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IZA DP No. 15296

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MAY 2022

ISSN: 2365-9793

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ABSTRACT

How Does the Economic Uncertainty Affect Asset Prices under Normal and Financial Distress Times?

By using a nonlinear VAR model, we investigate whether the response of the US stock and housing markets to uncertainty shocks depends on financial conditions. Our model allows us to change the response of the US financial markets to volatility shocks in periods of normal and financial distress. We find strong evidence that uncertainty shocks have adverse effects on the US financial markets, irrespective of financial conditions. Moreover, our empirical results show that the rebound in US housing prices, which fell sharply in the economic turmoil, is state-dependent. This reflects the Fed's expansionary monetary policy to stabilize the US housing market. Furthermore, our findings reveal that economic agents who closely monitor the impact of uncertainty on the US stock and housing markets should also consider financial frictions in the US economy.

JEL Classification: C32, E32, E44, G01, G12, R31

Keywords: asset prices, economic uncertainty, financial conditions, regime switching, US

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1. Introduction

The 2007 sub-prime mortgage crisis (GFC) created unprecedented pressure on the US financial markets. Many people lost their homes, and the fallout created economic stagnation. Because traditional sources of macroeconomic instability have been questioned in the aftermath of the financial crisis, two elements have emerged as key drivers of business cycle fluctuations: uncertainty and financial frictions (Caldara et al., 2016; Stock and Watson, 2012). As for uncertainty, we can list the studies examining the cyclical effect of uncertainty on various macroeconomic indicators in the literature. The effect of uncertainty has been examined theoretically and empirically on household consumption (Carroll and Samwick, 1998; Kimball, 1990), investments (Caballero, 1991), and firms' demand (Bloom, 2009). Additionally, Christiano *et al*. (2014) show that the recent financial crisis makes lenders more uncertain about the market value of potential borrowers' mortgage-backed securities. And this results in increased uncertainty that would raise the cost of external finance. Furthermore, studies such as Bernanke (1983), Bloom (2014), and others predict that rising uncertainty reduces economic activity through traditional real frictions. In addition to the real friction channel, recent studies have put forth the importance of financial friction (credit market conditions) in the propagation of uncertainty shocks (Alessandri and Mumtaz, 2019; Arellano et al., 2011; Balcilar et al., 2021; Caldara et al., 2016; Gilchrist et al., 2014; Nalban and Smădu, 2021).

The heightened uncertainty has a great impact on financing conditions and market expectations. Therefore, prices of financial assets (e.g., equities, high-yield bonds, commodities) must adapt to new market conditions. The decline in financial asset prices may have a negative impact on household consumption and corporate investment through the wealth effect. For example, people may lower their consumption to compensate for the loss in their net wealth when equity prices fall (Nalban and Smădu, 2021). Furthermore, according to the relationship between investment and Tobin's Q, there is a positive relationship between corporate investment and the stock market. The most common explanation for this relationship is that stock prices reflect the marginal product of capital (Tobin J., 1969). Also, aggregate demand can be influenced by the sharp movements in asset prices through the value changes of collateral that are required for borrowers to access credit and receive funds. Fernández-Villaverde and Guerrón-Quintana (2020) have recently reviewed the literature on uncertainty shocks and the business cycle. Their empirical findings show that a real business cycle model is augmented with financial frictions and uncertainty shocks.

Jensen et al. (2020) point out that adverse business cycle asymmetry[1] is a general characteristic of the US economy (see, e.g., Acemoglu and Scott, 1997; Clements and Krolzig, 2003; Hamilton, 1989; Morley and Piger, 2012; Neftçi, 1984) and this asymmetric effect has become much more pronounced over the past three decades. In general, such studies find substantial evidence to support the idea that contractions are steeper than expansions and that expansions are longer than contractions. Recent studies have also tried to understand whether there is a close relationship between aggregate economic uncertainty and asymmetric business cycles (Huang et al., 2021) for the US economy. Our study is closely related to this growing strand of literature. Studies in this field empirically suggest that large and negative cyclical component shocks relate to high macroeconomic uncertainty. During periods of high uncertainty, the probability distribution of output growth skews to the left, and this increases economic growth vulnerability.

Our main motivation is based on the fact that central banks conduct expansionary monetary policy to make it easier for individuals and companies to borrow and spend money. Thus, central banks aim to re-establish the debt-credit link in the financial market and to eliminate the aggregate uncertainty in the economy. The achievement of this goal is critical for the US stock and housing markets, which are the two most affected financial markets after financial shocks hit the economy in 2007. The effect of economic uncertainty and financial stance on assets has been revealed by various studies in the literature. For instance, Hirata et al. (2013) and Burnside et al. (2016) suggest that uncertainty tends to keep housing demand low, reducing housing returns. Likewise, shocks to uncertainty have a negative impact on stock market performance by disturbing both expected firms' cash flows and discount rates (Arouri et al., 2016; Kang et al., 2017; Kang and Ratti, 2013; Pástor and Veronesi, 2012). According to Stock and Watson (2012), the shocks that produced the Great Recession are principally related to financial disruptions and increased uncertainty. Moreover, Caldara et al. (2016) find that uncertainty shocks have a substantial economic and statistical impact on the stock market as well as real economic activity. Therefore, we want to add to this debate by answering the following question: *Do uncertainty shocks affect the US housing and stock markets differently across normal and distressed financial regimes*?

[1] Asymmetry has been defined in business cycles in a variety of ways in the literature. In this study, we associate the asymmetry with the response of US financial assets to uncertainty shocks during two different financial states. On the other hand, we also measure asymmetric responses by changing the sign and size of the shocks.

Our study complements the recent literature by employing the nonlinear VAR suggested in a recent study by Alessandri and Mumtaz (2019) and examining how the response of the US housing and stock markets to uncertainty shocks depends on aggregate financial conditions. Our contribution is three-fold. First, we extend the literature examining the asymmetric impact of an uncertainty shock on the real economy to include financial assets. In so doing, we show that financial friction is an important transmission channel that differentiates the impact of aggregate uncertainty on the US housing and stock markets. Second, we use the generalized forecast variance decomposition method to quantify the overall role of uncertainty in the business cycle. Last but not least, we also adjust the size and sign of the total volatility shocks and measure their asymmetric effects under distinct financial conditions.

We estimate a nonlinear data-driven model by using US monthly data covering the period between January 1971 and December 2021. Our main results can be summarized as follows: First, uncertainty shocks have deteriorating impacts on the US financial markets irrespective of financial conditions. Second, the impact of an uncertainty shock on S&P 500 dividends and US real house prices varies significantly between normal and distressed financial conditions. Uncertainty shocks reduce US housing prices, and it takes a long time for the shocks to fully dissipate in good times. When financial markets are in distress, however, the impact is quite large, and the recovery is faster. That is, the recovery of the US housing markets after volatility shocks is state-dependent. Third, uncertainty accounts for most of the US financial condition index when a shock hits the economy during financial distress. Finally, the response of US financial assets to uncertainty shocks exhibits both sign and size asymmetries. Our findings have significant policy and investment implications.

The remainder of the paper is organized as follows. Section 2 describes the methodology. Section 3 describes the data and provides descriptive statistics. Section 4 presents the empirical findings with discussion, and Section 5 summarizes and concludes the paper.

