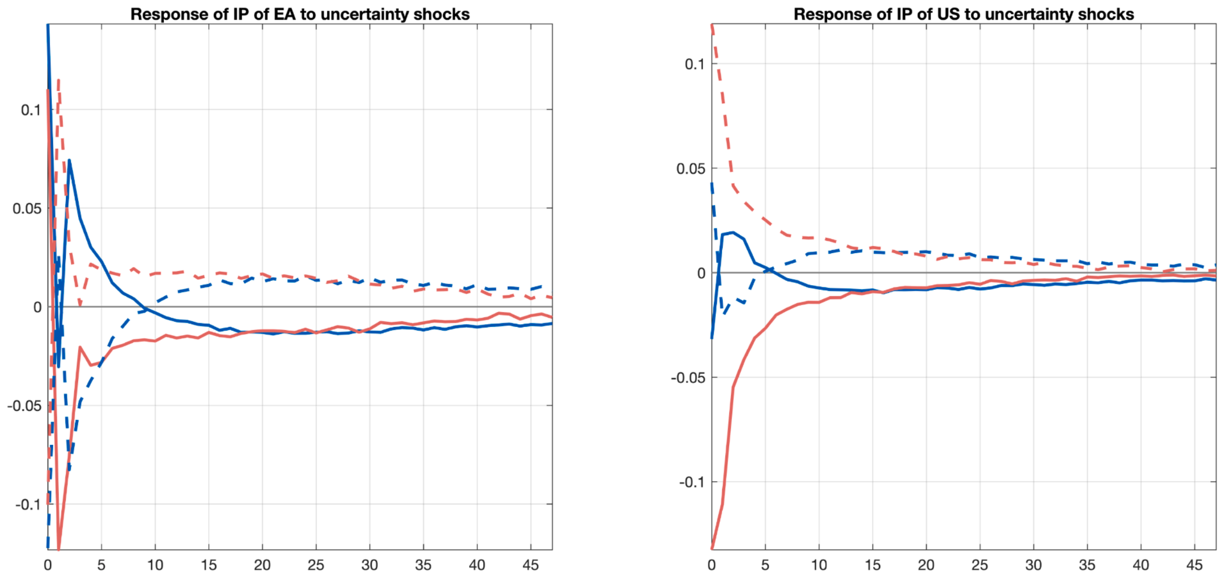

Fig. 9. Sign asymmetry of volatility shocks. Note: The figure presents median impulse responses of industrial productions of the EA (left panel) and the US (right panel) to one standard deviation positive (solid lines) and negative (dashed lines) shocks in the overall economic volatility in normal (blue color) and crises periods (red color). See note to Fig. 3 for further details. (For the interpretation of the color references in this figure, the reader may refer to web version of this article.). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

