

ARTICLE

Is there a national housing market bubble brewing in the United States?[†]

Rangan Gupta¹, Jun Ma², Konstantinos Theodoridis^{3,4}, and Mark E. Wohar^{4,5,*}

¹Department of Economics, University of Pretoria, Pretoria, 0002, South Africa

²301 Lake Hall, Department of Economics, Northeastern University, Boston, MA, 02115 USA

³Cardiff Business School, Cardiff University, Aberconway Building, Colum Drive, Cardiff CF10 3EU, UK

⁴European Stability Mechanism, 6a Circuit DE LA Foire Internationale, 1347 Luxembourg, Luxembourg

⁵College of Business Administration, University of Nebraska at Omaha, 6708 Pine Street, Omaha, NE 68182, USA

*Corresponding author. Email: mwohar@unomaha.edu

Abstract

We use a time-varying parameter dynamic factor model with stochastic volatility estimated using Bayesian methods to disentangle the relative importance of the common component in Federal Housing Finance Agency house price movements from state-specific shocks, over the quarterly period of 1975Q2 to 2017Q4. We find that the contribution of the national factor in explaining fluctuations in house prices is critical. We then use a Bayesian change-point vector autoregressive model that allows for different regimes throughout the sample period, to study the impact of aggregate supply, aggregate demand, (conventional) monetary policy, and term-spread shocks, identified based on sign restrictions on the national component of house price movements. While monetary policy and other shocks are found to be quite dominant early on, we find evidence that the national factor has been detached from the identified macroeconomic shocks since 2014, thus suggesting that a “national bubble” might be brewing again in the US housing market.

Keywords: House prices; time-varying dynamic factor model; change-point vector autoregressive model; macroeconomic shocks

1. Introduction

In a seminal contribution related to the (regional and national) housing market of the USA [Del Negro and Otrok (2007)] used a Bayesian dynamic factor model (DFM) to deduce the importance of the common component in the Office of Federal Housing Enterprise Oversight’s (OFHEO’s), now the Federal Housing Finance Agency’s (FHFA’s), house price movements relative to state- or region-specific shocks, estimated on quarterly state-level data from 1986 to 2005. The authors found that, while movements in house prices have been mainly driven by the local component, the period of 2001–2005 was different in the sense that the overall increase in house prices was a national phenomenon, though “local bubbles” were important in some states. As a next step, [Del Negro and Otrok (2007)] used a (constant parameter) vector autoregressive (VAR) to investigate the role of monetary policy in explaining the movements of the common component of house price. The authors concluded that the impact of monetary policy shocks, identified based on sign restrictions, on the national house price factor was marginal. Within the context of trying to explain the movement in overall US house prices based on macroeconomic shocks, a recent study by Plakandaras et al. (2018) employed a Bayesian time-varying parameter VAR

[†]We would like to thank two anonymous referees for many helpful comments. However, any remaining errors are solely ours. The views expressed in this paper solely represent those of the authors and should not be interpreted as the views of the European Stability Mechanism.

covering the period of 1830–2016. This is undoubtedly an important question since according to recent financial accounts data of the USA, residential real estate represents about 83.7% of total household non-financial assets, 28.3% of total household net worth, and 24.6% of household total asset.¹ Based on a model which identified (permanent) technology, price and financial (money) shocks, and (temporary) housing market-related demand/supply shocks, these authors found that technology shocks dominate in driving the US housing market.² This finding further corroborates the analysis of conditional volatilities and correlations with macroeconomic shocks. Interestingly, these results are in line with those obtained earlier by Iacoviello and Neri (2010) from a micro-founded dynamic stochastic general equilibrium model of the US economy, which incorporated an explicit housing sector.

Motivated by the findings of the two above-mentioned VAR-based studies, that is, there are possibly more important other shocks than just monetary policy surprises that drive house prices in the USA,³ we aim to revisit the work of Del Negro and Otrok (2007), based on updated data covering the quarterly period of 1975–2017. Understandably, recent data allow us to include the tumultuous episodes of the “Great Recession,” the global financial crisis (GFC) (as well as the European sovereign debt crisis) that followed thereafter, and unconventional monetary policy decisions in the wake of the zero lower bound (ZLB) of monetary policy rates, with the roots of all these events associated with the bursting of the US housing bubble and the subprime mortgage crisis [Leamer (2015)]. Besides, using updated data, we extend the work of Del Negro and Otrok (2007), and the general literature which concentrates primarily the role of (conventional and more recently, unconventional) monetary policy shocks (rather than other macroeconomic surprises) in driving the US housing market (see Eickmeier and Hofmann (2013), Rahal (2016), Simo-Kengne *et al.* (2016), and Huber and Punzi (2020) for detailed reviews in the regard),⁴ in the following ways: (i) instead of the constant parameter DFM originally used by Del Negro and Otrok (2007), we estimate an extended version of the traditional DFM with time-varying loadings and stochastic volatility (DFM-TV-SV, henceforth), as developed by Del Negro and Otrok (2008), to obtain the national and local factors associated with US state-level house price movements. As pointed out by these authors, an assumption of most DFMs is that both the stochastic process driving volatility and the nature of comovement among variables have not changed over time, but large amount of recent empirical work has shown that the assumption of structural stability is invalid for many macroeconomic aggregate and regional data sets of the USA [Gupta *et al.* (2018b)], including house prices [Canarella *et al.* (2012), Karoglou *et al.* (2013), Simo-Kengne *et al.* (2016), Huang (2019)]. Naturally, a DFM model with fixed parameters is less likely to do well at describing house price data. As such, the generalized DFM-TV-SV not only captures changing comovements among the house prices of the 50 states and the District of Columbia by allowing for their dependence on common factors to evolve over time, but also allows for stochastic volatility in the innovations to the processes followed by the factors and the idiosyncratic components; (ii) unlike [Del Negro and Otrok (2007)], and inspired by Plakandaras *et al.* (2018), we identify not only monetary policy shocks but also aggregate supply, aggregate demand, and term-spread shocks based on sign restrictions, to analyze the impact of these shocks on the national component of house price movements. It must be realized that the spread shock is important for us, since the time period of our analysis involves the period of ZLB and hence, that of unconventional monetary policy, which in turn involved compression of the long-term yield spread; (iii) furthermore, different from the constant parameter VAR model used by Del Negro and Otrok (2007), we estimate changes in macroeconomic dynamics by using an innovative change-point VAR model, proposed by Liu *et al.* (2019), that allows for different regimes throughout the sample period while studying the impact of the various shocks on the common component of the state-level housing prices. This approach enables the VAR model to endogenously identify changes to the structure of the US economy as well as variations to the properties of the exogenous shocks during the sample period. Consistent with evidence of time-varying effects of macroeconomic variables on the (regional) housing market of the USA [Bork and Møller (2015), Li *et al.* (2015), Nyakabawo *et al.* (2015), Bork *et al.* (2019),

Christou et al. (2019), Huang (2021)], the change-point VAR model with nonrecurrent states offers a novel way to estimate changes in the transmission mechanism of a variety of shocks over an extensive period, and (iv) since we estimate a DFM-TV-SV model, we are also able to recover the stochastic volatility of the national factor, which we also incorporate into our change-point VAR model. This in turn, even though our primary focus is on house prices, allows us to simultaneously, as an aside, analyze the impact of the various identified shocks on the (common) housing market volatility, which have been shown to be also driven by macroeconomic variables [Miller and Peng (2006), Fairchild and ShuWu (2015), André et al. (2017), Plakandaras et al. (2018)], besides housing returns [Miles (2008)].⁵ As pointed out by Segnon et al. (2021) with housing serving the dual role of investment and consumption, the effects of housing on savings and portfolio choices are extremely important questions, and hence, understanding the drivers of the house price volatility cannot be ignored because it has individual portfolio implications, as it affects households' investment decisions regarding tenure choice and housing quantity. But more importantly, including the national factor of the stochastic volatility of the states in our change-point VAR allows us to control the possible effect of real estate uncertainty on the corresponding national component of house prices (over and above the identified macro shocks), as has been shown to play an important role in driving the US housing market [Christidou and Fountas (2018), Thanh et al. (2018)].

At this stage, it must be pointed out that there is widespread worry among academicians and policy authorities alike that, the ultra-low interest rate environment, along with the rise in liquidity caused by unconventional monetary policy measures that followed in the wake of the GFC, is inflating new housing bubbles [Jordà et al. (2015a, 2015b), Blot et al. (2018), Alpert (2019), Rosenberg (2019)]. Hence, distinguishing the national factor from local factors in the housing market and determining what fraction of the variation in house prices across the states is explained by the common component remain important questions, since answering them allows us to deduce whether the US economy is facing a “national bubble” or “local bubbles.” While “local bubbles” are attributable to circumstances that are specific to each geographic market given the widespread acceptance that housing markets are partially segmented [Apergis and Payne (2012), Montañés and Olmos (2013), Barros et al. (2013), Miles (2015)], by linking the national price factor to (conventional and unconventional) monetary policy and other macroeconomic shocks, we will be able to gauge the part of common regional housing market movement attributable to changes in fundamentals (wider array of macroeconomic shocks, besides the monetary policy shock) and the portion that could be due to speculation or pricing errors. Naturally, our analysis has tremendous significance from the policy perspective, if indeed the national factor dominates the local factors in explaining state-level housing price movements, and monetary policy shocks have had a role to play in driving the common component. These findings would in turn also align our study to the large existing literature (see, e.g., Galí and Gambetti (2015) and Caraiani et al. (2018) for comprehensive reviews) on the relationship between monetary policy and bubbles in asset (housing) markets.

To the best of our knowledge, this is the first paper to use a Bayesian DFM-TV-SV model to first decompose the state-level house price movements of the USA into a national and local factors and then use a Bayesian change-point VAR to analyze the impact of aggregate supply, aggregate demand, monetary policy, and term-spread shocks (identified based on sign restrictions) on the common component. The remainder of the paper is organized as follows: Section 2 discusses the data used and the two methodologies associated with the DFM-TV-SV and the change-point VAR, Section 3 presents the empirical results from these two models, and Section 4 concludes.

2. Data and methodologies

2.1. Data

To be consistent with Del Negro and Otrok (2007), we use the FHFA (then OFHEO) seasonally adjusted house price indexes for the 50 US states and District of Columbia over the quarterly

period of 1975Q1 to 2017Q4, with the start date driven by the availability of the house price data, and the end of the sample corresponding to the latest data at the time of writing this paper. The FHFA house price indexes provide a broad measure of the movement of single-family house prices. The FHFA indexes are weighted, repeat-sales data, that is, they measure average price changes in repeat sales or refinancings on the same properties. This information is obtained by reviewing repeat mortgage transactions on single-family properties whose mortgages have been purchased or securitized by Fannie Mae or Freddie Mac since January 1975. In particular, we use the quarterly “All-Transactions Indexes.”⁶ To create a real version of house price, we deflate the indexes by the (seasonally adjusted) Consumer Price Index (CPI) of the USA, derived from the FRED database of the Federal Reserve Bank of St. Louis. We work with the quarter-on-quarter (QoQ) version of the real house price indexes to obtain the national and local factors from the DFM-TV-SV model for both real housing returns and the corresponding stochastic volatilities.

As far as the data used in the change-point VAR are concerned, besides the two national factors of real housing returns and stochastic volatility, we include data on the federal funds rate (FFR), QoQ growth rate of seasonally adjusted real gross domestic product (GDP), QoQ growth of the CPI measuring the inflation rate, and the term spread, which was defined as the difference between 10-year government bond yield and the FFR. Data on FFR, real GDP, and the long-term government bond yield are again sourced from the FRED database. The transformations of the data imply that our effective sample covers the period of 1975Q2 to 2017Q4.

2.2. The generalized DFM

In this section, we present a generalized DFM that is employed to decompose the real housing returns in all states into a common (or national) factor and an idiosyncratic (or state-specific) factor. The DFM is often used to tease out the common movements among multiple time series and has become a standard tool since the work by Stock and Watson (1989). We generalize the standard DFM with constant parameters to one that allows for time-varying loading parameters and the stochastic volatility (DFM-TV-SV, henceforth). As such, the generalized DFM-TV-SV captures important time-varying comovements among multiple time series. Formally, our model specification closely follows Del Negro and Otrok (2008) and is specified as follows⁷:

$$r_{i,t} = \beta_{i,t} \cdot f_t + e_{i,t} \tag{1}$$

Here, $r_{i,t}$ is the first difference of the natural log of the real house price for state i at time t . f_t is the national factor that affects all house prices at time t , and $\beta_{i,t}$ is the time-varying loading parameter of this national factor. $e_{i,t}$ is the idiosyncratic factor.

The common factor and the idiosyncratic factors are assumed to be independent from each other. Therefore, the variance decomposition of our model is given by:

$$Var(r_{i,t}) = \beta_{i,t}^2 \cdot Var(f_t) + Var(e_{i,t}) \tag{2}$$

Note that either the time-varying loading parameters or the stochastic volatility of the factors enables the factors contributions to the total variations of each variable to vary over time.

Following the standard practice in this literature, we model the common factor f_t using a stationary AR(p) process:

$$f_t = \phi_1^f f_{t-1} + \phi_2^f f_{t-2} + \dots + \phi_p^f f_{t-p} + \exp(h_t^f) \cdot \varepsilon_t^f \tag{3}$$

where $\varepsilon_t^f \sim i.i.d.N(0, \sigma_f^2)$. Therefore, the shock to the factor has a stochastic volatility, and its time-varying volatility is governed by $\exp(h_t^f)$.

To keep the model parsimonious, we employ a driftless random walk process to capture the time variation of the volatility:

$$h_t^f = h_{t-1}^f + \sigma_f^h \cdot \xi_t^f, \quad \xi_t^f \sim i.i.d.N(0, 1) \tag{4}$$

The factor loading $\beta_{i,t}$ varies over time and is also assumed to follow a random walk process:

$$\beta_{i,t} = \beta_{i,t-1} + \sigma_i^\beta \cdot \eta_{i,t}; \quad \eta_{i,t} \sim i.i.d.N(0, 1) \tag{5}$$

Here, shocks to the loading parameters in different series are assumed to be orthogonal to each other.⁸

The idiosyncratic factor follows a stationary AR(q) process:

$$e_{i,t} = \phi_{i,1}e_{i,t-1} + \phi_{i,2}e_{i,t-2} + \dots + \phi_{i,q}e_{i,t-q} + \exp(h_{i,t}) \cdot \varepsilon_{i,t} \tag{6}$$

where $\varepsilon_{i,t} \sim i.i.d.N(0, \sigma_i^2)$. The stochastic volatility of the idiosyncratic factor follows a random walk process:

$$h_{i,t} = h_{i,t-1} + \sigma_i^h \cdot \xi_{i,t}, \quad \xi_{i,t} \sim i.i.d.N(0, 1) \tag{7}$$

Here, we assume that the shocks to the stochastic volatility in different factors are independent from each other. This assumption simplifies the estimation algorithm.

As usual, some normalizations of the factor rotations are needed before the model can be identified and estimated. The loading parameters and the variance of the shock to the common factor are not separately identifiable. We choose to set $\sigma_f^2 = 1$ to achieve the identification. Following Del Negro and Otrok (2008), we also restrict that the time-varying volatility all starts from zero for the same identification purpose. We demean each series before the estimation since the means of factors are not separately identifiable. Finally, following works such as Neely and Rapach (2011) and Bhatt et al. (2017), we set $p = q = 2$ to keep the model parsimonious.