2. Methodology

In this section, we present an overview of the empirical model that follows the methodology suggested by Alessandri and Mumtaz (2019) and describe estimation of the impulse-response functions. Also, we describe the estimation and calculation of the impulse-response functions at the end of sections. The model basically depends on a threshold VAR (TVAR) model with time-varying volatility that permits the system dynamics to shift between two different financial states. Thus, the TVAR model is given by the following equation:

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

where $X_t = \{Y_t, P_t, D_t, R_t, H_t, Q_t, F_t\}$ is a set of seven endogenous variables: real industrial production index (Y_t), inflation rate (P_t), real dividends of S&P 500 index (D_t), shadow short rate (R_t), real home prices (H_t), real S&P 500 stock prices (Q_t), and national financial conditions index (F_t). The variables enter the TVAR model in this order. Also, all parameters of the system $\{c_i, \beta_{ij}, \lambda_{ij}, \Omega_i\}_{i=1,2}$ as described in Eq. (1) vary across different financial regimes in the US. Moreover, the λ_t represents the aggregate uncertainty and is treated as a latent state variable that arises from the volatility of the shocks during the sample period. The lag length of our VAR models is suggested as 2 by the Bayesian Information Criteria. We also set the delay for the transition variable as 1 because the nonlinearity effect is stronger compared to other delay values.

Besides, $\tilde{S}_t$ represents the embedded indicator function and distinguishes two different financial regimes (calm and financially distressed periods). In our application, the regime is determined by the level of the US financial condition index with regards to an estimated critical threshold value, z^*:

$$\tilde{S}_t = 1 \Leftrightarrow f_t^{US} \leq z^*, \text{ and } \tilde{S}_t = 0 \Leftrightarrow f_t^{US} \geq z^* \tag{2}$$

where both the delay d and the threshold z^* are unknown parameters. These two sets of parameters can be considered as reflecting the dynamics of the economy during normal ($\tilde{S}_t =$

1) and stressful times ($\tilde{S}_t = 0$). Moreover, the time-varying covariance matrix (Ω_{it}) of the residuals (e_t) plays a crucial role in our analysis. It is factored as follows:

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

where A_1 and A_2 are lower triangular matrices and they evolve as a random walk described in (Primiceri, 2005). Finally, the volatility process can be characterized by the following equations:

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

where η_t is an independent and identically distributed innovation with variance Q. Following Carriero et al. (2016) and Alessandri and Mumtaz (2019), we assume that the time variation of the variance–covariance matrix of the structural shocks is driven by the volatility process, λ_t. This single and scalar time-varying volatility enters the conditional mean as a covariate. Besides, we also assume that all structural shocks have the same weight in λ_t. Compared to its peers (i.e., observed proxies for uncertainty: VIX, economic policy uncertainty index, etc.), this model-based latent uncertainty approximation represents aggregated uncertainty in the economy more broadly (Nalban and Smădu, 2021). Now we can describe the conceptual framework that underpins the transmission mechanism of uncertainty shocks. An adverse uncertainty shock (that is $\eta_t > 0$) raises the level of uncertainty across the economy. Therefore, this causes to an upward shift in e_t, decreasing of the forecasting accuracy of the future economic states, X_{t+n}.

We estimate the TVAR model by using the Bayesian method. The Gibbs sampling algorithm is employed to estimate the posterior distributions of model parameters. To save space and not to overwhelm the readers with technical details, we propose that interested readers take a glance at the Appendix of Alessandri and Mumtaz (2019). However, we would like to draw attention to the following points. To begin, given a draw of the state variable, the model reduces to a standard threshold VAR after the corresponding model's simple generalized least squares transformation to make the errors homoscedastic. Secondly, the conditional posterior distribution of the VAR parameters under normal and financial distress times, the threshold, and delay parameters all take the same values as in a standard threshold VAR (Alessandri and Mumtaz, 2017). Moreover, the delay parameter, d, follows a multinomial distribution. The threshold value, on the other hand, is drawn from its non-standard posterior distribution via the Metropolis-Hastings algorithm as established by Chen and Lee (1995). Next, we may split the data set into regime-specific observations after determining the values for the threshold and delay parameters. The conditional posterior distribution of A can easily be obtained given the residuals of the VAR and λ_t. Besides, the variance, S, can be sampled from the inverse Gamma distribution. Finally, we use the independent Metropolis algorithm proposed by Jacouier et al. (1994) to draw state-variable, λ_t.

We then proceed to obtain generalized impulse response functions (GIRF) using a Monte Carlo procedure as described in Koop et al. (1996). For a given regime (S=0,1) and its regime-dependent history (X_{t-1}^S), the impulse response functions can be defined as

$$IRF_t^S = E(Y_{t+n} \backslash \Psi_t, X_{t-1}^S, \mu) - E(Y_{t+n} \backslash \Psi_t, X_{t-1}^S) \tag{5}$$

where Ψ_t stands for all parameters and hyperparameters, n is the horizon, and μ represents the shock of interest. The impulse responses are calculated as the difference between two conditional expectations based on simulations of the model. The first and second terms in the right-hand side in Eq. 5 imply a shock scenario and a no change alternative, where the system is not perturbed. It's worth noting that the impulsive responses are influenced by the specific history of the system prior to the realization of shock. In other words, depending on the size and sign of the shock, the economy may change from normal to distressed dynamics during the simulation horizon, or vice versa. This is especially important because, although if both scenarios are assigned to normal periods, the economy may react differently when the financial distress indicator is at its historical low level or just below the critical threshold.

3. Data and descriptive statistics

We employ seven variables in our analysis, and we just focus on the effect of aggregate uncertainty shocks on the real dividend (DIV), real stock prices (SP500), real house prices (HP), and Chicago Fed's National Financial Conditions Index (FCI). The US macroeconomic variables, i.e., industrial production (IP), consumer price index (CPI), and shadow interest rate[2] (SSR), are used for control variables. For IP, CPI, DIV, HP, and SP500, we take the first difference of the logarithm (i.e., $g_t = \ln(x_t/x_{t-1}) \times 100$), while we include the SSR and FCI in levels. The survey data are obtained from various sources: First, the shadow interest rate introduced by Wu and Xia (2016) is obtained from the Federal Reserve Bank of Atlanta website[3]. Second, the Case-Shiller real national home price index and real dividends for the S&P 500 are taken from Robert Shiller's website[4]. Third, the financial condition index is collected from the Federal Reserve Bank of Chicago website[5]. Finally, all other data is obtained from DataStream.

Table 1 contains summary statistics for all variables, while the related time series are plotted in Figure 1. All series can be considered stationary according to standard unit root tests.

4. Results

Our findings are organized into two subsections. The first section shows that uncertainty shocks have a substantially greater impact on US stock and housing markets when credit conditions are tight. The second section illustrates how credit frictions generate sign asymmetry and measures the influence of uncertainty shocks on the US business cycle.