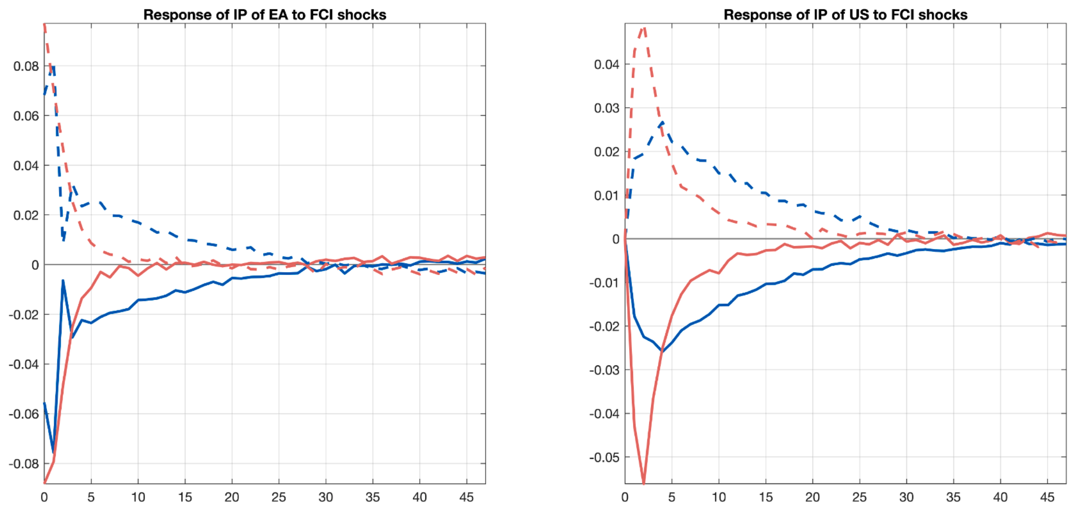

Fig. 10. Sign asymmetry of financial conditions shocks. Note: The figure presents median impulse responses of industrial productions of the EA (left panel) and the US (right panel) to one standard deviation positive (solid lines) and negative (dashed lines) shocks in the financial conditions of the US in normal (blue color) and crises periods (red color). See note to Fig. 3 for further details. (For the interpretation of the color. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

6. Sensitivity analysis

The conclusions reached in the preceding section hold up well to numerous modifications to the benchmark model specification. In particular, the findings hold up even after post-COVID-19 and pre-euro observations are excluded from the sample,[10] when additional variables are added, such as the US unemployment rate and the EA composite financial stress variables, when timing assumptions are changed, and when narrative sign restrictions are used to identify uncertainty shocks, as in Antolín-Díaz and Rubio-Ramírez (2018) and Ludvigson et al. (2017). In this section, we also exclude post-COVID-19 and pre-euro observations from the sample, although this does not have a notable effect on the estimates. The outcomes of these sensitivity assessments are succinctly presented here.

6.1. Extended information set

The benchmark model relies on a data set that is extremely rich in financial information because the financial conditions index is included, but it could be rather weak in real information because of the small number of variables. Given its complex dynamic structure and numerous variables, the TVAR model frequently has estimation problems. Our STVAR definition is a sizable model by itself, making it infeasible to add several other variables to the model. In this section, we add two extensions, though. We redo the benchmark analysis and add the US unemployment series to the model as a first robustness check. Thus, by including the US unemployment series (U), denoted u_t^{US}, the specification of X_t in Eq. (1) is expanded to become $X_t = (g_t^{US}, u_t^{US}, \pi_t^{US}, R_t^{US}, f_t^{US}, g_t^{EA}, \pi_t^{EA}, R_t^{EA})'$. In the second extension, we add the composite financial stress index (FSI) for the euro area, which also allows us to analyze how EA financial stress affects the US. The composite financial stress index for the EA is measured by the Composite Indicator of Systemic Stress (CISS) Index provided by the ECB.

Estimation results of the extended model with the US unemployment rate are given in Fig. 11. We do not report the effect of the FCI shock and FEVDs since our purpose is to check for the sensitivity of the results. Our empirical results suggest that a sudden increase in unemployment follows a rise in uncertainty, particularly in financial stress regimes. In terms of asymmetries between financial regimes, the sensitivity analysis results for both EA and the US reveal that impulsive responses remain qualitatively identical to the baseline model. Also, when the economy is in trouble, the asymmetrical effect of aggregate uncertainty shocks on EU and US shadow-short rates becomes more noticeable and stronger.

In the second extension of the benchmark model, we include the EA financial stress variable. In this case, the vector of variables in Eq. (1) is defined as $X_t = (g_t^{US}, \pi_t^{US}, R_t^{US}, f_t^{US}, f_t^{EA}, g_t^{EA}, \pi_t^{EA}, R_t^{EA})'$, where f_t^{EA} denotes the composite financial stress index (FSI) for the EA. The results for the extended benchmark model, which includes the FSI of EA, are given in Fig. 12. In this case, we only consider the effect of the FSI shocks of the EA. The impulse responses of output and inflation to aggregate volatility shocks show a similar pattern, with no significant difference. But the extended model illustrates noticeable changes regarding the responses of shadow interest rates when adding FSI to the benchmark model. For instance, after 8 months, the EA shadow interest rate rises to its maximum in the benchmark model, while it falls to its minimum in the extended model during normal times. Even if the patterns of the estimated IRF differ from those obtained from the benchmark TVAR model, the responses of the US shadow short rate during different financial conditions are substantially asymmetric. Moreover, the asymmetrical effect regarding the response of FCI in the baseline model disappears in the extended model. Similar to those in a stress regime, the aggregate uncertainty shock increases the US financial condition index considerably during tranquil periods.