2.3. Estimation procedure

We estimate this DFM-TV-SV model using the Monte Carlo Markov Chain (MCMC) Bayesian estimation method. Specifically, we employ the well-established Gibbs sampling algorithm by breaking the model into several blocks and sampling sequentially from posterior conditional densities. The idea of the Gibbs sampling algorithm is that when the algorithm converges after the initial burn-in draws, these random draws from the conditional densities altogether constitute a good approximation of the underlying joint densities. Applying the law of large numbers, the numerical integration can be easily taken to obtain the marginal densities of the parameters and the state variables of our interest. Most blocks in the model are linear and Gaussian, and as a result the standard algorithms in Kim and Nelson (1999) are readily applicable. The stochastic volatility introduces a non-Gaussian feature into the model. We apply the procedure proposed in Kim et al. (1998) that utilizes a mixture of normal densities to approximate the underlying non-Gaussian distribution in order to simulate the stochastic volatility. This procedure has been widely used in the literature, see, for example, Stock et al. (2007) and Primiceri (2005).

We briefly outline the Gibbs sampling estimation algorithm below. Further details are given in Appendix A.2.

1. Cast the model into its state-space form as given in Appendix A.2 and draw the national factor $\{f_t\}_{t=1}^T$ from the conditional density:

$$f \left(\{f_t\}_{t=1}^T \mid \left\{ \{\beta_{i,t}\}_{t=1}^T \right\}_{i=1}^n, \phi_f, \{\phi_{i,e}\}_{i=1}^n, \{\sigma_i^2\}_{i=1}^n, \left\{ h_t^f \right\}_{t=1}^T, \left\{ \{h_{i,t}\}_{t=1}^T \right\}_{i=1}^n, \left\{ \{r_{i,t}\}_{t=1}^T \right\}_{i=1}^n \right),$$

where $\phi_f = (\phi_1^f, \phi_2^f, \dots, \phi_p^f)'$, and $\phi_{i,e} = (\phi_{i,1}, \phi_{i,2}, \dots, \phi_{i,q})'$ for $i = 1, 2, \dots, n$.

2. Draw the AR parameters of the common factor from the conditional density:

$$f\left(\phi_f \mid \{f_t\}_{t=1}^T, \{h_t^f\}_{t=1}^T\right)$$

Draws of the AR parameters outside the unity circle are discarded to ensure the stationarity.

3. Sample the AR and variance parameters for each idiosyncratic factor from the conditional density:

$$f\left(\phi_{i,e}, \sigma_i^2 \mid \{f_t\}_{t=1}^T, \{\beta_{i,t}\}_{t=1}^T, \{h_{i,t}\}_{t=1}^T, \left\{\{r_{i,t}\}_{t=1}^T\right\}_{i=1}^n\right)$$

Because the idiosyncratic factors are orthogonal to each other, these draws can be made one by one for each $i = 1, 2, \dots, n$. Again, to ensure the stationarity any draw of the AR parameters outside the unity circle is discarded.

4. Draw the loading parameters and the shock variance parameters from the conditional density:

$$f\left(\{\beta_{i,t}\}_{t=1}^T, (\sigma_i^\beta)^2 \mid \{f_t\}_{t=1}^T, \phi_{i,e}, \sigma_i^2, \{h_{i,t}\}_{t=1}^T\right)$$

Again, due to the orthogonality condition, these draws can be made one by one for each $i = 1, 2, \dots, n$.

5. Draw the stochastic volatility of the common factor from the conditional density:

$$f\left(\{h_t^f\}_{t=1}^T, \sigma_f^h \mid \{f_t\}_{t=1}^T, \phi_f\right)$$

And draw the stochastic volatility of the idiosyncratic factor from the conditional density:

$$f\left(\{h_{i,t}\}_{t=1}^T, \sigma_i^h \mid \{f_t\}_{t=1}^T, \{\beta_{i,t}\}_{t=1}^T, \phi_{i,e}, \{r_{i,t}\}_{t=1}^T\right)$$

Starting with initial values, we repeat steps (1) through (5) for $(D + S)$ number of times. Here, D is the initial burn-in draws needed for the algorithm to converge, and the results are based on the saved S number of draws. We set D to 2000 and S to 8000.

2.4. Change-point VAR model

This section reviews the empirical model used for structural analysis. It also discusses how the marginal likelihood of the model is applied to determine: (i) the number of regimes and (ii) the order of lags. A similar framework has been applied by Kapetanios *et al.* (2012) and Liu *et al.* (2019).

To assess whether agents' responses to macroeconomic shocks vary across regimes, the following VAR model is estimated:

$$Z_t = c_S + \sum_{j=1}^K B_S Z_{t-j} + \varepsilon_t, \tag{8}$$

where $\varepsilon_t \sim N(\mathbf{0}, \Omega_S)$ and the data matrix Z_t contains quarterly data on the FFR, real GDP growth, inflation, term spread, and the national factors of real housing returns and volatility derived from the DFM-TV-SV model. B_S and Ω_S denote the VAR coefficient and covariance matrix, respectively, which vary across regimes.

The empirical model permits M breaks to take place at unknown dates, and as in Chib (1998) the evolution of these breaks is prescribed by the latent state variable, S_t . The latter state variable follows an M state Markov chain with restricted transition probabilities, $p_{ij} = p(S_t = j | S_{t-1} = i)$, given by

$$\begin{aligned}
 p_{ij} &> 0 \text{ if } i = j \\
 p_{ij} &> 0 \text{ if } j = i + 1 \\
 p_{MM} &= 1 \\
 p_{ij} &= 0 \text{ otherwise.}
 \end{aligned}
 \tag{9}$$

For example, if $M = 3$, the transition matrix is defined as

$$\tilde{P} = \begin{pmatrix} p_{11} & 0 & 0 \\ 1 - p_{11} & p_{22} & 0 \\ 0 & 1 - p_{22} & 1 \end{pmatrix}.$$

Equations (8) and (9) describe a Markov switching VAR with nonrecurrent states where transitions from one regime are restricted to happen sequentially. For example, to move from regime 1 to regime 3, the process has to visit regime 2. The transition matrix also precludes transitions to past regimes. As discussed in Sims et al. (2008), this is a Markov switching model where structural breaks are modeled as multiple change points. We believe that this approach is advantageous over standard Markov switching models as it permits the user to associate changes in the macroeconomic dynamics with structural breaks in the economy. For instance, it is shown below that the marginal likelihood metric selects the best “fitting” model as the one with three regimes. Furthermore, these regimes seem to coincide with the Great Inflation, Great Moderation, and Great Recession-ZLB periods.

2.5. Estimation and selection of the number of change points and lags

We follow Chib (1998) and adopt a Bayesian Gibbs sampling approach to the estimation of the change-point VAR models. Appendix B provides a detailed description of the prior and Appendix C describes the main steps of the algorithm. The only feature that is perhaps important to be mentioned here is that during the last regime, the policy rate does not respond to any variable into the system (to proxy for the ZLB). This characteristic is imposed via tight priors (see the discussion in the Appendix B).

The choice of the number of breakpoints is a crucial specification issue. The number of regimes is selected by comparing the marginal likelihood across models (i.e., different number of regimes or/and lags). The maximum number of regimes has been set equal to three, while the maximum number of lags equals to four. Both choices are driven by concerns regarding the limited number of observations per regime.⁹

Given m and l , the marginal likelihood is estimated based on Chib (1998) and Bauwens and Rombouts (2012):

$$\ln G(Z_t | m, k) = \ln f(Z_t | m, k, \Theta, \tilde{P}) + \ln p(\Theta, \tilde{P} | m, k) - \ln g(\Theta, \tilde{P} | Z_t, m, k) \tag{10}$$

where $\ln G(Z_t | m, k)$ denotes the marginal likelihood, $\ln f(Z_t | m, k, \Theta, \tilde{P})$ is the likelihood, while $\ln p(\Theta, \tilde{P} | m, k)$ and $\ln g(\Theta, \tilde{P} | Z_t, m, k)$ are the prior and posterior distribution of the VAR parameter vector, respectively. Note that $\ln G(Z_t | m)$ does not depend on the parameters of the model and in theory it can be evaluated at any value of the parameters. Following standard practices, we evaluate the marginal likelihood at the posterior mean. The first two terms on the right-hand side of equation (10) are easily evaluated, whereas the calculation of the normalizing constant $\ln g(\Theta, \tilde{P} | Z_t, m)$ requires some work. As described in detail in Bauwens and Rombouts

Table 1. Sign restrictions

Variables	Shocks			
	Demand	Supply	Monetary policy	Slope
Policy rate	+	-	+	0
GDP growth	+	+	-	-
Inflation	+	-	-	-
Term spread	?	?	?	+
House prices factor	?	?	?	?
House prices volatility factor	?	?	?	?

Notes: All sign restrictions have been imposed for 4 periods. During the ZLB regime, the policy rate does not respond to the demand and supply shock as well (i.e., additional zero restrictions).

(2012), this term can be evaluated by considering reduced Gibbs runs on an appropriate factorization of $g(\Theta, \tilde{P} | Z_t, m)$. We use 10,000 additional Gibbs replications to evaluate $g(\Theta, \tilde{P} | Z_t, m)$ at the posterior mean.

2.6. Shock identification

This section explains briefly the identification scheme employed in this paper, and it is motivated by the work of Uhlig (2004), Mountford and Uhlig (2009), and Barsky and Sims (2011). The identified shocks maximize their contribution on selected variables and also satisfy the sign restrictions described in Table 1, which are imposed for four periods.

The mapping between reduced and structural errors is given by

$$\varepsilon_t = A_{0,S} v_t \tag{11}$$

For any orthogonal matrix D ($DD' = I$, where I is the identity matrix), the above mapping can be written as

$$\varepsilon_t = A_{0,S} D_S v_t$$

Since

$$\Omega_S = A_{0,S} D_S D_S' A_{0,S}' = A_{0,S} A_{0,S}'$$

Using the companion form of the VAR(p) model, the impulse of variable j and the impulse of shock i in the period h can be expressed as

$$IRF_{i,j}(h) = J_j B_S^{h-1} A_{0,S} D_S J_i' \tag{12}$$

where J_i and J_j are selection matrices of zeros and ones.

In Uhlig (2005), the matrix D_S results from the following minimization problem:

$$D_S^* = \arg \min \sum_{j \in \mathcal{I}_+} \sum_{h_j = \tilde{h}_j}^{H_{j,+} \in H_+} f \left(-\frac{J_j B_S^{h-1} A_{0,S} D_S J_i'}{\sigma_{j,S}} \right) + \sum_{j \in \mathcal{I}_-} \sum_{h_j = \tilde{h}_j}^{H_{j,+} \in H_+} f \left(\frac{J_j B_S^{h-1} A_{0,S} D_S J_i'}{\sigma_{j,S}} \right) \tag{13}$$

s.t.

$$D_S D_S' = I$$

where $\sigma_{j,S}$ is the standard deviation of variable j and $f(x) = \begin{cases} 100x & \text{if } x \geq 0 \\ x & \text{otherwise} \end{cases}$. Finally, \mathcal{I}_+ is the

index set of variables, for which identification of a given shock restricts the impulse response to be positive and \mathcal{I}_- is the index set of variables, for which identification restricts the impulse response to be negative. The use of this scheme is to identify “meaningful” macroeconomic shocks and to study how these disturbances affect house price movements.

Although the identification scheme employed shares many similarities with the one developed by Mountford and Uhlig (2009) and Barsky and Sims (2011), two features of the proposed methodology are of worth to be mentioned explicitly. The first point is that the matrix D_S is regime dependent, meaning that the above maximization problem (expression 13) needs to be performed for each regime. More importantly, no restriction is placed on the house price level and volatility factors. In other words, our approach about the effects of “standard” macroeconomic shocks on the series that describe the evolution of the common components associated with real housing returns and stochastic volatility is agnostic.

Table 1 reports the sign restrictions employed to identify a demand, supply, monetary policy, and term-spread shock. The restrictions for the first three shocks are uncontroversial, and they have been used in the literature extensively. Although the last shock has been studied in a number of papers Kapetanios et al. (2012), Baumeister and Benati (2013), and Liu et al. (2019) (among others), it is less common and aims to capture movements at the long end of the yield curve that are not induced by variations in the policy rate. During the Great Moderation period, this shock could reflect the foreign capital inflows to the USA, capturing the so-called savings glut phenomenon [Sá et al. (2014), Sá and Wieladek (2015), Cesa-Bianchi et al. (2018)], while during the ZLB period, this shock could proxy the Federal Reserve’s unconventional policies.

3. Empirical results

In this section, we present the estimation results of the DFM-TV-SV model as described in Section 2.2 and when applied to the quarterly real housing returns in 50 states and the District of Columbia. We first present the national factor of the real housing returns together with its time-varying stochastic volatility and then discuss its time-varying contributions to real housing returns in all states, followed by discussions of the implied time-varying cross-state correlation and the cross-state volatility dispersion from the DFM-TV-SV model. Finally, we turn our attention to analyzing the impact of sign restrictions-based identified aggregate demand, aggregate supply, monetary policy, and credit shocks on the evolution of the national factor using a change-point VAR model.

3.1. The national factor of the real housing returns

Figure 1 plots the national factor (in a solid line), together with the 90% probability intervals (in dotted lines)¹⁰. One important advantage of this generalized DFM is that it allows exposures of the real housing returns in all states to the national factor to vary over time and thus permits a time-varying integration of the local housing market with the national market. The national factor started to increase in 1975 but then declined in the late 1970s through the early 1980s. Since around the mid-1980s, the national factor had steadily risen for an extended period of time until about 2006, when the national factor plunged leading to a severe financial crisis and recession in 2007–2009. The national real housing returns factor leveled off around 2010 and has rebounded sharply since 2011. The dynamics of the national factor of real housing returns estimated from our DFM-TV-SV model is in general consistent with those findings documented over the common period of the past literature (see, e.g., Del Negro and Otrok (2007) and Fairchild and ShuWu

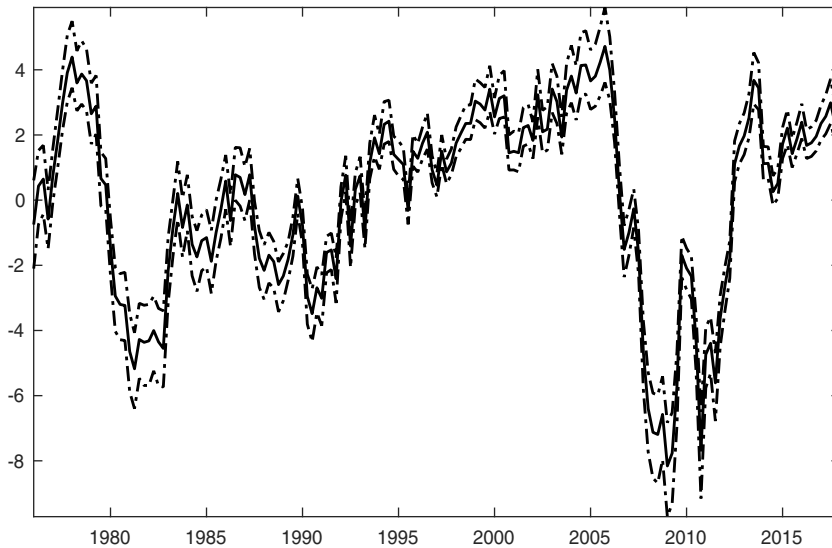


Figure 1. The national factor.