4.1. Measuring economic uncertainty and its effects on financial markets

Figure 2 shows that the estimated economic uncertainty is measured by the median log stochastic volatility, which strongly correlates with the level of the financial conditions index. Note that our uncertainty measure is directly linked to agents' ability to form predictions of the future state of the economy. It's worth noting that our uncertainty measure is obtained from the prediction capability of our VAR model regarding the future state of the US economy. On the other hand, the FCI is a comprehensive index that is built using a combination of factors such

[2] To control monetary policy implemented by Fed correctly, we use the shadow interest rate measure recommended by (Wu and Xia, 2016). Wu and Xia (2016) recommend employing shadow interest rates when monetary policy enters the zone known as the zero lower bound (ZLB), which invalidates the traditional monetary policy tool. They show that the shadow interest rate reflects both the conventional interest rate rule in normal times and unconventional monetary policies such as QE and lending facilities at the ZLB.
[3] https://www.atlantafed.org/cqer/research/wu-xia-shadow-federal-funds-rate
[4] http://www.econ.yale.edu/~shiller/data.htm
[5] https://www.chicagofed.org/publications/nfci/index

as currency and asset prices. Positive values of the FCI show tighter financial conditions than historical average financial conditions, while negative values of the FCI illustrate looser financial conditions than historical average financial conditions. The gray-shaded areas show the periods with FCI values above 0.0435, which are identified as the financial distress or crisis regime periods. The length of recent tight financial markets has decreased significantly as compared to earlier decades. This can be explained by the effect of fast and ultra-loose monetary policies implemented by the Fed after the 2007 global financial and COVID-19 crises.

Figure 3 plots the size of the US monetary base and broader monetary aggregates from January 1960 to December 2021. The gray-shaded areas show economic recessions in the US. We take the start of December 2007 as the index is equal to 100. As shown in the graph, a tremendous increase in the monetary base stands out after the 2007 sub-prime and the COVID-19 crises. Due to the unwillingness of banks to convert their reserves into loans during periods of economic uncertainty, the broader aggregates did not increase at the same rate as the monetary base (Fawley and Neely, 2013). In several rounds of quantitative easing in the US, the Fed purchased various types of assets (particularly treasuries and mortgage-backed securities) in different quantities. The usual mechanism through which this unconventional monetary policy is thought to be successful inside the bank lending channel is capital gains. Large-scale asset purchases (LSAPs) reduce yields and raise prices on banks' present asset holdings. Hence, this improves the condition of banks' balance sheets and leads them to more lending in multiple sectors (Chakraborty et al., 2020).

Fig. 4 plots the generalized impulse response functions (GIRFs) for one standard deviation of a positive uncertainty shock. The responses regarding good and bad financial times, namely low and high FCI periods, are depicted in black and red, respectively. The uncertainty in the US economy hits the real dividends after 4 months, and this effect is more pronounced during financial turmoil than normal times (Fig. 4-panel a). We can rationalize this result by saying that firms deleverage by reducing the real dividends distributed to households in response to increasing borrowing costs as emphasized by (Akinci, 2021). Brianti (2021) discusses the effects of financial shocks and uncertainty shocks on business-cycle fluctuations and their potential monetary policy consequences. He also hypothesizes that firms prefer to put current resources into a cash reserve as a precautionary measure in case of an uncertainty shock. However, firms will prefer to hold less cash after a financial shock due to increased implicit insurance costs. Based on cash holding motives, he rationalizes that a financial shock has negative pressure on stock dividends while an uncertainty shock leads to an increase in dividends due to a precautionary motive of the household. This paper contributes to this strand of the literature, and our findings reveal that uncertainty shocks have a more volatile effect on reel dividends during the financial turmoil in the US.

Irrespective of the financial regime, a rise in uncertainty lowers real house prices in the US (Fig. 4-panel b). The response of real house prices to an instantaneous volatility shock is much more rapid and pronounced in the crisis regime. First of all, our findings show that the negative effect of the uncertainty shock on the mortgage yield is consistent with the results of previous studies (André et al., 2017; Antonakakis et al., 2015; Chien and Setyowati, 2021; Christidou and Fountas, 2018; Christou et al., 2019). Furthermore, the peak fall in real house prices is nearly twice as large during financial distress (–0.04% versus –0.02%). This result is consistent with what we expect in the housing market because the mortgage credit crunch emanating from financial frictions reduces the demand for houses. Hence, the fall in demand naturally reduces the price of houses in the US. Furthermore, our findings suggest that the recovery of the housing market following an uncertainty shock is state dependent and displays a faster rebound when the shock occurs during a financial crisis. This situation reflects the most likely outcome of the Fed's ultra-loose monetary policy, which succeeds in improving the credit conditions in the US housing market. Compared to other financial assets, we find that the negative effect of an uncertainty shock on real house prices converges to zero along the horizontal axis over a longer period. This can be explained by the fact that, unlike other financial assets, the housing market is a durable consumer good for households.

Similar to the findings for real house returns, an uncertainty shock diminishes stock returns considerably regardless of the financial situation (Fig. 4-panel c). This finding is supported by a number of empirical contributions, including those by Antonakakis et al. (2013), Antonakakis et al. (2016), Arouri et al. (2016), and Kang and Ratti (2013) for the United States. Our paper contributes to this growing literature by considering the asymmetric effect that is coming from different financial states. In parallel with the findings of Stock and Watson (2012), our empirical findings show that the impact of an instantaneous shock is nearly twice as great during financial distress times. It's also worth mentioning that the stock market's reaction to uncertainty shocks fades after almost a year. The duration of this effect is lower than that on other financial assets. Panel (d) of Fig. 4 reveals that the impact of aggregate uncertainty on the FCI is more abrupt and roughly six times larger during periods of financial distress (0.32% versus 0.05%). In general, we obtain the same financial constraints mechanisms for financial asset markets as for the real economy (see Alessandri and Mumtaz, 2019 and Nalban and Smădu, 2021) when we examine the peak value of adverse uncertainty shocks. That is, when financial conditions are tighter, uncertainty shocks become much more significant, and their propagation to financial markets becomes much more powerful.

All in all, our empirical findings obtained from generalized impulse response analysis are consistent with the results of studies (e.g., Acemoglu and Scott, 1997; Clements and Krolzig, 2003; Hamilton, 1989; Huang et al., 2021; Jensen et al., 2020; Morley and Piger, 2012; Neftçi, 1984), which support the notion that contractions are steeper than expansions and the length of expansions exceeds that of contractions.

4.2 Asymmetric effects of uncertainty shocks

We use a generalized forecast error variance decomposition (GFEVD) during normal and financial crisis situations to assess the overall effect of heightened uncertainty in the associated financial assets. Fig. 5 illustrates the contribution of volatility shocks to the FEVs of corresponding variables[6] included in the model. As found by previous studies (e.g., Alessandri and Mumtaz, 2019; Balcilar et al., 2021; Nalban and Smădu, 2021), uncertainty shocks are found to be a strong driver of financial conditions in both regimes, but their contribution is roughly three times greater during financial distress times (Fig. 5-panel d). As for real dividends, we find that uncertainty is more important in bad times (Fig. 5-panel a). For instance, the fraction of real dividend variance accounted for by uncertainty shocks is somewhat more than three times greater when the economy is experiencing financial distress, at approximately 6% versus 2%[7]. Furthermore, uncertainty shocks account for nearly 13% of real house prices in good times and nearly 8% of bad times over a 24-month horizon. This finding supports the view that the Fed's aggressive monetary policy eases financial conditions in the US housing market. Therefore, the ability of economic uncertainty to explain US house prices during stressful times decreases compared to the normal period. Panel (c) of Fig. 5 shows that uncertainty explains almost 2% of the FEV of real stock prices under both financial regimes.