6.2. Narrative sign restrictions

Following the DSGE literature and Alessandri and Mumtaz (2019), we assumed that uncertainty is exogenous, which means that the error term η_t of the volatility process in Eq. (2) is uncorrelated with the error terms e_{jt}, $j = 1, 2, \cdots, N$, of all variables included in the measurement Eq. (1), i.e. $E(\eta_t e_{jt}) = 0, j = 1,2,\cdots,N$. Following Alessandri and Mumtaz (2019), we relaxed this assumption in order to generalize the benchmark model. This generalized model allows unrestricted and regime-dependent residual covariances. This structure is distinguished by the correlation between first- and second-moment shocks, and the ability of uncertainty to adapt endogenously to changes in macroeconomic fundamentals. In this scenario, however, there is a problem since uncertainty shocks cannot be separated from level shocks without additional assumptions. Following Antolín-Díaz and Rubio-Ramírez (2018) and Ludvigson et al. (2017), we identify uncertainty shocks via narrative sign restrictions. The restrictions we impose are especially based on the empirical characteristics of the variables over the period 2007M1-2011M12, during which major shocks of uncertainty occurred. The narrative sign restrictions we employ to identify uncertainty shocks assume that uncertainty shocks (i) increase volatility, (ii) have a negative effect on output in both the US and EA, and (iii) have a negative effect on prices in both the US and EA. In addition, we assume that large uncertainty shocks (at least three standard deviations) occurred in November 2008.

[10] Based on the suggestion of an anonymous referee, we also estimated the model for two different subsamples since our sample period covers the periods of the COVID-19 and the period before the introduction of the euro. The first subsample estimation covers the period from 1995M1 to 2019M12 to exclude the COVID-19 period, while the second subsample covers the period from 1999M1 to 2019M12 to exclude both the pre-euro and post-COVID-19 periods. Estimation results in terms of the estimated stochastic volatility and impulse response functions show negligible sensitivity to the exclusions of the pre-euro and post-COVID-19 periods, likely because we already use the first 20 observations to initialize the priors and the post-COVID-19 period has only 12 observations in our sample. We do not report these results because they have no impact on our conclusions. Complete details of these results are available upon request from the authors.