Notes: The solid black line is the median of the posterior distribution, while the dotted lines represent the 5% – 95% percentiles.

(2015)). We explain this pattern below by identifying various shocks in the context of a change-point VAR framework.

Figures 2 and 3 plot the time-varying loading parameters of the national factor, together with the 90% probability intervals, for the growth of real house price in each state. Overall, the exposures of the real housing returns in all states to the national factor vary substantially over time. These loading parameters appear to be positive for all states at all time periods, indicating that there is no identification issue. The dynamic patterns of these time variations also display substantial heterogeneity across states. A number of states, including Alaska, California, Delaware, Florida, Hawaii, Idaho, Illinois, Maryland, Nevada, New York, Oregon, Virginia, Vermont, Washington, and Wisconsin, all witnessed a steady increase in the exposures of their real housing returns from the early 1990s to the pre-crisis period. Interestingly, many other states, including Arkansas, Colorado, Connecticut, DC, Iowa, Indiana, Kansas, Kentucky, Louisiana, Massachusetts, Maine, Mississippi, North Dakota, Nebraska, New Hampshire, Ohio, Oklahoma, Rhode Island, South Dakota, Texas, Utah, West Virginia, and Wyoming, all experienced a steady decline in the exposures of their real house price growth in the same period.

Figure 4 shows the stochastic volatility of the national factor with its 90% probability interval. There is a rapid and substantial increase in the stochastic volatility of the national factor from around 1998 to around 2011, followed by a large decline afterwards. Figures 5 and 6 plot the stochastic volatility of each state-specific factor. Overall, there is a substantial time variation in the stochastic volatility for all idiosyncratic factors, and there is a substantial heterogeneity in the dynamic patterns across states.

Recall, from equation (2), that both the time-varying loading parameters and the stochastic volatility of the national and the state-specific factors jointly determine the time-varying contributions of the national factor to the total variations of the growth in real house price in the states. Figures 7 and 8 show the dynamic evolution of the relative contribution of the national factor to the real housing returns in all states. The relative contribution of the national factor has increased since the mid-1980s for most states. These include states that have experienced an overall steady increase in its loading of the national factor, such as California and New York, and states that have

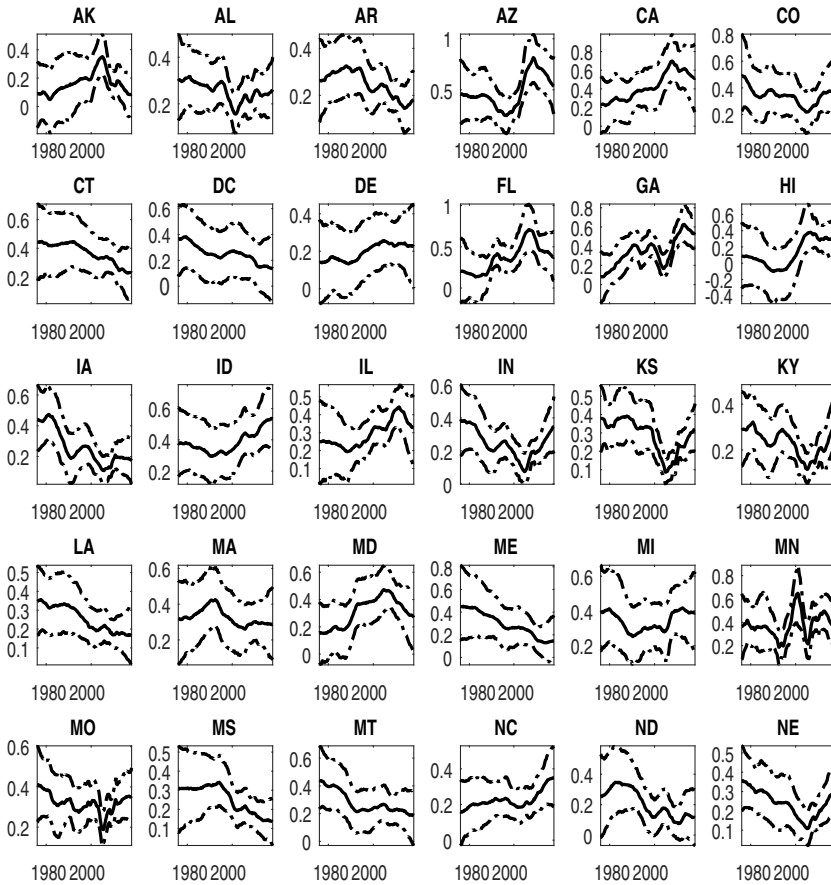


Figure 2. Time-varying loading parameters of the national factor.
 Notes: The solid black line is the median of the posterior distribution, while the dotted lines represent the 5% – 95% percentiles.

witnessed a decline in its loading of the national factor, such as Connecticut and Massachusetts. For the latter group of states, it seems that the decline in the loading of the national factor is more than offset by a large increase in the stochastic volatility of the national factor and a large decline in the stochastic volatility of the idiosyncratic factor, resulting in an increasing relative contribution of the national factor. To quantify the relative contribution of the national factor to the total variations, we note that the contribution of the national factor for the full sample period in all states is 44.85% on average. This contribution is only about 28.85% on average during the period from 1975Q1 to 1989Q4, rises to as much as 52.12% during the period from 1990Q1 to 2006Q4, and remains as high as 55.08% during the period from 2007Q1 to 2017Q4. Although the contribution of the national factor has declined somewhat after the financial crisis in some states, we conclude that overall the role of the national factor in explaining the house prices in all states is not only critical but also has been increasing to become more important than the local factors since around 1990. These findings are broadly in line with previous works such as Del Negro and Otrok (2007), but recall the sample period of that study ended in 2005 and hence did not cover the most recent periods, including that of the GFC which corresponded with a tumultuous period of the US housing market. Given the dominance of the national factor in explaining state-level house price movements, especially since 1990, identifying the role of various macroeconomic shocks in

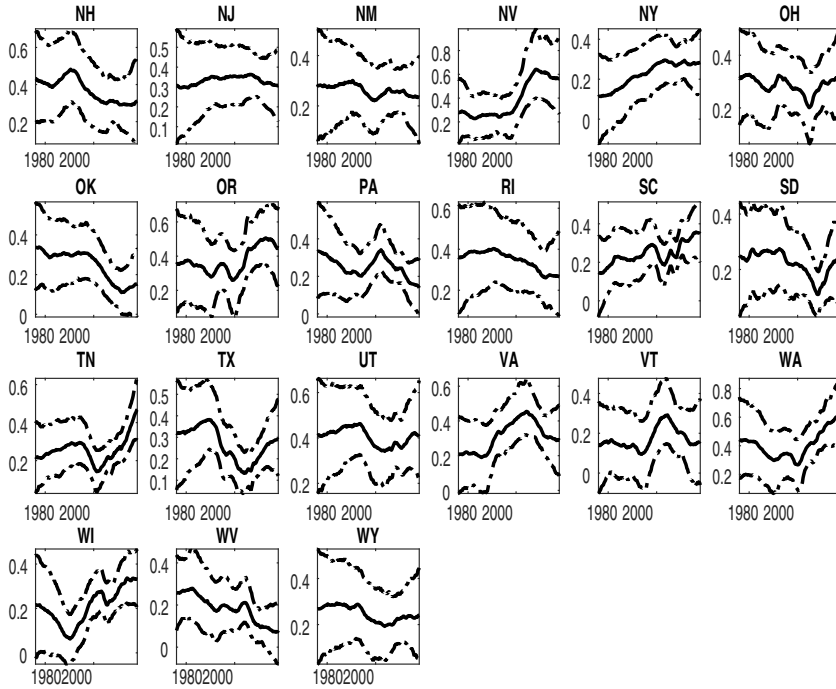


Figure 3. Time-varying loading parameters of the national factor—continued.
 Notes: The solid black line is the median of the posterior distribution, while the dotted lines represent the 5% – 95% percentiles.

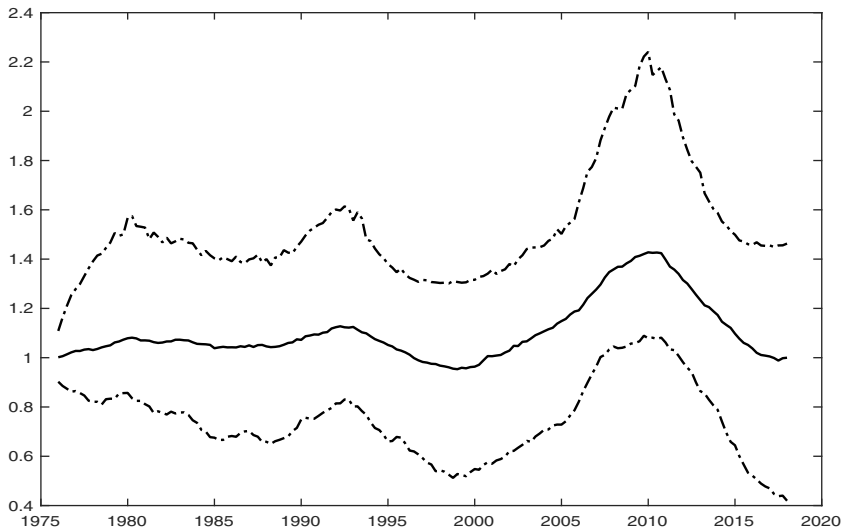


Figure 4. The stochastic volatility of the national factor.
 Notes: The solid black line is the median of the posterior distribution, while the dotted lines represent the 5% – 95% percentiles.

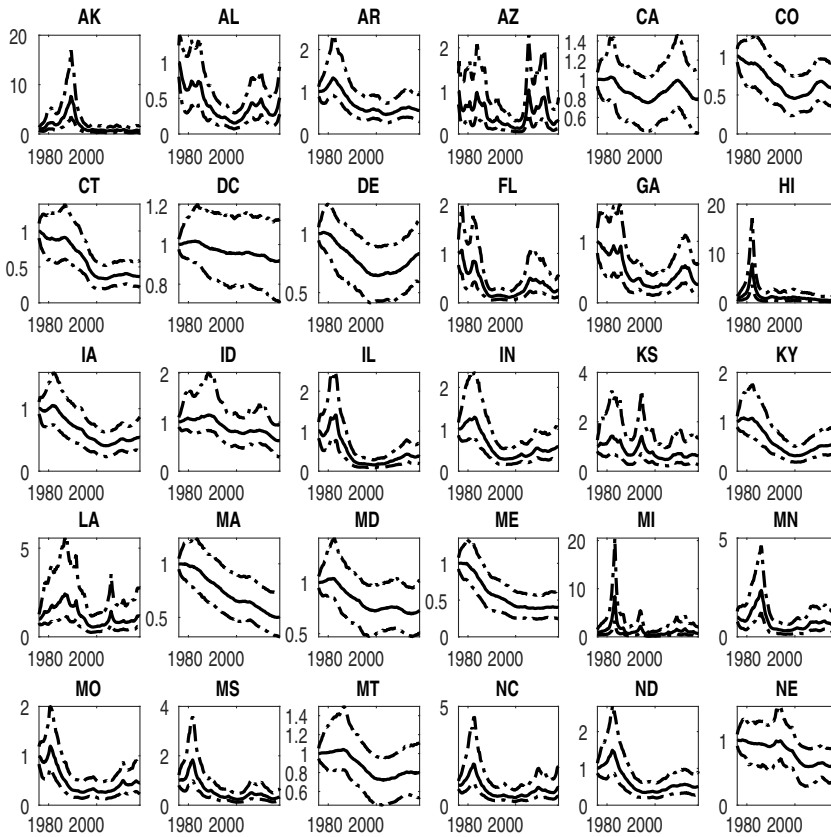


Figure 5. The stochastic volatility of the individual factor.

Notes: The solid black line is the median of the posterior distribution, while the dotted lines represent the 5% – 95% percentiles.

driving this common real housing returns component in a regime-specific context is clearly of paramount importance, and this is what we focus on in detail below in a short while.

3.2. Cross-state time-varying correlation

The generalized DFM as employed here can capture potentially time-varying comovements among multiple series. To this end, we compute the implied correlation for each pair of states and present the average of these pairwise correlations at each time point in Figure 9. The average cross-state correlations increased from the mid-1980s till around 2011 and then declined until the end of the sample. The increase in this correlation was more rapid in 1985–1995 than in 1996–2005. This correlation increased more rapidly again between 2005 and 2011, which may have been driven by the financial crisis.

3.3. Cross-sectional dispersion in volatility

Another metric that can be computed based on the DFM-TV-SV model to usefully summarize the dynamic patterns of these growth in real house prices is the volatility dispersion, which is the standard deviation of the implied volatility of all states, as shown in Del Negro and Otrok (2008). In Figure 10, we present this time-varying volatility dispersion and the decomposition of it into the

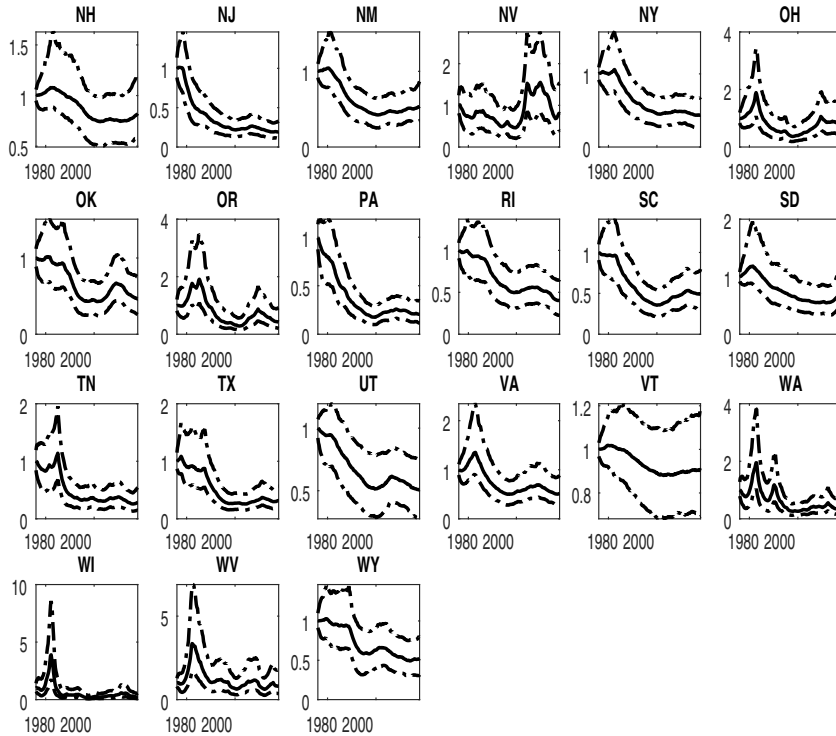


Figure 6. The stochastic volatility of the individual factor—continued.
 Notes: The solid black line is the median of the posterior distribution, while the dotted lines represent the 5% – 95% percentiles.

component driven by the national factor and that by the state-specific factor. We find that there is a large increase in the volatility dispersion at the beginning of the sample period till around the mid-1980s, followed by a large decline. The third panel in this figure indicates that this rise and decline in the total volatility dispersion is primarily attributed to the idiosyncratic factor. The total volatility dispersion increased between 2000 and 2009 again and then declined until the end of the sample. The second panel suggests that this is primarily due to the national factor.