[6] Since this study focuses on the impacts of volatility shocks on the financial markets during different financial states, we do not report the various analysis results regarding the other control variables.
[7] All the numbers in this sub-section are compared according to 24-month forecast error variance decomposition results.

These estimates are smaller than those of Caldara et al. (2016), who find that that uncertainty accounts for more than 10% of the FEV for stock prices under the σ–EBP identification scheme. However, they find smaller fraction effects like ours for the EBP–σ identification scheme.

Given the nonlinear structure of the model, the size and sign of the shock may influence the response of variables. To understand this, we change both the sign and the size of the uncertainty shocks to the nonlinear VAR system. Firstly, we just vary the sign of the shock, and we measure the response of corresponding variables to negative uncertainty shocks and compare their effects with positive shock during both financial states. Fig. 6 shows that financial crises amplify the effects of volatility shocks on all financial assets except real stock prices, irrespective of their size and direction. The sign asymmetry is generally more prominent in the crisis regime.

Fig. 7 reports the cumulative responses to small versus large positive shocks, defined respectively as one and three standard deviation shocks, during normal and financial distress episodes. On the other hand, we do the same analysis for negative shocks as shown in Fig. 8. When we compare all of the outputs, some important issues stand out. First, a good shock has a greater impact on the US housing market than a bad shock. But this situation is not valid for the US stock market. That is, the US stock market is more responsive to adverse economic shock. Second, there exists a size asymmetry irrespective of the shock sign at all times. Third, when a large positive volatility shock hits the US financial markets, especially in real dividends and house prices, their impact is permanent in the long run, irrespective of the financial conditions in the US economy. However, when financial assets are under the influence of a large negative (good) shock, we see that the effect of the shock fades in the long run.

Two theoretical factors may be used to explain this asymmetry: (i) the strong relationship between volatility and credit conditions; and (ii) the state-dependent character of the financial-real-economy linkage. An increase in volatility in bad times may keep the economy in a situation where financial conditions are tight and the volatility multiplier is large. A decrease in volatility, on the other hand, leads to a relaxing of financial conditions, which can help the economy return to a good regime where borrowing restrictions are less restrictive and the volatility multiplier is lower.

5. Conclusion

Academic studies broadly agree that adverse uncertainty shocks have a destructive impact on real economic cycles and financial friction is the main source of volatility shock transmission. Although there are numerous papers investigating the response of the real economy to heightened uncertainty under distinct financial conditions, few deal with financial assets from this perspective. Our primary goal is to contribute to this strand of literature and to investigate whether some important US financial assets respond asymmetrically to uncertainty shocks during distinct financing conditions. Using monthly US data from January 1971 to December 2021, we estimate a nonlinear VAR model to evaluate the impact of uncertainty shocks on the US housing and stock markets. The aggregate uncertainty used in the model is captured by the volatility of the economy's structural shocks, and its transmission mechanism is allowed to shift according to different financial conditions.

Model simulations indicate that uncertainty shocks always have deteriorating effects on the US financial markets. Their impact on US financial markets is more severe, but the recovery in the US housing markets appears to be faster during financial distress. Moreover, we find that uncertainty shocks are an important contributor to the variance of US financial assets in bad times. On the other hand, uncertainty shocks can explain most of the US housing market's fluctuations in good times than in bad times. This can be shown as evidence in support of the Fed's monetary policy effectiveness in reducing uncertainty in the US housing market. Furthermore, we also document that the US financial markets respond differently when different types of volatility shocks (shocks of different magnitude and sign) hit the economy.

Our analysis can be further extended by examining the effect of US monetary policy on asset prices by using very high frequency data to refine the understanding of the Fed's FOMC meeting announcements on the US financial markets during different financial conditions. This may contribute to and bring different perspectives to the existing literature, such as (Bernanke & Kuttner, 2005; Ehrmann & Fratzscher, 2004; Gurkaynak et al., 2011; Kuttner, 2001; Swanson, 2021). Another potential extension of our paper could rely on an investigation of the impact of global uncertainty on emerging markets by considering global credit market conditions. This could aid our understanding of the role of international funds flows in mitigating global uncertainty shocks on emerging markets during various structured macro-financial crises.

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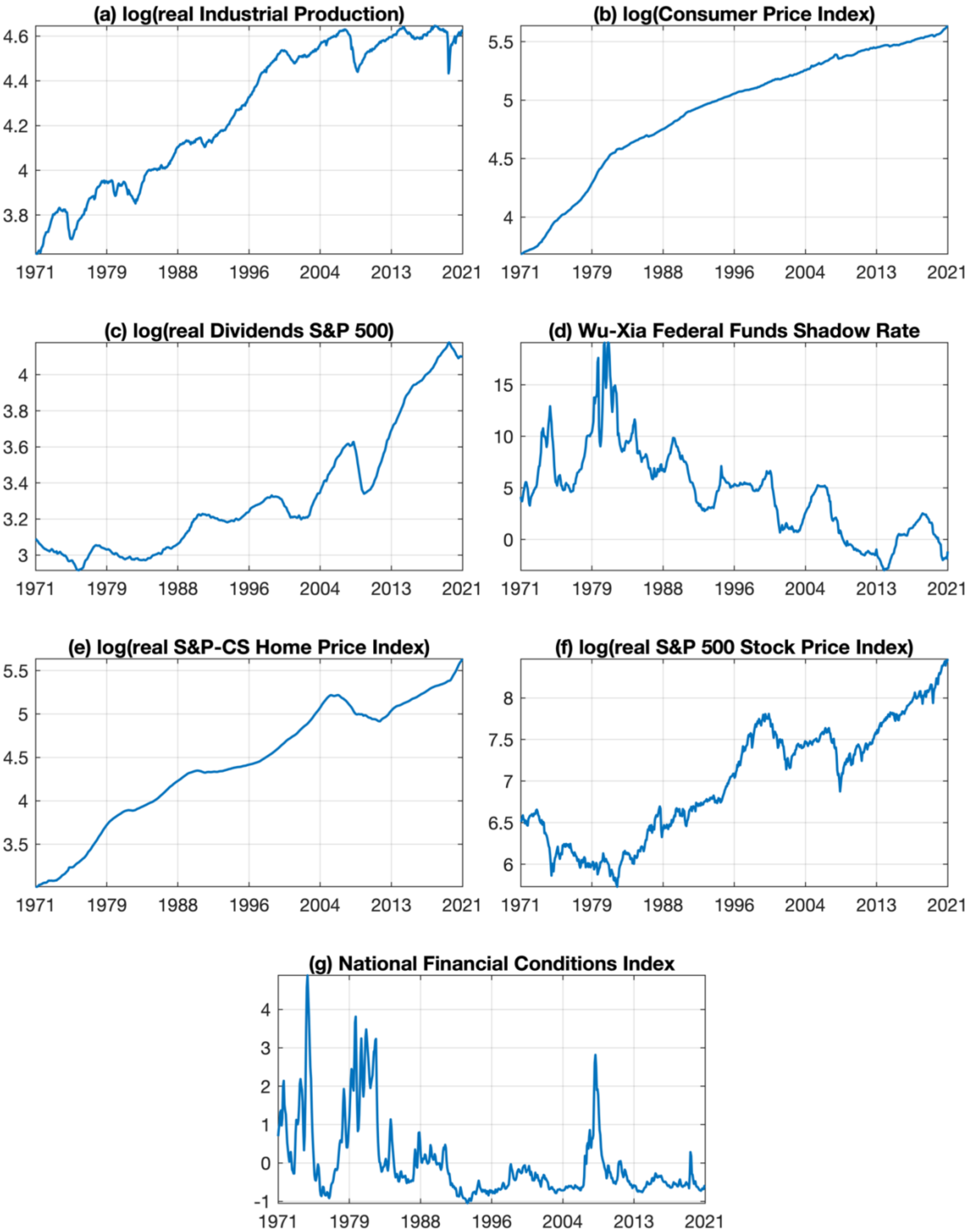
APPENDIX