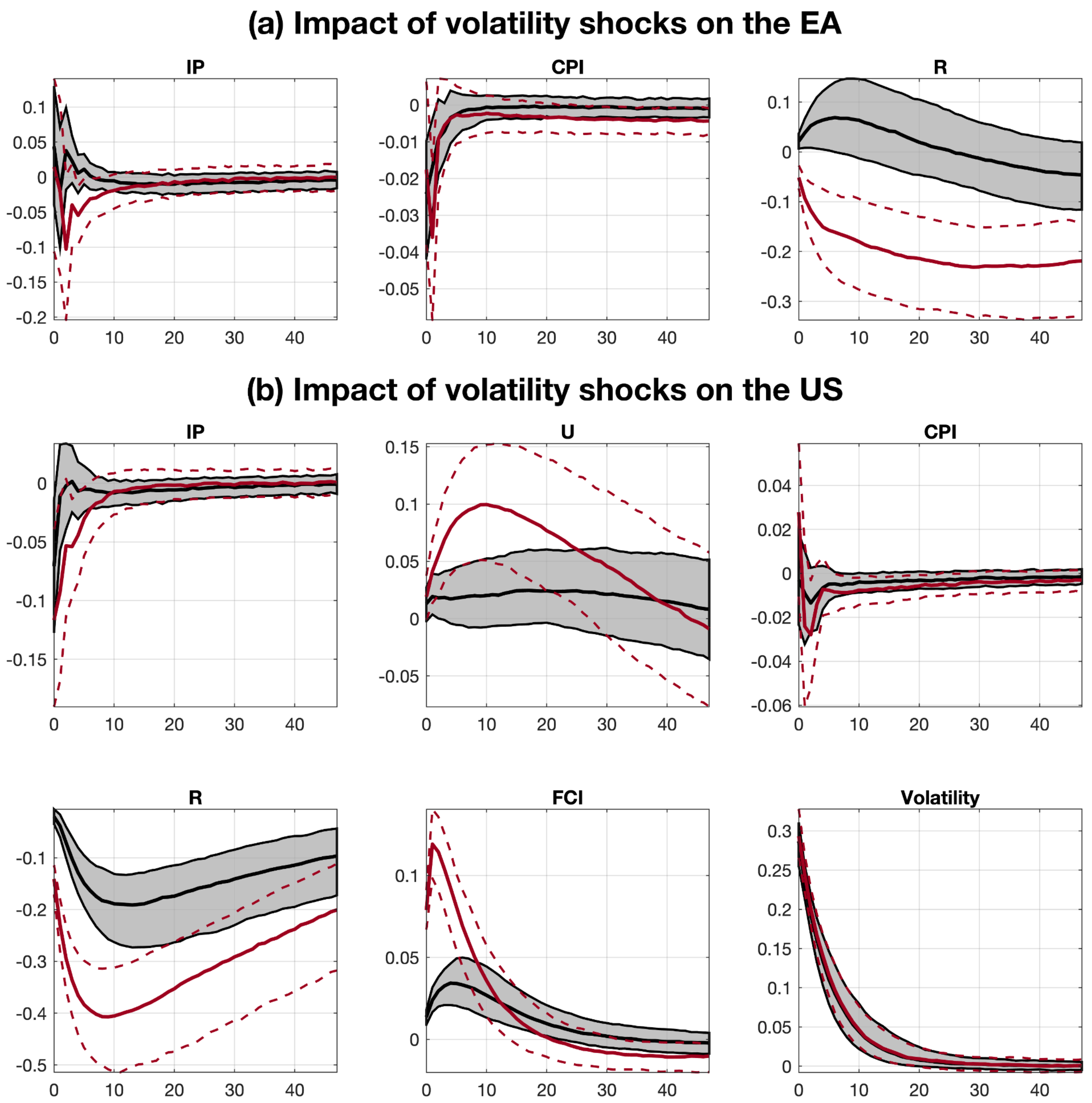

Fig. 11. Extended model with the US unemployment. Note: The figure presents the median impulse responses and 68% confidence bands for a one standard deviation shocks in normal (black lines) and crises periods (red lines). The estimation period is 1996:M11-2019:M12. The crises regime corresponds to the state where the FCI of US exceeds the estimated threshold of −0.3641. See note to Fig. 3 for further details. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Impulse responses to uncertainty shocks under the narrative sign restrictions are given in Fig. 13. We find that volatility shocks are shown to have a larger drop in EA and the US output after around 6 months during stress times. Likewise, the response of EA inflation to corresponding shocks in bad times is stronger after almost 12 months. Moreover, as compared to EA inflation, the effect of volatility shocks on US inflation reaches its minimum faster. Our empirical findings also suggest a flip in the sign of both the EA and the US shadow-short rate response. It’s also worth noting that volatility shocks have a smaller but asymmetrical contemporaneous effect on overall volatility, which gradually fades over time. In addition, the confidence intervals of IRFs are typically observed to be greater during bad times. This situation is most likely a result of the increasing model complexity and the identification challenge in the switching process. Overall, these results are generally in line with those obtained by Alessandri and Mumtaz (2019) and Nalban and Smădu (2021), i.e., the IRFs of the output, inflation, and interest rate shocks are altered substantially during bad times after conducting narrative sign restrictions to the baseline model. Nevertheless, the IRFs estimated in the narrative sing restrictions model in good times are almost unchanged.