3.4. Change-point VAR model specification and evolution of regimes

Next, we focus our attention on the change-point VAR, using which we analyze the impact of various identified macroeconomic shocks on the national factors of real housing returns and stochastic volatility.¹¹ We start with the discussion of the dynamic specification of the model. Table 2 reveals that the model that gets the most support from the data is the most flexible one. In words, the data prefer a model with three regimes and four lags.¹²

Figure 11 helps us to understand the model selection implied by the marginal likelihood statistic. The evolution of the regimes coincides with the three phases of inflation and, consequently, the policy rate during the time interval considered in this study. Namely, the first regime is associated with high inflation and policy rate (“Great Inflation”). In contrast, the second regime overlaps (mostly) with the Great Moderation (stable low inflation and policy rate) and the final regime with the ZLB period. Interestingly, the second regime more or less corresponds to sample period used by Del Negro and Otrok (2007) under the rationale that this sample corresponds to a single monetary policy regime and thus helps in correctly identifying the monetary policy shocks. The “good-luck” versus “good-policy” and ZLB literature document that the dynamics across these

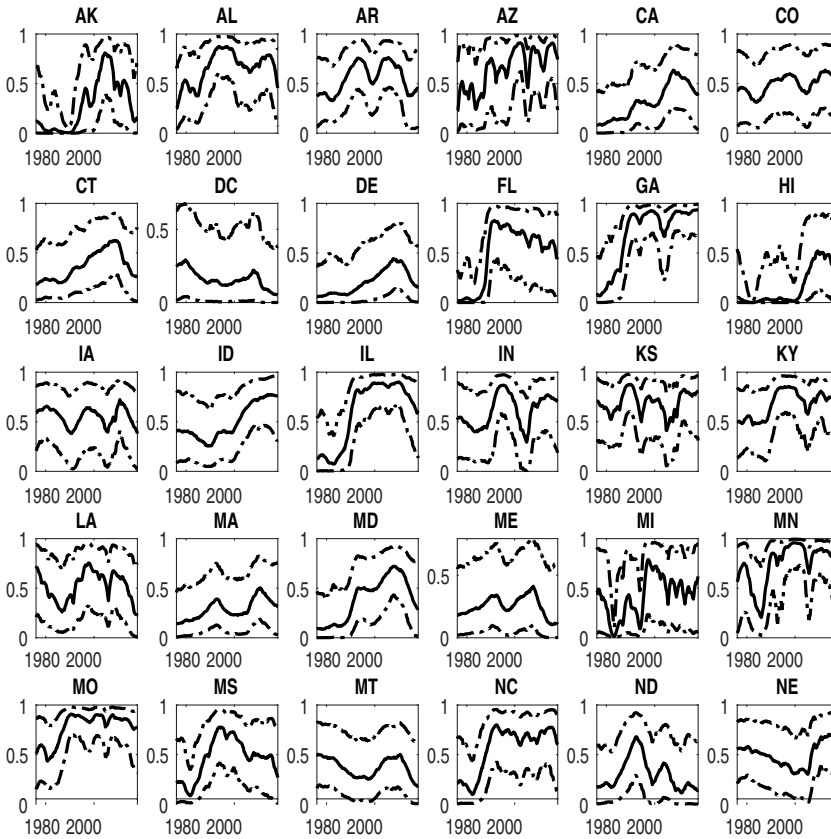


Figure 7. Time-varying variance contributions of the national factor.
 Notes: The solid black line is the median of the posterior distribution, while the dotted lines represent the 5% – 95% percentiles.

different regimes are dramatically different (see Sims and Zha (2006), Cogley and Sargent (2005), and Liu et al. (2019) among others). In addition, when we look at these three regimes, we observe the first regime being characterized by the declining national factor of real housing returns and then recovery of the same with low volatility,¹³ followed by the rapid increases with eventual collapse and highly volatile national factors in the second regime, and then finally the recovery of the common component with declining variability in the wake of expansionary unconventional monetary policies. As a result, a model with sufficient flexibility is required to capture accurately the extensive non-linearities in the data. The results displayed in Table 2 are inline with this rationale.

3.5. Shocks

The evident time-varying importance of the national real housing returns factor in explaining movements at the state-level especially post-1990 tends to suggest that the housing market boom before the collapse in 2007, and then again the recovery after that is not necessarily purely driven by local factors (“local bubbles”). Hence, this section is devoted to studying the responses of the economy including the national housing market factors of returns and volatility, to each identified shocks and whether these responses are regime dependent. The importance of the shock across all three regimes is also assessed in this section.

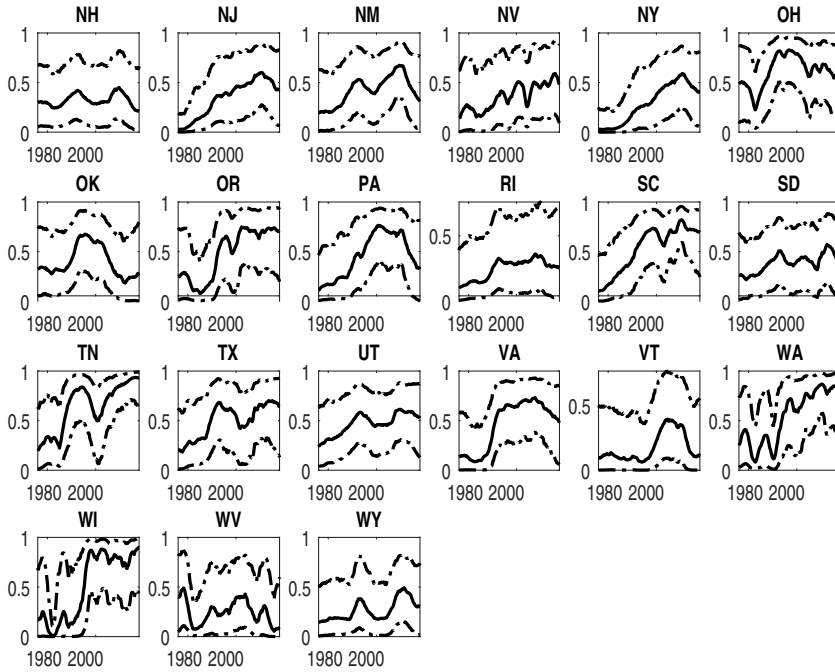


Figure 8. Time-varying variance contributions of the national factor—continued.
 Notes: The solid black line is the median of the posterior distribution, while the dotted lines represent the 5% – 95% percentiles.



Figure 9. The time-varying average of cross-states correlations.
 Notes: The solid black line is the median of the posterior distribution, while the dotted lines represent the 5% – 95% percentiles.

3.5.1. Demand shock

Figure 12 illustrates responses to a demand shock. To remind the reader, the effects of the shock on the term spread, the real housing returns factor, and the house prices volatility factor are left unrestricted. Figure 12 makes apparent that the transmission of the shock to the macroeconomy varies

Table 2. Marginal likelihood comparison

Regimes/Lags	1	2	3	4
2	-3204.35	-2364.70	-703.00	-135.34
3	-749.32	-78.69	349.55	703.91

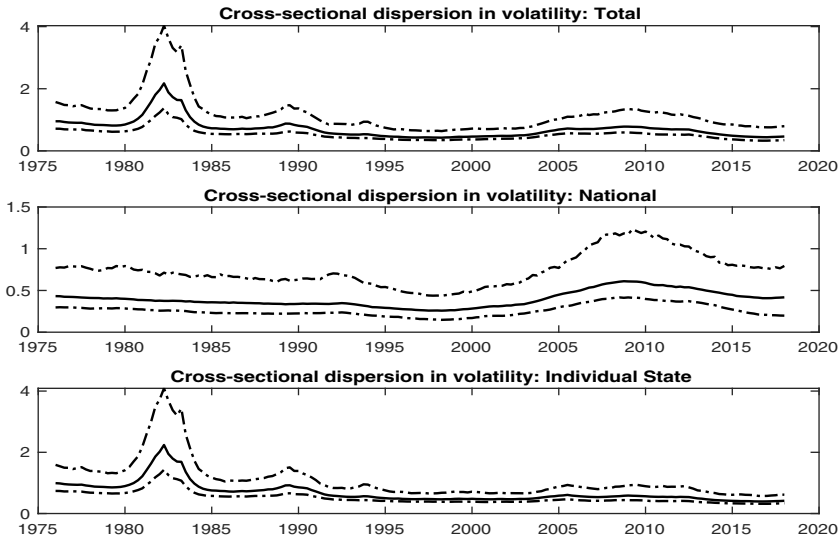


Figure 10. The total volatility dispersion and its decomposition into the national and the individual components. Notes: The solid black line is the median of the posterior distribution, while the dotted lines represent the 5% – 95% percentiles.

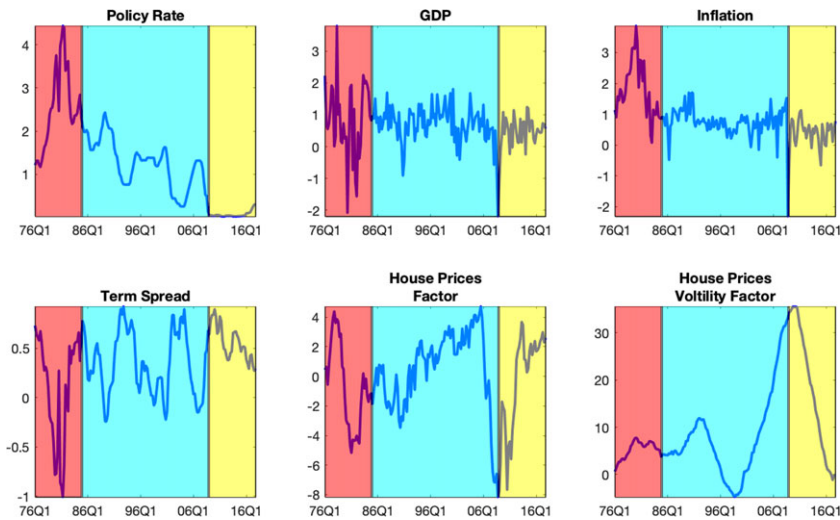


Figure 11. Evolution of regimes. Notes: Observed data (solid blue line), regime 1 (red shaded area), span between 1975Q1 and 1984Q4, regime 2 (blue shaded area) between 1985Q1 and 2008Q4, and regime 3 (yellow shaded area) between 2009Q1 and 2017Q4.

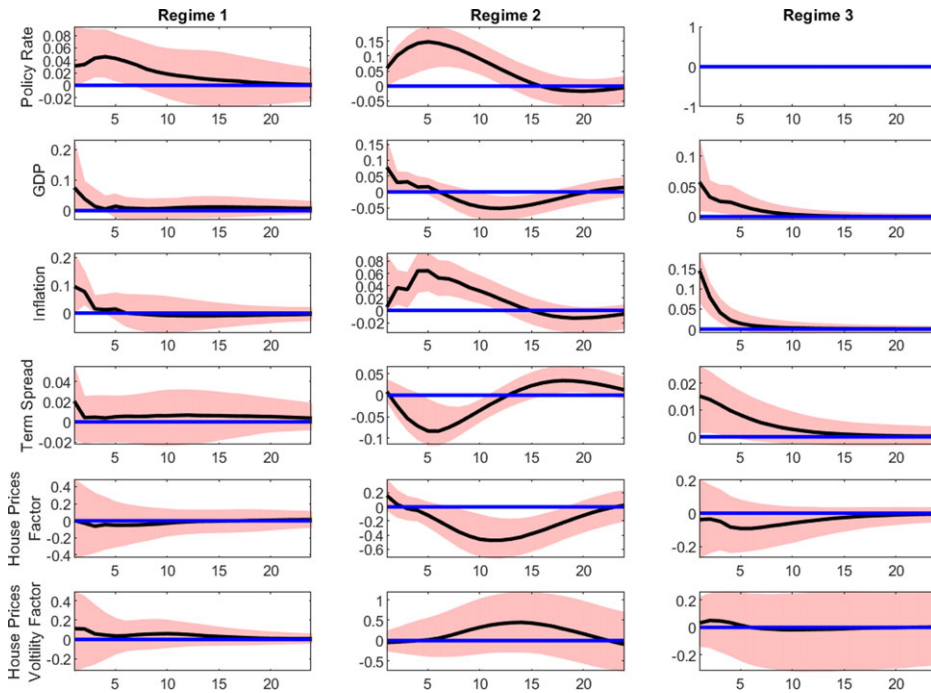


Figure 12. Impulse responses: demand shock.

Notes: The solid (black) line represents the (pointwise) median, while the shaded area captures the 16% – 84% percentiles of the posterior distribution. The shock has been normalized to increase GDP growth by 1 percentage point in the second quarter.

dramatically across the three regimes. The shock seems to have a larger effect on the economy during the “Great Moderation” (regime 2), and the forecast variance decomposition also confirms this (Figure 13 and Table 3). Although the effect on the real GDP growth is comparable across the three regimes, inflation rises substantially more in the second regime, and this leads to a protracted increase in the interest rate. Despite the long-lasting policy rate increase, the term-spread falls indicating that the long-term interest rate rises by less than the short end of the yield curve, perhaps due to well-anchored inflation expectation during the Great Moderation. The housing factor increases initially, but this is only a short-lasting effect, since as monetary authorities start “fighting” higher inflation and the policy rate increases, the real housing returns factor falls.

During the Great Moderation, the demand shock explains 50% of the variability of the policy rate, indicating that the Federal Reserve’s intense effort to mitigate the inflationary consequences of the shock. This elevated impact is also reflected on GDP (20%), inflation (20%), term spread (35%), real housing returns factor (30%), and real house price volatility factor (20%).

3.5.2. Supply shock

The responses of output growth, inflation, and the policy rate are stronger in the first than in the other two regimes (Figure 14). The stimulative monetary policy needed for the (negative) output gap to be closed leads to the higher housing returns factor in regimes 1 and 2. This effect is supported further by the strong (income) growth in the economy, which also leads to lower volatility of the national factor of housing returns for regimes 1 and 2.

The forecast variance contribution of the shock does not seem to vary across the 1st and 2nd regimes and it fluctuates between 10% and 20% (Figure 13 and Table 3). The supply shock plays a

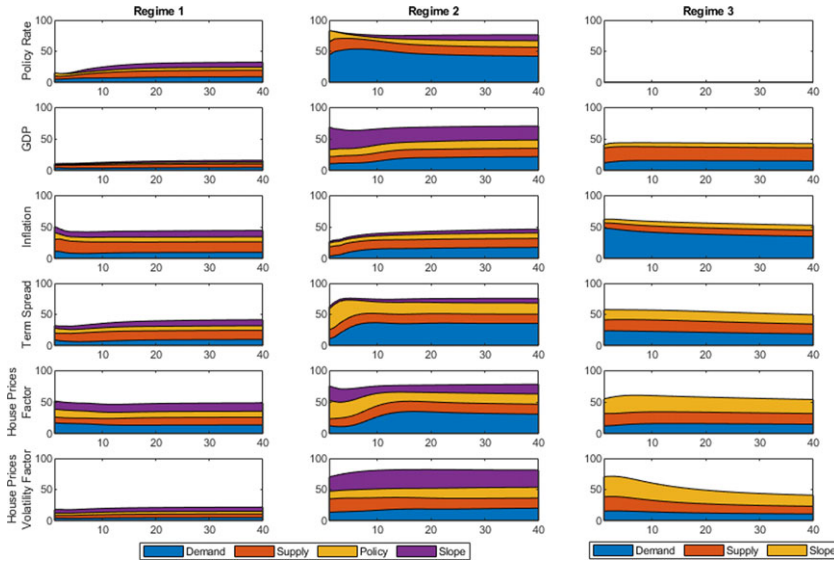


Figure 13. Forecast variance decomposition.

more important role during the 3rd regime, with its contribution to GDP growth, and the factors of real housing returns and stochastic volatility rising above 20%.