Table 1. Descriptive statistics

	Real IP Growth	CPI Inflation	Real Dividends Growth	Shadow Federal Funds Rate	Real House Price Growth	Real Stock Price Returns	Financial Conditions Index
Mean	0.162	0.319	0.165	4.660	0.429	0.320	0.001
SD	1.004	0.331	0.630	4.283	0.502	4.432	1.004
Min	-14.610	-1.786	-2.979	-2.986	-1.630	-24.804	-1.048
Max	6.012	1.794	1.987	19.100	2.101	14.317	4.885
Skewness	-5.327	0.128	-0.878	0.577	-0.488	-0.687	2.031
Kurtosis	78.839	4.179	3.443	0.436	1.595	2.429	4.021
JB	162221.862***	451.289***	384.350***	39.155***	90.398***	200.753***	838.310***
Q(1)	44.966***	253.137***	417.848***	601.994***	510.653***	0.517	578.041***
Q(4)	50.539***	584.780***	1174.806***	2296.799***	1685.350***	3.115	1885.929***
ARCH(1)	5.976**	132.124***	410.229***	541.372***	426.146***	20.904***	511.046***
ARCH(4)	19.351***	136.808***	414.477***	552.766***	426.880***	25.967***	563.722***

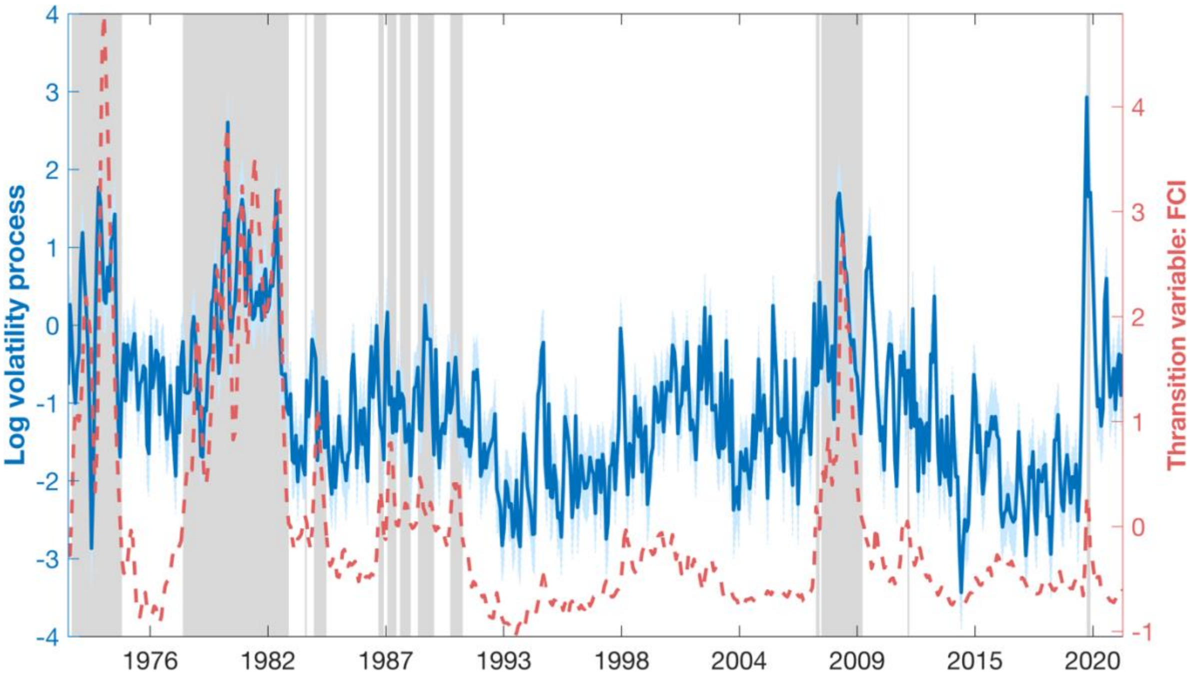
Note: Descriptive statistics for the growth rate of real industrial production (IP), inflation based on consumer price index (CPI), growth rate of real dividends (DIV) for S&P 500 stocks, Wu and Xia (2016) shadow federal funds rate (SSR), growth rate Case-Shiller real home prices (HP), returns on real S&P 500 stock price index (SP500), and the national financial conditions index (FCI) are reported in the table. Growth rates are in percent. The data is at monthly frequency and covers the period 1971:M2-2021:M12 with 611 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 fourth [Q(4)] order serial correlation test, and also first [ARCH(1)] and fourth [ARCH(4)] order autoregressive conditional heteroskedasticity test.

Figure 1. Time series plots of the data



Note: The figure plots the logarithm of real industrial production index, logarithm of consumer price index, logarithm of real dividends, Wu-Xia shadow federal funds rate, logarithm of Case-Shiller real home prices, logarithm of real S&P 500 stock prices, and national financial conditions index. for the period 1971:M1-2021:M12.

Figure 2. Financial regimes and the estimated economic uncertainty



Note: The figure displays the financial conditions index (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 1972:M12-2021:M12. The log volatility is estimated by the threshold VAR model (TVAR) explained in Section 2. The estimated threshold value is 0.0435. Periods with the values of FCI above is 0.0435 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.)

Figure 3 US monetary base and M2 expansion (Index:2007M12=100)