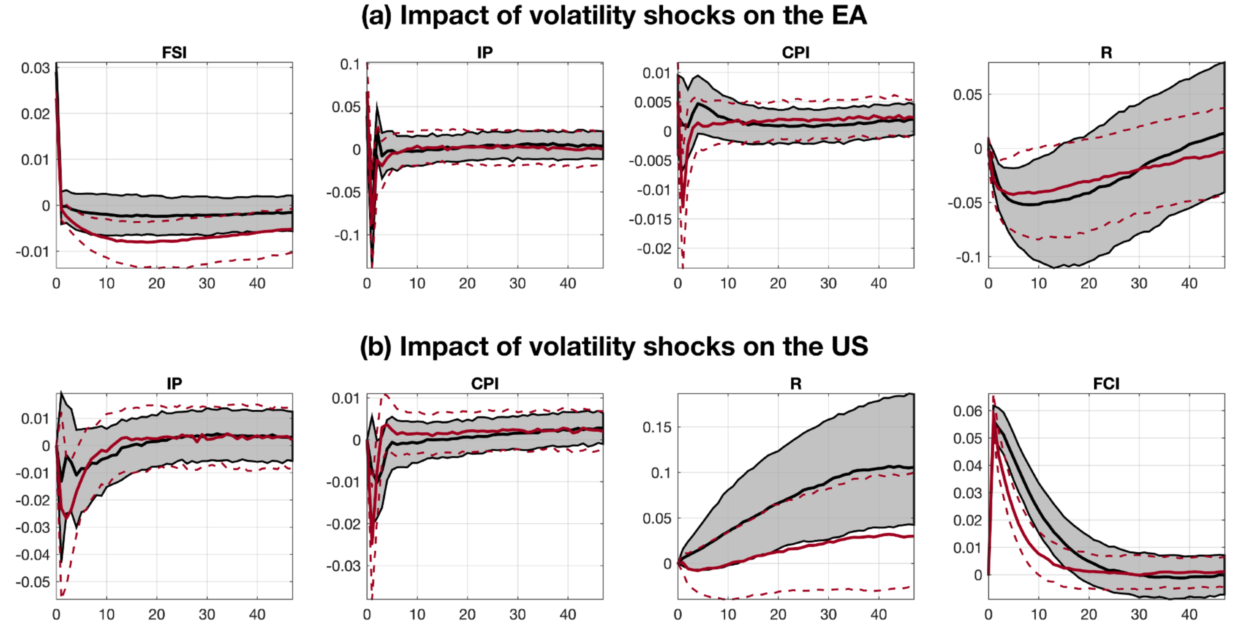

Fig. 12. Extended model with the euro area financial stress index. Note: The figure presents the median impulse responses and 68% confidence bands for a one standard deviation shocks in normal (black lines) and crises periods (red lines). The estimation period is 1996:M11-2019:M12. The crises regime corresponds to the state where the FCI of US exceeds the estimated threshold of −0.3498. See note to Fig. 3 for further details. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