3.5.3. Policy shock

A policy “cut” increases output growth persistently during the second regime (Figure 15). Interestingly, the term spread rises approximately by 200 basis points suggesting that long-term interest rates do not decrease as much as the policy rate. The stimulative environment created by the Federal Reserve leads to higher values of the real housing returns factor during the Great Moderation, while this effect is insignificant in the first regime. This highly accommodative policy results in higher volatility of the national housing returns factor, although this effect is not precisely estimated.

The forecast variance contribution to GDP growth and inflation is admittedly quite small (Figure 13 and Table 3), which is in line with a number of existing studies (see Bernanke et al. (2005), Smets and Wouters (2007), and Justiniano et al. (2010) among others). On the other hand, the contribution of the policy shock on the term spread and national housing returns factor rises to (almost) 30%,¹⁴ indicating the strong link between policy actions and decision of agents to invest in either long-term or/and housing debt.

3.5.4. Slope shock

The slope shock is a perturbation that lowers the long end of the yield curve, while the policy rate remains constant contemporaneously (Figure 16). In the first regime, the shock stimulates demand and inflation. As the authorities start increasing the policy rate to restore price stability, the national house price factor starts falling with (about) a year delay, while the corresponding volatility increases contemporaneously. These effects carry over to the next regime. However, the response of volatility of the national housing returns factor is not precisely estimated. As the economy moves into the ZLB regime, the responses of the level and volatility of common factors change sign. In this regime, real housing returns factor increases and volatility falls (but again, the latter response is not precisely estimated). Recall that, the slope shock in the last regime proxies the

Table 3. Forecast variance contributions

	H = 1Q			H = 4Q			H = 12Q			H = 40Q		
	R = 1	R = 2	R = 3	R = 1	R = 2	R = 3	R = 1	R = 2	R = 3	R = 1	R = 2	R = 3
Demand	5	44	0	6	52	0	7	50	0	9	42	0
Supply	5	21	0	5	18	0	9	14	0	11	14	0
Policy	5	18	55	3	7	55	4	6	55	5	10	55
Slope	0	0	0	1	1	0	6	5	0	8	9	0
Demand	4	11	12	4	12	15	4	17	16	5	22	15
Supply	4	11	23	5	12	23	5	13	22	6	13	21
Policy	1	11	17	1	11	16	2	12	16	3	13	17
Slope	2	35	6	1	30	6	2	24	6	3	22	7
Demand	11	4	48	8	8	45	9	16	41	10	18	35
Supply	19	15	8	19	15	9	17	14	10	17	14	10
Policy	11	6	13	7	6	13	8	7	14	8	9	18
Slope	10	3	6	8	3	7	9	4	7	10	6	8
Demand	9	11	24	6	25	24	8	36	22	10	35	19
Supply	11	14	18	13	17	18	15	15	18	15	15	16
Policy	8	34	8	6	31	8	7	19	10	7	18	16
Slope	4	4	17	5	3	16	7	5	16	10	7	15
Demand	17	13	12	16	11	14	14	31	16	14	31	15
Supply	9	11	20	9	14	19	10	17	19	12	16	17
Policy	12	29	7	12	25	7	10	17	9	9	16	13
Slope	13	23	23	12	20	27	13	11	25	13	15	22
Demand	4	13	15	4	14	16	4	18	14	5	20	11
Supply	4	21	23	5	22	23	5	19	17	6	16	12
Policy	4	12	8	4	13	8	4	14	15	4	17	27
Slope	6	23	33	6	27	32	6	30	26	7	28	18

Notes: The table reports the posterior mean forecast variance shares. $R = 1$, $R = 2$, and $R = 3$ indicate regimes 1, 2, and 3, respectively. While $H = 1Q$, $H = 4Q$, $H = 12Q$, and $H = 40Q$ refer to forecast horizons, 1 quarter, 4 quarter, 1 year, and 10 years, respectively.

Federal Reserve's unconventional policies adopted to repair macroeconomic stability (something which we will return to below) in the wake of the Great Recession.

The shock seems to have a limited effect on the macroeconomic variables including the term spread (Figure 13 and Table 3). An exception is the contribution of the GDP on growth during the Great Moderation, especially at short horizons such as one quarter and one year, whereby the shock explains 35% and 30% of the variability of growth. The contribution of the shock to the slope of the yield curve rises as the forecast horizon increases. However, the magnitude of this effect is (approximately) 15%. Interestingly, the contribution of the term-spread shocks is much higher for the remaining two variables (between 20% and 30%). What seems to be more noteworthy is the fact that the contribution of the shock peaks in the third regime.

3.6. Sensitivity analysis

It is illustrated in the Appendix D that the results are robust: i) when the value of the hyperparameter that controls the tightness of the VAR coefficients is increased (looser priors), ii) when the unemployment (instead of the GDP growth) series, derived from the FRED database, is used

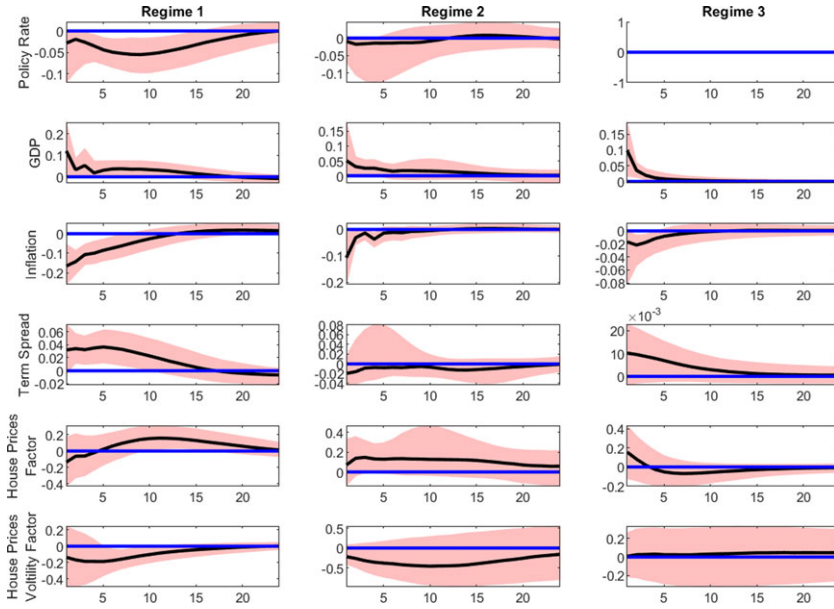


Figure 14. Impulse responses: supply shock.

Notes: The solid (black) line represents the (pointwise) median, while the shaded area captures the 16% – 84% percentiles of the posterior distribution. The shock has been normalized to increase GDP growth by 1 percentage point in the second quarter.

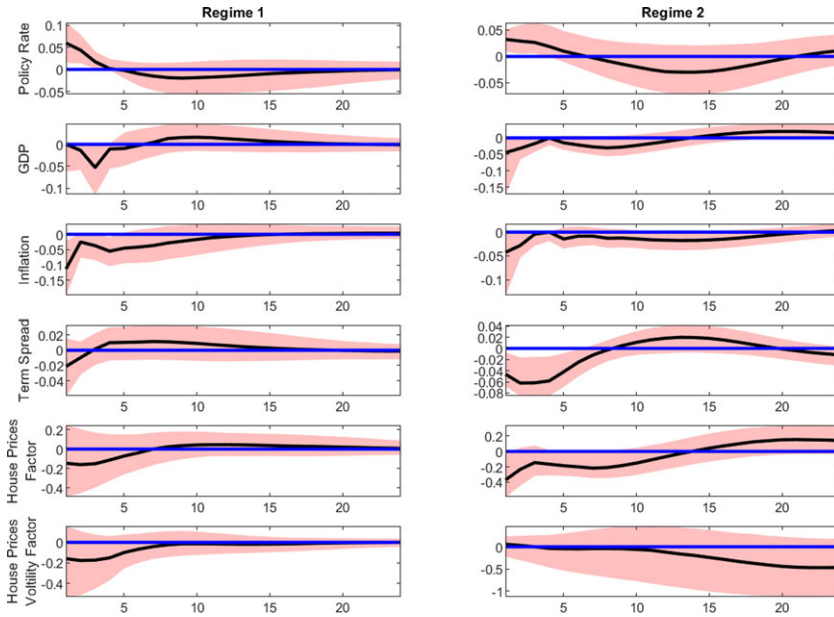


Figure 15. Impulse responses: policy shock.

Notes: The solid (black) line represents the (pointwise) median, while the shaded area captures the 16% – 84% percentiles of the posterior distribution. The shock has been normalized to increase GDP growth by 1 percentage point in the second quarter.

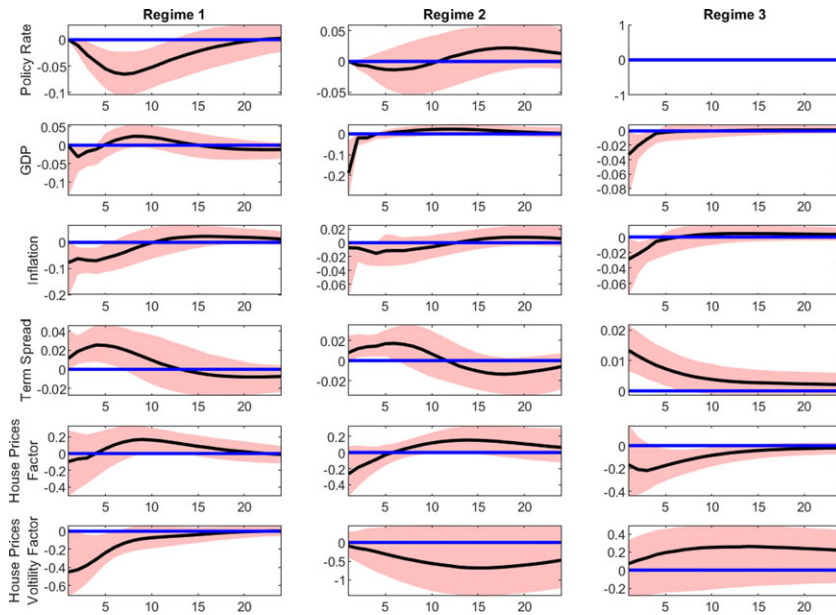


Figure 16. Impulse responses: slope shock.

Notes: The solid (black) line represents the (pointwise) median, while the shaded area captures the 16% – 84% percentiles of the posterior distribution. The shock has been normalized to increase GDP growth by 1 percentage point in the second quarter.

to proxy the real sector of the economy, and iii) when the dynamic order to the VAR is reduced to 3, 2, and 1 lags (per regime).¹⁵

3.7. The national housing returns factor and identified shocks

The discussion in this section is concentrated on the national real housing returns factor in relation to not only conventional and unconventional monetary policy shocks but also aggregate demand and aggregate supply innovations. Table 3 illustrates that the identified macroeconomic economic shocks explain between 50% and 70% of the variability of the national housing returns factor (depending on the horizon and the regime). This message is further reinforced by Figure 17, where the identified shocks account for (almost) all the historical evolution of the common component of state-level growth in real house prices during the first and second regimes. The explanatory power of the identified shocks collapses during the Great Recession, while it improves in the period between 2011Q1 and 2014Q2 but breaks down again from 2014Q3 till the end of the sample (2017Q4).¹⁶

Several interesting facts emerge from both Table 3 and Figure 17. The first one is that, unlike in the high inflation regime, conventional monetary policy played almost no role in the growth of the national factor related to the housing market during the Great Moderation—a result in line with Del Negro and Otrok (2007); if anything, its contribution is rather negative [Nelson *et al.* (2018)]. This finding is consistent with the work of Justiniano *et al.* (2017) and Justiniano *et al.* (2019) where the authors explain that factors related to the credit supply and demand, and not monetary policy, are behind the increase of house prices (and housing debt/leverage). In this study, credit supply and demand shocks are not identified explicitly, but are probably captured by the demand, supply, and slope shocks in our model and, interestingly, the contribution of all these three types of shocks to the national factor of real housing returns is positive during this period, which, in

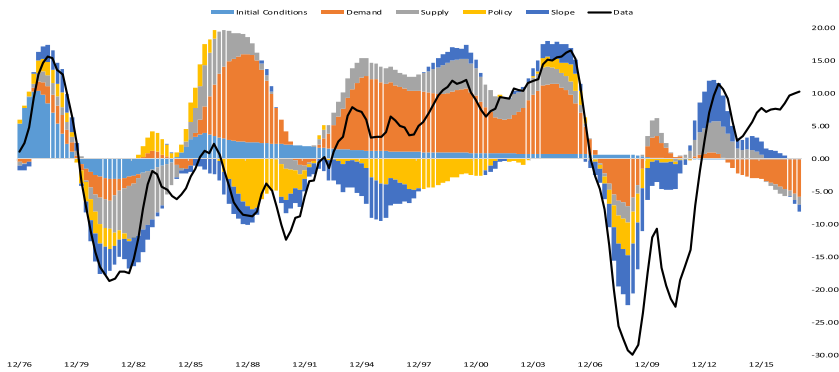


Figure 17. Historical decomposition of real housing returns factor.

Notes: The historical decomposition is calculated for each posterior draw. The (posterior) mean of these calculations is reported here. The quarter-on-quarter contributions have been aggregated to annual changes contributions. The same transformation is applied for the data series.

turn, corroborates the findings of Plakandaras et al. (2018), especially in terms of the importance of the aggregate supply shocks.

The national real house price growth factor collapsed during the Great Recession, with one-third of this fall not being explained by the shocks identified. During this period, the (conventional) monetary policy is constrained by the ZLB, which started binding at the beginning of the 2009. Interestingly, substantial negative policy contribution started cumulating a few quarters before the ZLB, and these adverse effects picked up during the ZLB period (persistence effect). This anecdotal evidence could suggest that the inability of monetary authorities to lower the policy rate, which cannot be modeled as a shock, could explain a large part of the unexplained wedge.

Although quantitative easing (QE) was introduced in the last quarter of 2008, the model suggests that the slope (or QE) shock started contributing positively to the economy around 2012. This period coincides with the introduction of the open-ended QE3 and the forward guidance (FG) unconventional monetary policy. This does not mean that the first two QE programs had no positive effects on recovering the housing market, as this question cannot be answered from the historical decomposition and in turn requires the knowledge of the counterfactual profile of the national factor in the absence of the QE1 and QE2 programs. However, the assumption that the large positive contributions by the slope shock during the third regime are associated with explicit guidance about future policy rate would be consistent with the point made in the previous paragraph. In other words, what matters most for agents when it comes to house prices is the systematic part of the monetary policy described by the policy rate.