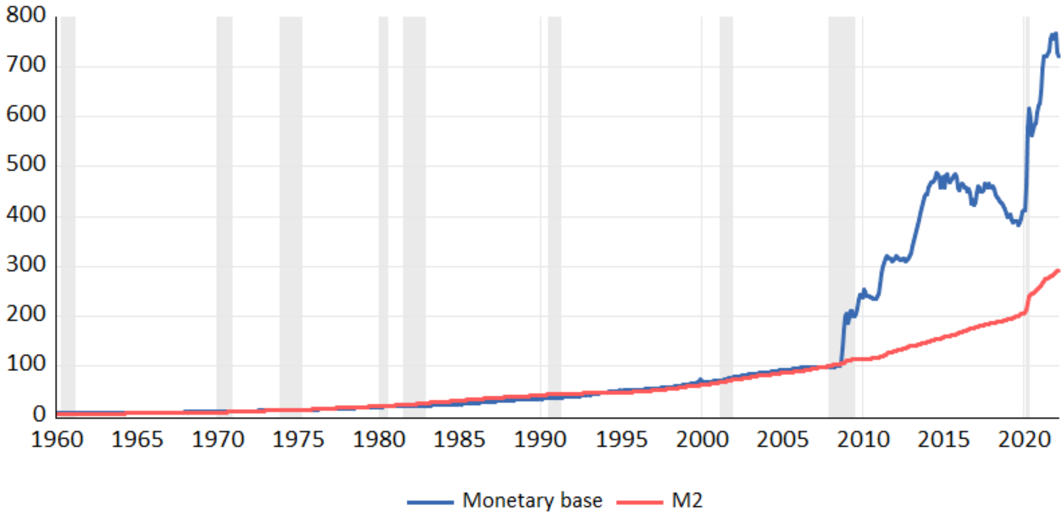
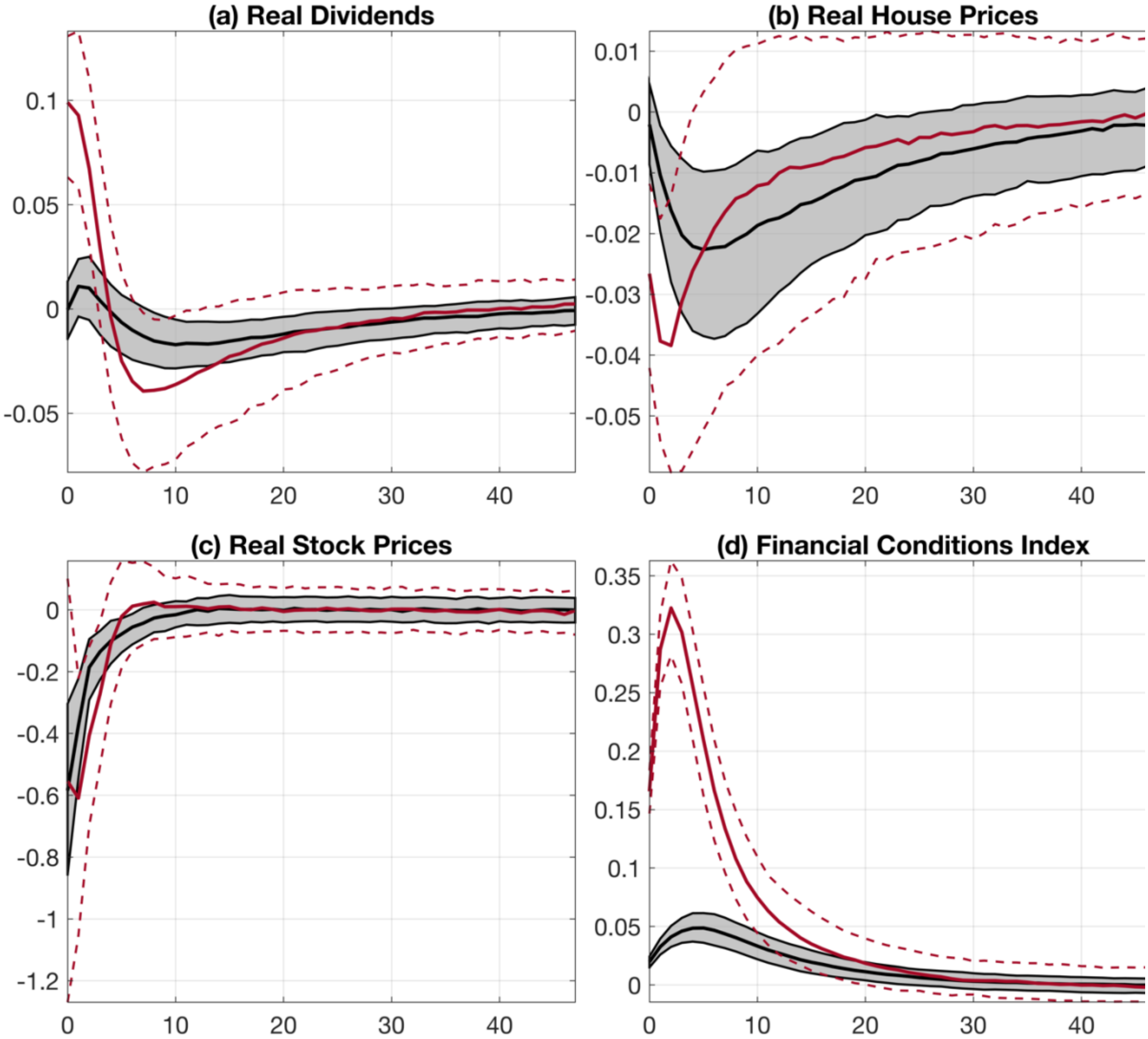
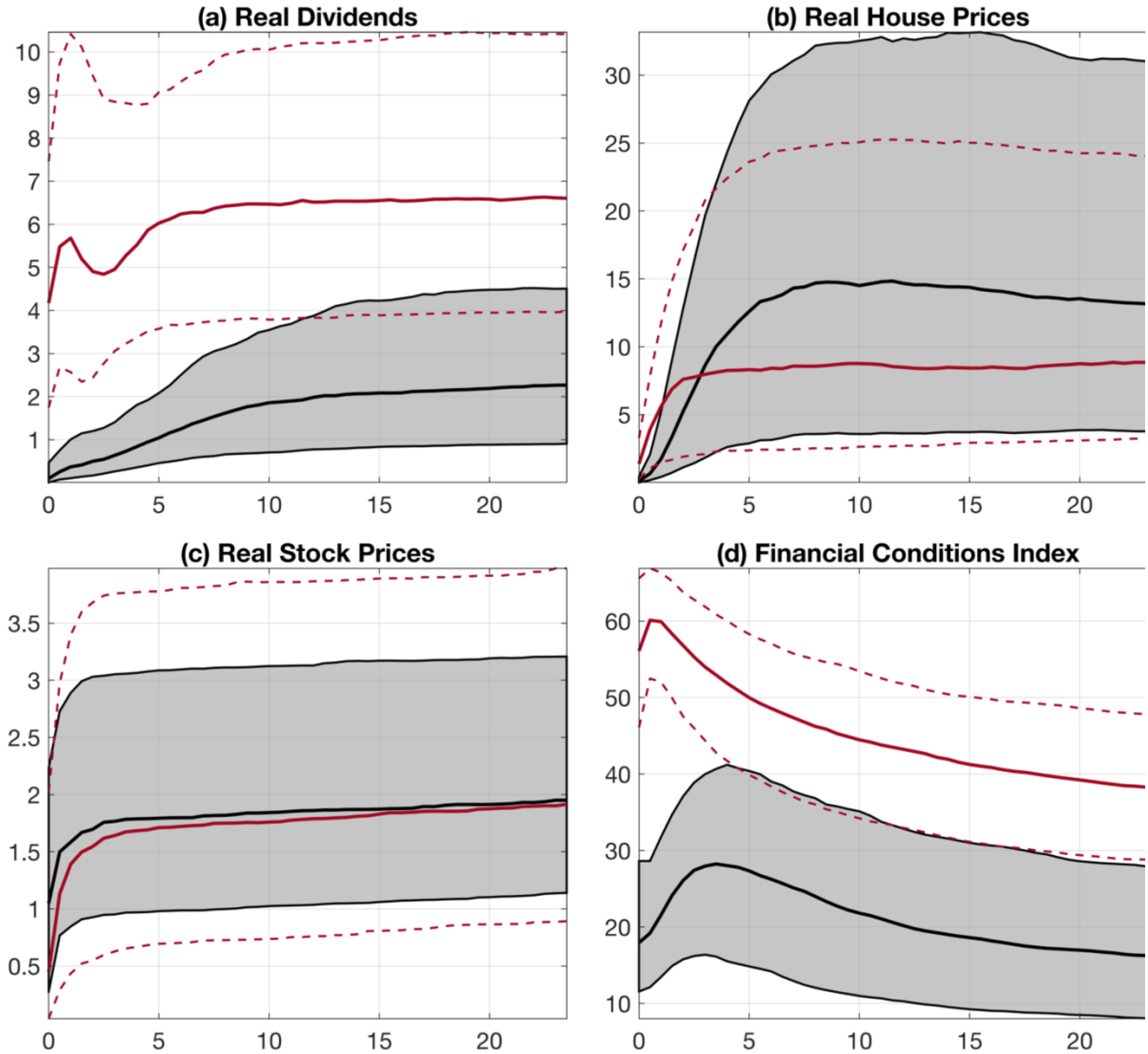