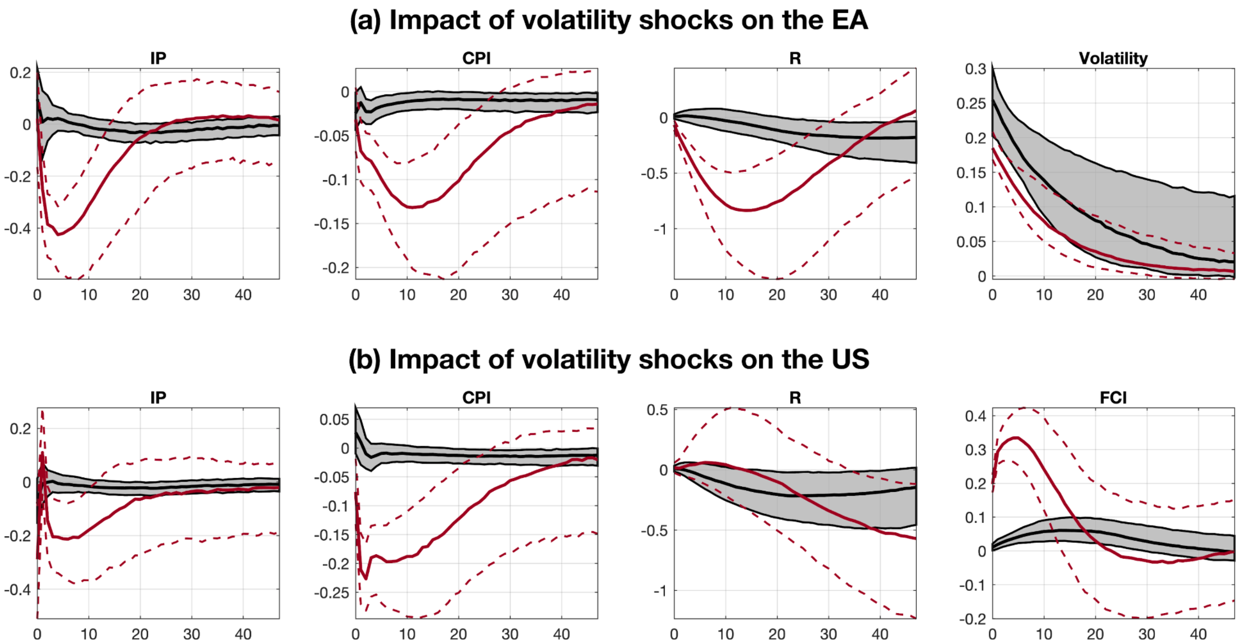

Fig. 13. Generalized model estimates with narrative sign restrictions. Note: The figure presents the median impulse responses and 68% confidence bands for a one standard deviation shocks in normal (black lines) and crises periods (red lines). The estimation period is 1996:M11-2019:M12. The crises regime corresponds to the state where the FCI of US exceeds the estimated threshold of −0.2657. See note to Fig. 3 for further details. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

7. Concluding remarks

After the Great Recession, the prolonged downturn and sluggish recovery in advanced economies make researchers embark on a quest for new conduits, inducing business cycles that last longer now than in the past. In addition to this, financial frictions are recognized as the main factor that increases economic uncertainty shocks. This study extends previous studies, which attempt to validate this hypothesis for a single county, including international uncertainty spillover on euro economic activity whenever US financial markets are in distress. Utilizing monthly US and euro area data covering the period from 1995M1 to 2020M12, we estimate a nonlinear VAR where aggregate uncertainty is calculated by the average volatility of both US and euro area structural shocks. Our empirical analyzes show that the rise in aggregate uncertainty and financial frictions harm the economic activity of our area at all times, but this devastating effect increases exponentially during times when the US is financially challenging. For example, the peak contraction in euro industrial production growth against aggregate uncertainty shocks during a financial crisis is nearly-four times larger than (−0.12 % versus −0.03 %) the peak contraction during normal times. Furthermore, the estimates reveal that the ECB acts more cautiously against uncertainty shocks while adopting hawkish monetary policies against financial shocks. In contrast to this, the Fed tends to follow more hawkish monetary policy in times of heightened uncertainty when we compare it to the ECB. Besides, we find strong evidence in favor of asymmetric effects regarding the contribution of uncertainty shocks in euro area economic variables during different US financial conditions. Overall, our study extends related studies (Alessandri & Mumtaz, 2019; Balcilar et al., 2020a; Christiano et al., 2014; Gilchrist et al., 2014) in the literature which investigates the role of both uncertainty and financial conditions on business cycles with considering the external financial environments in terms of the euro area. Thus, our results suggest that policy design in the euro area should be regime-dependent, and the policymakers should take into account US financial conditions more seriously to protect its economic activity against aggregate uncertainty shocks.

CRediT authorship contribution statement

Mehmet Balcilar: Conceptualization, Methodology, Formal analysis, Writing – original draft, Data curation, Software. **Zeynel Abidin Ozdemir:** Writing – review & editing. **Huseyin Ozdemir:** Writing – original draft, Software. **Gurcan Aygun:** Writing – original draft, Software. **Mark E. Wohar:** Writing – review & editing, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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