Finally, the real housing returns factor post-2014 has decoupled again from the identified macroeconomic shocks. This perhaps reflects the concerns, as also as outlined above in the introduction, from important policy institutions and policy-makers (see, e.g., Borio (2019) and Carstens (2019), among others) that low interest rates led many investors to search for higher returns that are also subject to elevated risks. Moreover, studies like Bork et al. (2019), Balcilar et al. (2021), Bouri et al. (2021), and Gupta et al. (2021) have recently highlighted the importance of behavioral factors such as sentiment and uncertainty in playing crucial roles, beyond standard macroeconomic and financial variables, in driving house price movements, that is, both returns and volatility for the overall and regional USA.¹⁷ In light of this, our findings should not come as a surprise and carry important implications from the perspective of modeling the US housing market. In particular, such behavioral variables should then be explicitly included, and shocks to them analyzed, while performing structural analyses of macroeconomic and financial shocks on the housing market. From the policy perspective, if these shocks are indeed important relative to conventional shocks for the US housing market, then policy authorities would need to target these behavioral variables to indirectly affect the movements in housing returns and volatility,

especially given evidence that sentiment and uncertainty are not necessarily exogenous and are indeed predictable [Marfatia *et al.* (2020), André *et al.* (2021), Ludvigson *et al.* (2021), Salisu *et al.* (2021)].

3.8. Identifying conventional and unconventional monetary policy shocks using external instruments

This section scrutinizes the role of both conventional and unconventional monetary policy on the real housing returns factor.¹⁸ In the first stage, the monetary policy (conventional and unconventional) shocks are identified from interest rate surprises that take place in a narrow window (30 min) before and after the policy meetings by using the methodology developed by Swanson (2021). In the second phase, proxy SVAR techniques (as in Mertens and Ravn (2013) and Mertens and Ravn (2014)) identify the effects on house prices.

3.8.1. Proxy SVAR

This section briefly reviews the shock identification methodology proposed by Mertens and Ravn (2013) and Mertens and Ravn (2014). Although, the scheme proposed initially was for a fixed-coefficient VAR model, the studies of Mumtaz and Petrova (2018) and Mumtaz and Theodoridis (2020) illustrate how the process can be extended to allow for time and regime dependence, respectively.

The fundamental idea of this methodology is that a “proxy” (ϕ_t) that is correlated with the shock of interest (v_t^m) and uncorrelated with the remaining shocks (v_t^*) is used to identify the structural shock. These conditions can be expressed as follows:

$$\begin{aligned} E(\phi_t, v_t^m) &= \alpha \neq 0 \\ E(\phi_t, v_t^*) &= 0 \end{aligned} \tag{14}$$

As explained in Mertens and Ravn (2013) and Mertens and Ravn (2014), the identification of structural shocks (i.e., the first column of $A_{0,S}$) can result as a solution of a generalized method of moments estimation problem that satisfies the moment conditions (14). The authors also illustrate that the structural shocks, v_t^m , can be simply derived by regression of ϕ_t on ε_t . For instance, let us assume that the fitted value of the v_t^m is given by:

$$\begin{aligned} \Pi_S \varepsilon_t &= E(\phi_t \varepsilon_t') \Omega_S^{-1} \varepsilon_t \\ &= \alpha_S A_{0,S}^m (A_{0,S} D_S D_S' A_{0,S}')^{-1} \varepsilon_t \\ &= \alpha_S \left(A_{0,S}^m (A_{0,S}^{-1})' \right) (A_{0,S}^{-1} \varepsilon_t) \\ &= \alpha_S v_t^m \end{aligned} \tag{15}$$

where Ω_S denotes the regime-dependent variance–covariance matrix of the VAR residuals, while moving from the third to the fourth line we employ the orthonormality properties of the identified matrix and mapping between the structural and reduced-form errors discussed above.

3.8.2. Narrative measures for conventional and unconventional monetary policy shocks

The strength of the identification scheme discussed in the previous section relies on the quality of the instrument used to identify the structural shock.¹⁹ As explained by Jarociński and Karadi (2020) and Miranda-Agrippino and Ricco (2021), changes in the forward interest rate contracts defined in a narrow window of 30 min before and after the policy announcements can contain also information that is related to the state of the economy and not, necessarily, to the reaction function of the monetary authority.

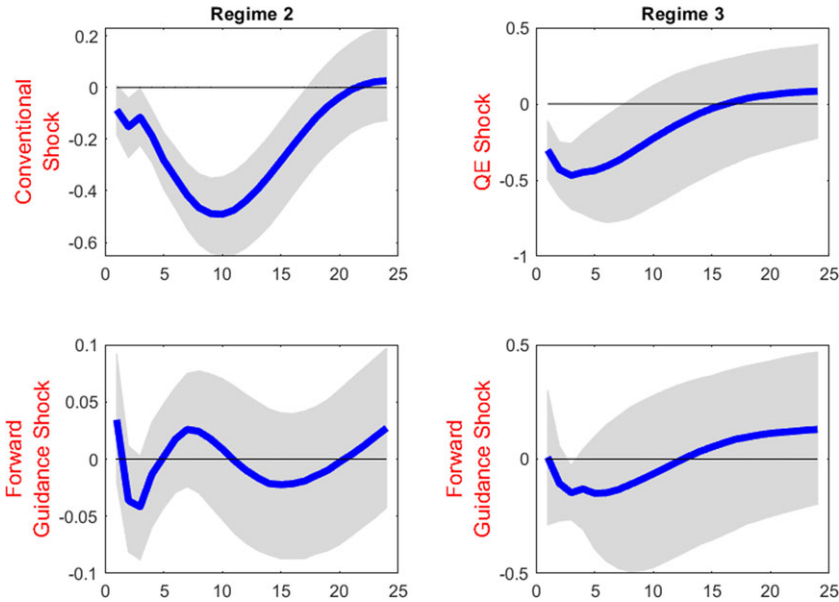


Figure 18. Responses of real housing returns factor across different types of adverse monetary policy shocks and across regimes.

Notes: The solid (black) line represents the (pointwise) median, while the shaded area captures the 16% – 84% percentiles of the posterior distribution.

Jarociński and Karadi (2020) propose a methodology that isolates the monetary policy shocks from the disturbances that contain “information” about the state of the economy. However, their scheme does not disentangle “conventional” monetary policy shocks from “unconventional” QE and FG ones. As discussed in the literature (see Andres et al. (2004), Chen et al. (2012), De Graeve (2016), and Liu et al. (2019) among others), the transmission mechanism of different monetary policy is not necessarily the same, meaning that the effects of conventional and unconventional monetary policy shocks on the real housing returns factor could be different.

Fortunately, Swanson (2021) and Altavilla et al. (2019) extend the methodology proposed by Gürkaynak et al. (2005) and achieve the identification of all three types of monetary policy shocks. Figure 18 reports the effects of different monetary policy shocks on the real housing returns factor across different regimes using the proxy SVAR techniques and the narrative measures. Before discussing the results, it is important to mention that the lack of available futures interest rate contracts for the USA prior to 1991, limits the evaluation exercise to regimes 2 and 3 and only.

Similar to the benchmark sign restrictions identification scheme, Figures 15 and 18 indicate that conventional monetary policy shocks have a sizeable effect on the real housing returns factor (first-row and first-column subplot). The latter effect appears to be more persistent and more precisely estimated when narrative measures are used. QE monetary policy shocks have again a large impact on the factor (first-row and second-column subplot). Interestingly, the QE shocks appear to be less persistent than conventional monetary policy shocks. Finally, FG monetary policy shocks do affect house price significantly.

The lack of a significant impact on the real housing returns factor from FG shocks might seem puzzling at first. However, this consideration might be addressed if the nature of interest rate shocks is understood. FG is nothing more than a communication policy that reveals information about the central bank’s reaction function in the future. As a result, it reduces uncertainty about the future monetary policy actions and, consequently, reinforces the effects of conventional and quantitative monetary policy decided today.

4. Conclusions

In this paper, we use a time-varying parameter dynamic factor model with stochastic volatility (DFM-TV-SV) estimated using Bayesian methods to disentangle the relative importance of the common component in FHFA house price movements from state-specific shocks, over the quarterly period of 1975Q2 to 2017Q4. We find that the contribution of the national factor in explaining fluctuations in house prices has declined somewhat after the financial crisis in some states, but overall the role of the national factor in all states is not only critical but also has been increasing and has become more important than the local factors since around 1990. This result suggests that, while “local bubbles” have been important in some states, overall the increase in house prices is a national phenomenon. We then use a Bayesian change-point VAR model that allows for different regimes throughout the sample period, to study the impact of not only (conventional) monetary policy shocks but also aggregate supply, aggregate demand, and term-spread shocks, identified based on sign restrictions, on the national component of house price movements, with the term-spread surprises measuring unconventional monetary policy decisions. We detect three regimes corresponding to the periods of “Great Inflation,” “Great Moderation,” and the episodes of the “Great Recession” and the GFC thereafter, associated with the ZLB. While conventional monetary policy is found to have played an important role in the historical evolution of the national factor of real housing returns of the USA in the first regime, other shocks are found to be quite dominant as well, especially during the second regime of the “Great Moderation,” with monetary policy shocks playing virtually no role in explaining the national housing market boom during this period. As far as the third regime is concerned, unconventional monetary policy shocks, associated with the phase 3 of the quantitative easing (QE3), are found to have led to a (delayed) recovery in the housing market. Since the DFM-TV-SV model also allows us to recover the national factor of housing market volatility, we could incorporate it into our change-point VAR to analyze what shocks play a role in driving this factor. In this context, again the role of monetary policy is limited, with dominant effect coming from the term-spread shock, followed by the aggregate supply and aggregate demand shocks. But perhaps more importantly, we find evidence of the national real housing returns factor to have got detached from the identified macroeconomic shocks, that is, fundamentals since 2014—somewhat similar to what was observed in terms of the low explanatory power of the shocks during the Great Recession. This result seems to suggest that a “national bubble” is brewing again in the US housing market,²⁰ resulting from the prolonged period of loose unconventional monetary policies following the recent financial crisis. Naturally, our findings call for careful monitoring of the behavior of house prices, in order for the policy authorities to decide whether or not to “lean against the wind,” by raising policy rates [Martin *et al.* (2022)]. Besides the cost of producing a future recession, whether such policies can in fact affect the housing market also remains debatable, given our finding of a limited role for conventional monetary policy in driving the US housing market historically. Perhaps, in this regard the role of macro-prudential tools become important, which are often considered as the best instruments to prevent the build-up of credit-driven bubbles, notably because they can be tailored to address specific market failures [Cerutti *et al.* (2017)].

Notes

1 See: <https://www.federalreserve.gov/releases/z1/20190920/html/b101h.htm>.

2 This result is actually in line with Gupta *et al.* (2019), who made similar observations for the Real Estate Investment Trusts sector of the US economy. Reverting back to the paper by Plakandaras *et al.* (2018), when the authors also conducted a comparative analysis for the United Kingdom (UK) over the period of 1845–1846, interestingly they found that monetary policy is the most important driver of house price.

3 In fact, Del Negro and Otrok (2007) clearly pointed out that there are indeed many other potential causes that led to the booming housing market before its collapse.

4 More recently, some studies have also emphasized the role of fiscal policy shocks in driving the US housing market in the wake of the ZLB (see Gupta *et al.* (2018a) and Montasser *et al.* (2020) for further details).

- 5 In this regard, the role of monetary policy in producing second moment macroeconomic effects for the US economy, including the equity market, has also been recently depicted by Mumtaz and Theodoridis (2020).
- 6 The data can be downloaded from: <https://www.fhfa.gov/DataTools/Downloads/Pages/House-Price-Index.aspx>.
- 7 As a robustness check, we also expand our dynamic factor model to include five regional factors that include Northeast, Midwest, West, Southeast, and Southwest following Del Negro and Otrok (2007). The resulting national factor from this expanded model is very similar to the national factor from the model without regional factors and the correlation between the two is 0.98. Furthermore, the variance decomposition results indicate that the contributions of the national factor to house price variations are little changed by adding regional factors. These results are available upon request.
- 8 It is straightforward to see that potential comovements in the factor loadings across all series can be captured by the common factor volatility. This was pointed out by Del Negro and Otrok (2008).
- 9 Allowing for a larger number of breakpoints and lags turns out to be an infeasible task as there are not enough observations per regime.
- 10 To provide diagnostics of the algorithm convergence, we follow Primiceri (2005) to compute the 20th-order sample autocorrelation of simulation draws for each parameter and state variable (averaged over the sample period for state variables) and plot them in Figure 19. These numbers are all around 0.2 and indeed most of them are far below 0.2. Our results are also robust to different initial values. We deem these results quite satisfactory as indication of the algorithm convergence.
- 11 An interesting area of future research in this regard would be to determine what state-specific characteristics drive the differences in exposures to the common factor.
- 12 Extending the search for a larger number of regimes or/and lags is not possible given the scale of the empirical model and the quarterly nature of the data. There are no enough observations per regime to ensure meaningful estimates.
- 13 This period is known to be associated with large structural changes in the credit market culminating into the end of regulation Q.
- 14 This is actually more than twice the figure of 13% detected by Del Negro and Otrok (2007) and could be an indication of our model picking up the existing nonlinearity in the relationships among the variables of the change-point VAR.
- 15 For all these exercises, the number of regimes is set equal to 3 as in the benchmark model.
- 16 Based on the suggestion of an anonymous referee, we extended our data until 2021Q1. However, these additional observations had almost no effect on the estimation. This should not come as surprise as the scale of the model is enormous (with close to 200 parameters) and 13 additional observations are not sufficient to change the inference dramatically. For instance, when we looked at the historical decomposition from the longer data set, the model interprets the COVID-19 pandemic as a demand shock mainly. More importantly, the increase in the housing returns seen during the corona virus crisis cannot be justified by fundamental shocks. This decoupling is what gives rise to overvaluation and, potentially, sharp correction concerns as it is explained in a recent IMF blog by Ahir et al. (2021) (among others). Complete details of these results are available upon request from the authors.
- 17 This line of reasoning is vindicated, when based on the suggestion of an anonymous referee, inclusion of a metric of macroeconomic uncertainty (as developed by Jurado et al. (2015)) and the excess bond premium (as per [Gilchrist and Zakrajsek (2012)]) continues to not only depict the decoupling but makes it even relatively larger. Complete details of these results are available upon request from the authors.
- 18 We would like to thank an anonymous referee for suggesting this line of analysis.
- 19 The methodology proposed by Caldara and Herbst (2019) deals also with “weak” instruments.
- 20 In this regard, as part of future research, it would be interesting to study the distributional impact of housing bubbles, as outlined theoretically in Graczyk and Phan (2021).