Figure 4. Impact of volatility shocks in normal and financial distress times



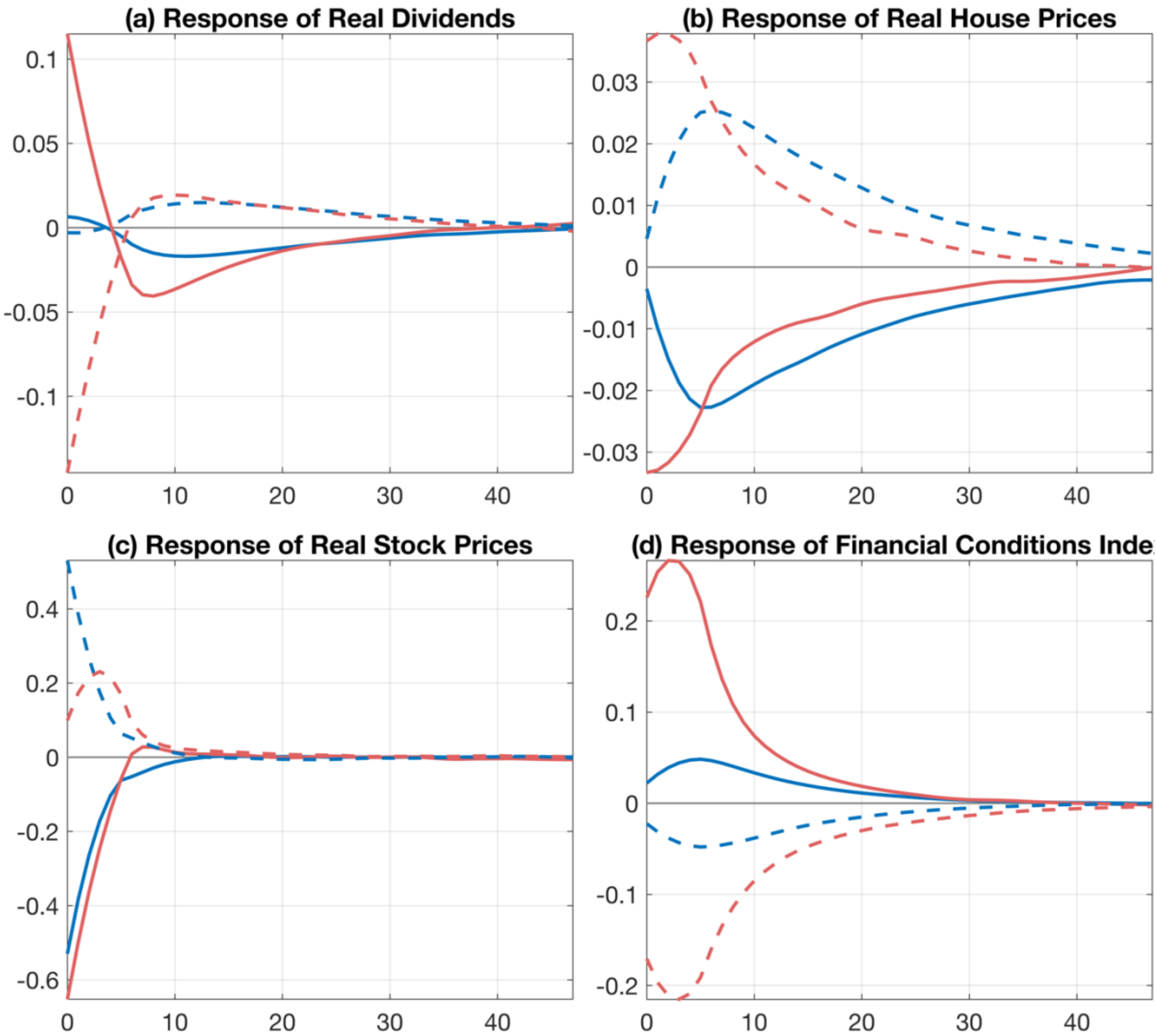
Note: The figure presents the median impulse responses and 68% confidence bands of the real dividends, real house prices, real stock prices, and financial conditions index for a one standard deviation increase in the overall economic volatility in normal and crises periods. The black lines indicate the impact of a one standard deviation increase in the aggregate volatility shocks on the response variables in normal times, while the red line shows the impact of the same shock during episodes of financial distress where the FCI exceeds the estimated threshold of 0.0435. 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 1972:M12-2021: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 1.

Figure 5. Forecast error variance decomposition for the effect of volatility shocks in normal and financial distress times



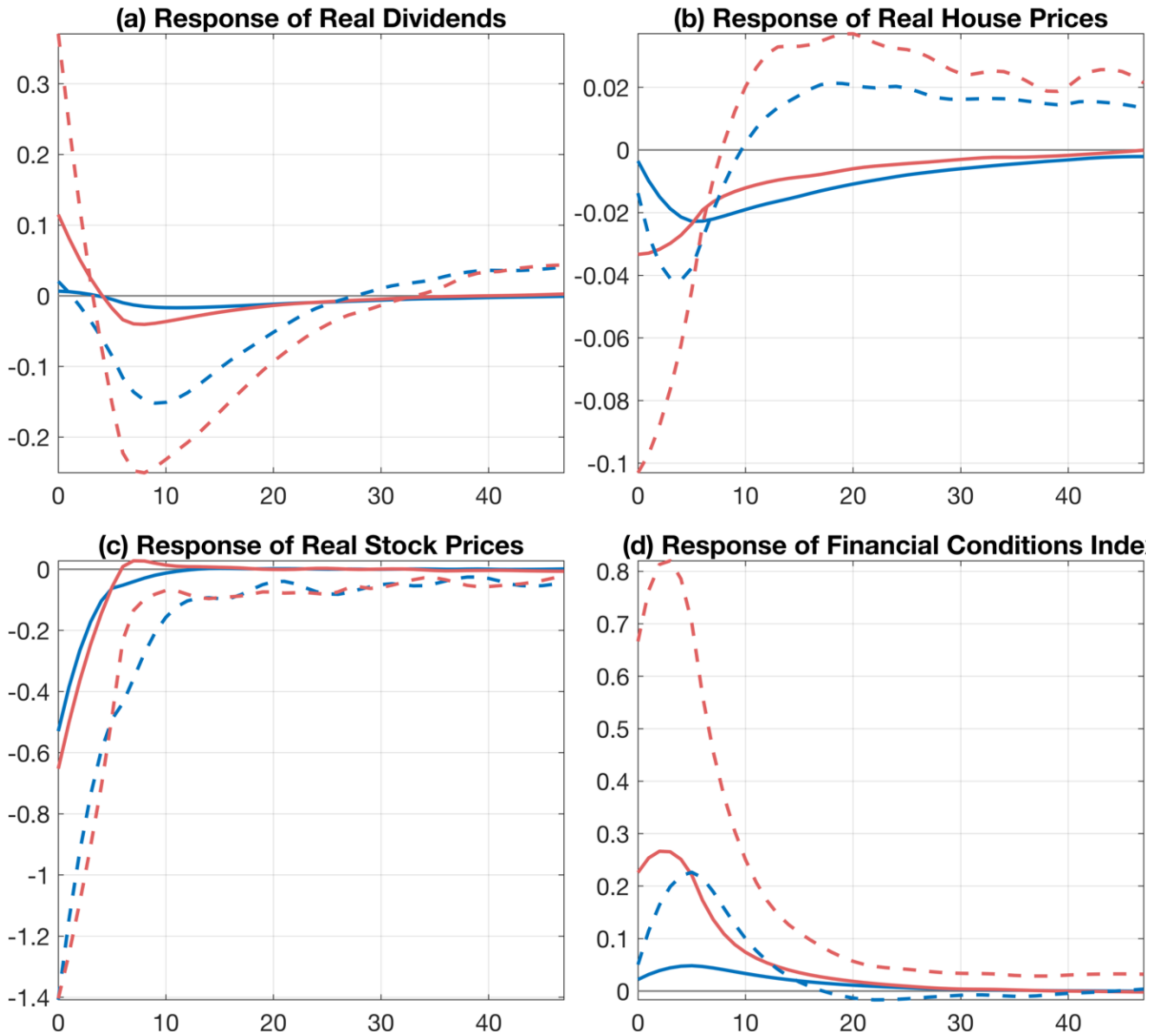
Note: The solid line in each panel shows the fraction of median forecast error variance explained by volatility shocks for one of the real dividends, real house prices, real stock prices, and financial conditions index. The gray shaded region and red dotted lines mark 68% confidence bands for median 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 exceeds the estimated threshold of 0.0435. 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 1972:M12-2021: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 1.

Figure 6. Sign asymmetry of volatility shocks



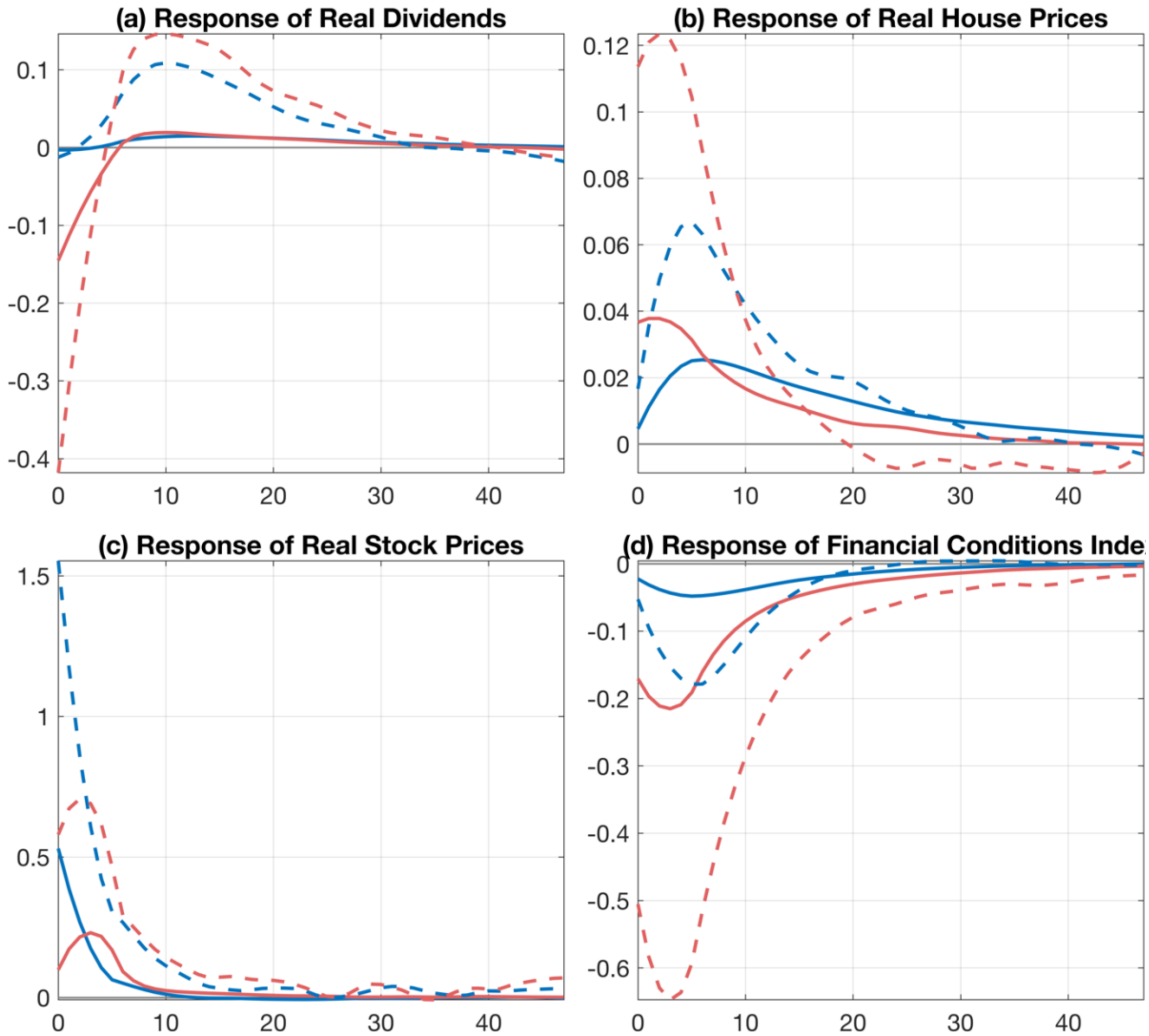
Note: The figure presents median impulse responses of the real dividends, real house prices, real stock prices, and financial conditions index to one standard deviation positive (solid lines) and negative (dashed lines) shocks in the overall economic volatility in normal (blue color) and crises (red color) periods. See note to Figure 3 for further details. (For the interpretation of the color references in this figure, the reader may refer to web version of this article.)

Figure 7. Size asymmetry of positive volatility shocks



Note: The figure presents median impulse responses of the real dividends, real house prices, real stock prices, and financial conditions index to one standard deviation (solid lines) positive and three standard deviation (dashed lines) positive shocks in the overall economic volatility in normal (blue color) and crises (red color) periods. See note to Figure 4 for further details. (For the interpretation of the color references in this figure, the reader may refer to web version of this article.)

Figure 8. Size asymmetry of negative volatility shocks



Note: The figure presents median impulse responses of the real dividends, real house prices, real stock prices, and financial conditions index to one standard deviation (solid lines) negative and three standard deviation (dashed lines) negative shocks in the overall economic volatility in normal (blue color) and crises (red color) periods. See note to Figure 4 for further details. (For the interpretation of the color references in this figure, the reader may refer to web version of this article.)