References

- Ahir, H., N. Biljanovska, C. Fu, D. Igan and P. Loungani (2021) *Housing Prices Continue to Soar in Many Countries Around the World*, IMF Blog.
- Alpert, D. (2019) What the federal reserve got totally wrong about inflation and interest rate policy: Getting real about rents. Available at: <https://blogs.cornell.edu/cradle/2019/02/11/what-the-federal-reserve-got-totally-wrong-about-inflation-and-interest-rate-policy-getting-real-about-rents/>. Accessed: 2020-02-07
- Altavilla, C., L. Brugnolini, R. S. Gürkaynak, R. Motto and G. Ragusa (2019) Measuring euro area monetary policy. *Journal of Monetary Economics* 108(C), 162–179.
- André, C., L. Bonga-Bonga, R. Gupta and J. W. M. Mwamba (2017) Economic policy uncertainty, US real housing returns and their volatility: A nonparametric approach. *Journal of Real Estate Research* 39(4), 493–513.
- André, C., D. Gabauer and R. Gupta (2021) Time-varying spillovers between housing sentiment and housing market in the united states. *Finance Research Letters* 42, 101925.
- Andres, J., J. D. Lopez-Salido and E. Nelson (2004) Tobin’s imperfect asset substitution in optimizing general equilibrium. *Journal of Money, Credit, and Banking* 36(4), 665–690.
- Apergis, N. and J. E. Payne (2012) Convergence in US house prices by state: Evidence from the club convergence and clustering procedure. *Letters in Spatial and Resource Sciences* 5(2), 103–111.
- Balcilar, M., E. Bouri, R. Gupta and C. K. Kyei (2021) High-Frequency predictability of housing market movements of the united states: The role of economic sentiment. *Journal of Behavioral Finance* 22(4), 490–498.

- Barros, C., L. Gil-Alana and J. Payne (2013) Tests of convergence and long memory behavior in US housing prices by state. *Journal of Housing Research* 23(1), 73–87.
- Barsky, R. and E. Sims (2011) News shocks and business cycles. *Journal of Monetary Economics* 58(3), 273–289.
- Baumeister, C. and L. Benati (2013) Unconventional monetary policy and the great recession: Estimating the macroeconomic effects of a spread compression at the zero lower bound. *International Journal of Central Banking* 9(2), 165–212.
- Bauwens, L. and J. V. K. Rombouts (2012) On marginal likelihood computation in change-point models. *Computational Statistics & Data Analysis* 56(11), 3415–3429.
- Bernanke, B., J. Boivin and P. S. Elias (2005) Measuring the effects of monetary policy: A factor-augmented vector autoregressive (FAVAR) approach. *The Quarterly Journal of Economics* 120(1), 387–422.
- Bhatt, V., N. K. Kishor and J. Ma (2017) The impact of EMU on bond yield convergence: Evidence from a time-varying dynamic factor model. *Journal of Economic Dynamics and Control* 82, 206–222.
- Blot, C., P. Hubert and F. Labondance (2018). Monetary policy and asset price bubbles, no 37, SCIENCES PO OFCE WORKING PAPER.
- Borio, C. (2019), *BIS Quarterly Review*, Media Briefing, 2019-09
- Bork, L. and S. V. Møller (2015) Forecasting house prices in the 50 states using dynamic model averaging and dynamic model selection. *International Journal of Forecasting* 31(1), 63–78.
- Bork, L., S. V. Møller and T. Q. Pedersen (2019) *A new index of housing sentiment*. Management Science.
- Bouri, E., R. Gupta, C. K. Kyei and R. Shivambu (2021) Uncertainty and daily predictability of housing returns and volatility of the United States: Evidence from a higher-order nonparametric causality-in-quantiles test. *The Quarterly Review of Economics and Finance* 82, 200–206.
- Caldara, D. and E. Herbst (2019) Monetary policy, real activity, and credit spreads: Evidence from bayesian proxy SVARs. *American Economic Journal: Macroeconomics* 11(1), 157–192.
- Canarella, G., S. Miller and S. Pollard (2012) Unit roots and structural change: An application to US house price indices. *Urban Studies* 49(4), 757–776.
- Caraiani, P., A. C. Călin and R. Gupta (2018) Monetary policy and bubbles in US REITs. *International Review of Finance*.
- Carstens, A. (2019). Monetary policy: 10 years after the financial crisis. *speech to the basler bankforum*.
- Carter, C. K. and R. Kohn (1994) On Gibbs Sampling for State Space Models. *Biometrika* 81, 541–553.
- Cerutti, E., S. Claessens and L. Laeven (2017) The use and effectiveness of macroprudential policies: New evidence. *Journal of Financial Stability* 28, 203–224.
- Cesa-Bianchi, A., A. Ferrero and A. Rebucci (2018) International credit supply shocks. *Journal of International Economics* 112, 219–237.
- Chen, H., V. Curdia and A. Ferrero (2012) The macroeconomic effects of Large-scale asset purchase programmes. *Economic Journal* 122(564), F289–F315.
- Chib, S. (1998) Estimation and comparison of multiple change-point models. *Journal of Econometrics* 86(2), 221–241.
- Christidou, M. and S. Fountas (2018) Uncertainty in the housing market, evidence from US states. *Studies in Nonlinear Dynamics & Econometrics* 22(2).
- Christou, C., R. Gupta and W. Nyakabawo (2019) Time-varying impact of uncertainty shocks on the US housing market. *Economics Letters* 180, 15–20.
- Cogley, T. and T. J. Sargent (2005) Drift and volatilities: Monetary policies and outcomes in the post WWII U.S. *Review of Economic Dynamics* 8(2), 262–302.
- De Graeve, F., Theodoridis Konstantinos, (2016) Forward Guidance, quantitative easing, or both? *National Bank of Belgium Working Paper Research* 305.
- Del Negro, M. and C. Otrok (2007) 99 luftballons: Monetary policy and the house price boom across U.S. States. *Journal of Monetary Economics* 54(7), 1962–1985.
- Del Negro, M. and C. Otrok (2008). Dynamic factor models with time-Varying parameters: Measuring changes in international business cycles, Federal Reserve Bank of New York, 326, Staff Report.
- Del Negro, M. and G. Primiceri (2015) Time varying structural vector autoregressions and monetary policy: A Corrigendum. *Review of Economic Studies* 82(4), 1342–1345.
- Eickmeier, S. and B. Hofmann (2013) Monetary policy, housing booms, and financial (im) balances. *Macroeconomic Dynamics* 17(4), 830–860.
- Fairchild, J. and J. M. ShuWu (2015) Understanding housing market volatility. *Journal of Money, Credit and Banking* 47(7), 1309–1337.
- Galí, J. and L. Gambetti (2015) The effects of monetary policy on stock market bubbles: Some evidence. *American Economic Journal: Macroeconomics* 7(1), 233–257.
- Gilchrist, S. and E. Zakrajsek (2012) Credit spreads and business cycle fluctuations. *American Economic Review* 102(4), 1692–1720.
- Graczyk, A. and T. Phan (2021) Regressive welfare effects of housing bubbles. *Macroeconomic Dynamics* 25(8), 2102–2127.
- Gupta, R., C. K. M. Lau, S. M. Miller and M. E. Wohar (2018a) US fiscal policy and asset prices: The role of partisan conflict. *International Review of Finance* 19(4), 851–862.
- Gupta, R., Z. Lv and W.-K. Wong (2019) Macroeconomic shocks and changing dynamics of the US REITs sector. *Sustainability* 11(10), 2776.

- Gupta, R., J. Ma, M. Risse and M. E. Wohar (2018b) Common business cycles and volatilities in US states and MSAs: The role of economic uncertainty. *Journal of Macroeconomics* 57, 317–337.
- Gupta, R., H. A. Marfatia, C. Pierdzioch and A. A. Salisu (2021) Machine learning predictions of housing market synchronization across US States: The role of uncertainty. *Journal of Real Estate Finance and Economics*.
- Gürkaynak, R. S., B. Sack and E. Swanson (2005) The sensitivity of Long-Term interest rates to economic news: Evidence and implications for macroeconomic models. *American Economic Review* 95(1), 425–436.
- Huang, M. C. (2019) A nationwide or localized housing crisis? Evidence from structural instability in US housing price and volume cycles. *Computational Economics* 53(4), 1547–1563.
- Huang, M. C. (2021) The more, the better? Forecasting gains from high-frequency housing prices in a Markov-switching dynamic factor model. *Macroeconomic Dynamics*, pp. 1–18.
- Huber, F. and M. T. Punzi (2020) International housing markets, unconventional monetary policy, and the zero lower bound. *Macroeconomic Dynamics* 24(4), 774–806.
- Iacoviello, M. and S. Neri (2010) Housing market spillovers: Evidence from an estimated DSGE model. *American Economic Journal: Macroeconomics* 2(2), 125–164.
- Jarociński, M. and P. Karadi (2020) Deconstructing monetary policy surprises—The role of information shocks. *American Economic Journal: Macroeconomics* 12(2), 1–43.
- Jordà, O., M. Schularick and A. M. Taylor (2015a) Betting the house. *Journal of International Economics* 96, S2–S18.
- Jordà, O., M. Schularick and A. M. Taylor (2015b) Leveraged bubbles. *Journal of Monetary Economics* 76, S1–S20.
- Jurado, K., S. C. Ludvigson and S. Ng (2015) Measuring uncertainty. *American Economic Review* 105(3), 1177–1216.
- Justiniano, A., G. E. Primiceri and A. Tambalotti (2010) Investment shocks and business cycles. *Journal of Monetary Economics* 57(2), 132–145.
- Justiniano, A., G. E. Primiceri and A. Tambalotti (2017) *The Mortgage Rate Conundrum*, National Bureau of Economic Research, Inc., NBER Working Papers, 23784.
- Justiniano, A., G. E. Primiceri and A. Tambalotti (2019) Credit supply and the housing boom. *Journal of Political Economy* 127(3), 1317–1350.
- Kadiyala, K. R. and S. Karlsson (1997) Numerical Methods for Estimation and Inference in Bayesian VAR-Models. *Journal of Applied Econometrics* 12(2), 99–132.
- Kapetanios, G., H. Mumtaz, I. Stevens and K. Theodoridis (2012) Assessing the economy-wide effects of quantitative easing. *Economic Journal* 122(564), F316–F347.
- Karoglou, M., B. Morley and D. Thomas (2013) Risk and structural instability in US house prices. *The Journal of Real Estate Finance and Economics* 46(3), 424–436.
- Kim, C. J. and C. R. Nelson (1999) *State-space models with regime switching: Classical and gibbs-sampling approaches with applications*. Cambridge MA: MIT Press.
- Kim, S., N. Shephard and S. Chib (1998) Stochastic volatility: Likelihood inference and comparison with ARCH models. *Review of Economic Studies* 65(3), 361–393.
- Koop, G. and D. Korobilis (2010) Bayesian multivariate time series methods for empirical macroeconomics. *Foundations and Trends in Econometrics* 3.
- Leamer, E. E. (2015) Housing really is the business cycle: What survives the lessons of 2008-09? *Journal of Money, Credit and Banking* 47(S1), 43–50.
- Li, X.-L., T. Chang, S. M. Miller, M. Balcilar and R. Gupta (2015) The co-movement and causality between the US housing and stock markets in the time and frequency domains. *International Review of Economics & Finance* 38, 220–233.
- Liu, P., K. Theodoridis, H. Mumtaz and F. Zanetti (2019) Changing macroeconomic dynamics at the zero lower bound. *Journal of Business & Economic Statistics* 37(3), 391–404.
- Ludvigson, S. C., S. Ma and S. Ng (2021) Uncertainty and business cycles: Exogenous impulse or endogenous response? *American Economic Journal: Macroeconomics* 13(4), 269–410.
- Marfatia, H. A., C. André and R. Gupta (2020) Predicting housing market sentiment: The role of financial, macroeconomic and real estate uncertainties. *Journal of Behavioral Finance* 23(2), 189–209.
- Martin, C., N. Schmitt and F. Westerhoff (2022) Housing markets, expectation formation and interest rates. *Macroeconomic Dynamics* 26(2), 491–532.
- Mertens, K. and M. O. Ravn (2013) The dynamic effects of personal and corporate income tax changes in the united states. *American Economic Review* 103(4), 1212–1247.
- Mertens, K. and M. O. Ravn (2014) A reconciliation of SVAR and narrative estimates of tax multipliers. *Journal of Monetary Economics* 68(S), 1–19.
- Miles, W. (2008) Volatility clustering in US home prices. *Journal of Real Estate Research* 30(1), 73–90.
- Miles, W. (2015) Regional house price segmentation and convergence in the US: A new approach. *The Journal of Real Estate Finance and Economics* 50(1), 113–128.
- Miller, N. and L. Peng (2006) Exploring metropolitan housing price volatility. *The Journal of Real Estate Finance and Economics* 33(1), 5–18.
- Miranda-Agrippino, S. and G. Ricco (2021) The transmission of monetary policy shocks. *American Economic Journal: Macroeconomics* 13(3), 74–107.
- Montañés, A. and L. Olmos (2013) Convergence in US house prices. *Economics Letters* 121(2), 152–155.

- Montasser, E., R. G. Ghassen, C. Jooste and S. M. Miller (2020) The time-Series linkages between US fiscal policy and asset prices. *Public Finance Review* 48(3), 303–339.
- Mountford, A. and H. Uhlig (2009) What are the effects of fiscal policy shocks? *Journal of Applied Econometrics* 24(6), 960–992.
- Mumtaz, H. and K. Petrova (2018) *Changing impact of shocks: a timevarying proxy SVAR approach*, Queen Mary University of London, School of Economics and Finance Working Papers 875.
- Mumtaz, H. and K. Theodoridis (2020) Dynamic effects of monetary policy shocks on macroeconomic volatility. *Journal of Monetary Economics* 114, 262–282.
- Mumtaz, H. and K. Theodoridis (2020) Fiscal policy shocks and stock prices in the United States. *European Economic Review* 129(C), 103562.
- Neely, C. J. and D. Rapach (2011) International comovements in inflation rates and country characteristics. *Journal of International Money and Finance* 30(7), 1471–1490.
- Nelson, B., G. Pinter and K. Theodoridis (2018) Do contractionary monetary policy shocks expand shadow banking? *Journal of Applied Econometrics* 33(2), 198–211.
- Nyakabawo, W., S. M. Miller, M. Balcilar, S. Das and R. Gupta (2015) Temporal causality between house prices and output in the US: A bootstrap rolling-window approach. *The North American Journal of Economics and Finance* 33, 55–73.
- Plakandaras, V., R. Gupta, C. Katraklidis and M. E. Wohar (2018) Time-varying role of macroeconomic shocks on house prices in the US and UK: Evidence from over 150 years of data. *Empirical Economics* 58(5), 2249–2285.
- Primiceri, G. (2005) Time varying structural vector autoregression and monetary policy. *Review of Economic Studies* 72(3), 821–852.
- Rahal, C. (2016) Housing markets and unconventional monetary policy. *Journal of Housing Economics* 32, 67–80.
- Rosenberg, S. (2019) The effects of conventional and unconventional monetary policy on house prices in the scandinavian countries. *Journal of Housing Economics* 46, 101659.
- Sá, F., P. Towbin and T. Wieladek (2014) Capital inflows, financial structure and housing booms. *Journal of the European Economic Association* 12(2), 522–546.
- Sá, F. and T. Wieladek (2015) Capital inflows and the US housing boom. *Journal of Money, Credit and Banking* 47(S1), 221–256.
- Salisu, A. A., R. Gupta and A. E. Ogbonna (2021) Point and density forecasting of macroeconomic and financial uncertainties of the USA. *Journal of Forecasting* 40(4), 700–707.
- Segnon, M., R. Gupta, K. Lesame and M. E. Wohar (2021) High-Frequency volatility forecasting of US housing markets. *Journal of Real Estate Finance and Economics* 62(2), 283–317.
- Simo-Kengne, B. D., S. M. Miller, R. Gupta and M. Balcilar (2016) Evolution of the monetary transmission mechanism in the US: The role of asset returns. *The Journal of Real Estate Finance and Economics* 52(3), 226–243.
- Sims, C. A., D. F. Waggoner and T. Zha (2008) Methods for inference in large multiple-equation Markov-switching models. *Journal of Econometrics* 146(2), 255–274.
- Sims, C. A. and T. Zha (2006) Were there regime switches in U.S. Monetary Policy? *American Economic Review* 96(1), 54–81.
- Smets, F. and R. Wouters (2007) Shocks and frictions in US business cycles: A Bayesian DSGE approach. *American Economic Review* 97(3), 586–606.
- Stock, J. and M. Watson (1989) New indexes of coincident and leading economic indicators. *NBER Macroeconomics Annual* 4, 351–409.
- Stock, J., M. Watson and W. H. U. S. I. B. H. to Forecast? (2007) Why has U.S. inflation become harder to forecast? *Journal of Money, Credit, and Banking* 39, 3–33.
- Swanson, E. T. (2021) Measuring the effects of federal reserve forward guidance and asset purchases on financial markets. *Journal of Monetary Economics* 118(C), 32–53.
- Thanh, N., J. S. Binh and G. Lee (2018) A new measure of real estate uncertainty shocks. *Real Estate Economics* 48(3), 744–771. doi: [10.1111/1540-6229.12270](https://doi.org/10.1111/1540-6229.12270).
- Uhlig, H. (2004) Do technology shocks lead to a fall in total hours worked? *Journal of the European Economic Association* 2(2-3), 361–371.
- Uhlig, H. (2005) What are the effects of monetary policy on output? Results from an agnostic identification procedure. *Journal of Monetary Economics* 52(2), 381–419.

A. Bayesian MCMC estimation algorithm

In this section, we provide further details of each step in the Gibbs sampling estimation algorithm.

A.1. Draws of the national factor

We follow a procedure as laid out in Kim and Nelson (1999) to reduce the dimensionality of the resulting state-space model so as to facilitate the estimation. Specifically, substitute equation (1) into equation (6) to yield the following state-space representation:

Measurement equation:

$$r_{i,t}^* = H_t \cdot Z_t + \exp(h_{i,t}) \cdot \varepsilon_{i,t} \tag{16}$$

Transition equation:

$$Z_t = F \cdot Z_{t-1} + \zeta_t \tag{17}$$

where in the measurement equation, $r_{i,t}^* = (1 - \phi_{i,1}L - \phi_{i,2}L^2)r_{i,t}$, $H_t = (\beta_{i,t}, -\phi_{i,1}\beta_{i,t-1}, -\phi_{i,2}\beta_{i,t-2})$. In the transition equation, the state vector is $Z_t = (f_t, f_{t-1}, f_{t-2})'$ and the matrix F is:

$$F = \begin{pmatrix} \phi_1^f & \phi_2^f & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \tag{18}$$

The shock vector is $\zeta_t = (\exp(h_t^f) \cdot \varepsilon_t^f, 0, 0)'$, and its variance matrix is denoted by Q_t .

Conditioning on the previous draws of $\{H_t\}_{t=1}^T$, $\left\{ \{h_{i,t}\}_{t=1}^T \right\}_{i=1}^n$, $\{\sigma_i^2\}_{i=1}^n$, F , and $\{Q_t\}_{t=1}^T$, we rely on the above state-space representation to take random draws of the national factor $\{f_t\}_{t=1}^T$. Formally, we employ the Kalman filter and the "filter forward and sample backwards" algorithm as in Carter and Kohn (1994). See Kim and Nelson (1999) for details of this standard algorithm.

A.2. Draws of the model parameters in the factor dynamics

Given previous draws of the common factor $(\{f_t\}_{t=1}^T)$ and its stochastic volatility $(\{h_t^f\}_{t=1}^T)$, the AR parameter of the common factor dynamics is sampled from the linear regression (3). The conjugate prior for ϕ_f is a Gaussian distribution with a zero mean and a variance that is an identity matrix.

Conditional on the previous draws of the common factor $(\{f_t\}_{t=1}^T)$ and the time-varying loading $(\{\beta_{i,t}\}_{t=1}^T)$, the idiosyncratic factor $(e_{i,t})$ can be computed from equation (1). Given the idiosyncratic factor together with its stochastic volatility $(\{h_{i,t}\}_{t=1}^T)$, the AR and the variance parameters are sampled from the linear regression (6). Again the conjugate prior for $\phi_{i,e}$ is a Gaussian distribution with a zero mean and a variance that is an identity matrix. In addition, the conjugate prior for the variance parameter is $\sigma_i^2 \sim IG(0, 0)$, where IG denotes the inverted-gamma distribution. This specification ensures a diffuse prior for the variance parameters.

Since in both cases, the factor volatility is time varying, and the regression errors are heteroskedastic. We re-scale the variables in each equation to make the errors homoskedastic, essentially doing a weighted least square. We sample these parameters from the transformed regression.

A.3. Draws of the loading parameters and the shock variance

Applying the same procedure as in Section (A.2) to reduce the dimensionality, we can cast the model into its following state-space representation:

Measurement equation:

$$r_{i,t}^* = X_{i,t} \cdot B_{i,t} + \exp(h_{i,t}) \cdot \varepsilon_{i,t} \tag{19}$$

Transition equation:

$$B_{i,t} = G \cdot B_{i,t-1} + \xi_{i,t} \tag{20}$$

where $r_{i,t}^* = (1 - \phi_{i,1}L - \phi_{i,2}L^2)r_{i,t}$, $X_{i,t} = (f_t, -\phi_{i,1} \cdot f_{t-1}, -\phi_{i,2} \cdot f_{t-2})$, $B_{i,t} = (\beta_{i,t}, \beta_{i,t-1}, \beta_{i,t-2})'$, $\xi_{i,t} = (\sigma_i^\beta \cdot \eta_{i,t}, 0, 0)'$, and the matrix G in the transition equation is

$$G = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

Because conditional on $r_{i,t}^*, X_{i,t}, h_{i,t}, \sigma_i, \sigma_i^\beta$, the loading parameters are independent across series, this step can be conducted for each series i . The algorithm “filter forward, sample backwards” in Carter and Kohn (1994) is employed to draw the latent factors $B_{i,t}$. Conditional on $B_{i,t}$, the variance parameter σ_i^β is sampled from the linear regression (5). For the variance parameter σ_i^β , we employ the conjugate prior: $(\sigma_i^\beta)^2 \sim IG(0.002, 2)$ with a relatively diffuse prior.

A.4. Draws of the stochastic volatility

Conditional on factors and corresponding parameters in the stochastic volatility process, the stochastic volatility of factors is independent from each other. As a result, we explain the sampling algorithm for the stochastic volatility of the common factor, and the same procedure applies to each idiosyncratic factor.

Given a draw of the common factor and other parameters, compute the random shock in equation (3):

$$f_t^* = f_t - \phi_1^f f_{t-1} - \phi_2^f f_{t-2} = \exp(h_t^f) \cdot \varepsilon_t^f \tag{21}$$

Square and take a natural logarithm of both sides to obtain the following state-space representation:

Measurement equation:

$$f_t^{**} = 2h_t^g f_t + \zeta_t^f \tag{22}$$

Transition equation:

$$h_t^f = h_{t-1}^f + \sigma_f^h \cdot \xi_t^f, \quad \xi_t^f \sim i.i.d.N(0, 1) \tag{23}$$

where $f_t^{**} = \ln(f_t^*)^2$, $\zeta_t^f = \ln(\varepsilon_t^f)^2$.

First note that the shocks ζ_t^f and ξ_t^f are independent. However, the shock ζ_t^f in the measurement equation is not normally distributed, and its distribution is $\ln\chi^2(1)$. Kim et al. (1998) propose an approach based on a mixture of normal densities to approximate the underlying non-normal distribution when utilizing the Kalman filter to draw the stochastic volatility in this context. Specifically, they suggest using seven normal densities with different means $m_k - 1.2704$ and variances τ_k^2 , for $k = 1, 2, \dots, 7$, with the component probabilities being θ_k . They carefully choose these values to closely replicate the exact density of $\ln\chi^2(1)$. Table 4 is taken from Kim et al. (1998) and reports these values.

Conditional on knowing f_t^{**} and the component probabilities of the seven normal densities, the above state-space model is approximately linear and Gaussian. Therefore, the standard sampling algorithm in Carter and Kohn (1994) can be employed again to draw the stochastic volatility. Given a sample of the stochastic volatility, the component probabilities are then updated using the Bayes’ rule. The specific sampling algorithm follows those in Primiceri (2005), Del Negro and Primiceri (2015), and Koop and Korobilis (2010). For the shock variance to the volatility process, we use the conjugate with a relatively diffuse prior: $IG(0.002, 2)$.

Table 4. Selection of the mixing distribution

δ	$Pr(\delta = k)$	m_k	τ_k^2
1	0.0073	-10.13	5.79596
2	0.10556	-3.9728	2.61369
3	0.00002	-8.5669	5.1795
4	0.04395	2.77786	0.16735
5	0.34001	0.61942	0.64009
6	0.24566	1.79518	0.34023
7	0.2575	-1.0882	1.26261

A.5. Diagnostics of the algorithm convergence

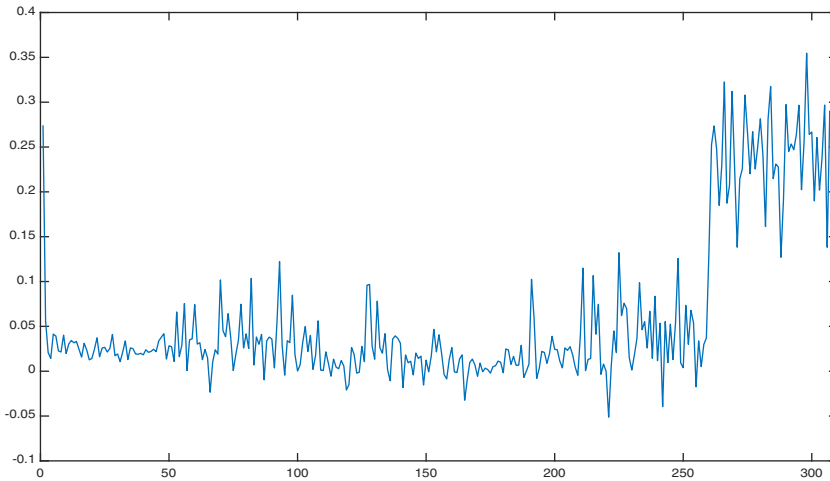


Figure 19. Convergence diagnostics for parameters and state variables.

Notes: 1–52 are the common factor and state-specific factors; 53–104 are stochastic volatilities; 105–208 are AR parameters; 209–259 are variance parameters for individual factors; 260–310 are factor loadings.

B. Description of the priors

The priors for the VAR(P) coefficients and the error covariance matrices are set via dummy observations. The normal inverse Wishart prior is defined as

$$Y_D = \begin{pmatrix} \frac{\text{diag}(\gamma_1 \sigma_1 \dots \gamma_N \sigma_N)}{\tau} \\ \mathbf{0}_{N \times (P-1) \times N} \\ \dots \\ \text{diag}(\sigma_1 \dots \sigma_N) \\ \dots \\ \mathbf{0}_{1 \times N} \end{pmatrix}, \text{ and } X_D = \begin{pmatrix} \frac{I_P \otimes \text{diag}(\sigma_1 \dots \sigma_N)}{\tau} \mathbf{0}_{NP \times 1} \\ \mathbf{0}_{N \times NP} \quad \mathbf{0}_{N \times 1} \\ \dots \\ \mathbf{0}_{1 \times NP} \quad c \end{pmatrix},$$

where σ_i for $i = 1, 2, \dots, N$ represents scaling factors, γ_i denotes the prior mean for the coefficients on the first lag, τ is the tightness of the prior on the VAR coefficients, and c is the tightness of the prior on the constant terms. In order to obtain a value for γ_i, σ_i , we estimate an AR(1) model via ordinary least squares (OLS) for each endogenous variable. γ_i is set equal to OLS estimate of the AR(1) coefficient, while σ_i is the standard deviation of the residual. The matrix J_P is defined as $\text{diag}(1, 2, \dots, P)$. We set $\tau = 0.1$ and $c = 1$ in our implementation. The value for τ implies a relatively high degree of shrinkage; however, the model is estimated using quarterly macroeconomic data and a larger number of both regimes and lags are considered in order to be confident that the dynamics of the data captured properly. A tight prior and a low number of observations per regime should bias the results against state variation. However, we know from the discussion in the text that this is not the case. Despite the tight priors, the estimation of the model reveals significantly different dynamics across regimes. Note that in the final regime covering the unconventional monetary policy period, we introduce an additional prior on the VAR coefficients that ensures that lagged coefficients on the non-dependent variables in the interest rate equation are close to zero. This prior is implemented via a prior covariance matrix with the diagonal elements corresponding to the coefficients of interest in the interest rate equation set to small values ($1e - 12$). The remaining diagonal elements are set to $1e12$.

The prior for the nonzero elements of the transition probability matrix p_{ij} is of the following form:

$$p_{ij}^0 = D(u_{ij}),$$

where $D(\cdot)$ denotes the Dirichlet distribution and $u_{ij} = 15$ if $i = j$ and $u_{ij} = 1$ if $i \neq j$. This choice of u_{ij} implies that the regimes are fairly persistent. The posterior distribution is

$$p_{ij} = D(u_{ij} + \eta_{ij}),$$

where η_{ij} denotes the number of times regime i is followed by regime j .

C. Description of the Gibbs sampling algorithm

The Gibbs sampling algorithm proceeds in the following steps:

1. **Sampling S_t** Following (Kim and Nelson 1999, Chapter 9), we use multi-move Gibbs sampling to draw S_t from the joint conditional density, $f(S_t | Z_t, c_S, B_{1,S}, \dots, B_{K,S}, \Omega_S, \tilde{P})$. Note that we impose the restriction that each regime must have at least $N \times K + 2$ observations, where N denotes the number of endogenous variables in the VAR, to ensure sufficient degrees of freedom for each regime.
2. **Sampling $c_S, B_{1,S}, \dots, B_{K,S}, \Omega_S$** Conditional on a draw for S_t , the model is simply a sequence of Bayesian VAR models. The regime-specific VAR coefficients are sampled from a normal distribution and the covariances are drawn from an inverted Wishart distribution. For the first M regimes, we use a normal inverse Wishart prior (see Kadiyala and Karlsson 1997). However, as described in detail below, we employ a (normal diffuse) prior distribution for the VAR coefficients to the final regime, which is compatible with the identification of the shock to the government bond spread. In our sample, the recent financial crisis coincides with the final regime of the estimated VAR model. The prior on the VAR coefficients in this regime implies that the policy rate does not respond to lagged changes in other endogenous variables. This assumption is compatible with restrictions used to identify the shock to the bond-yield spread and reflects the fact that policy rates have reached the ZLB.

3. **Sampling \tilde{P}** Given the state variables S_t , the nonzero elements of the transition probability matrix are independent of Z_t and the other parameters of the model, and they are drawn from a Dirichlet posterior.

D. Robustness analysis

D.1. Looser priors

This section illustrates that agents' responses to identified macroeconomic shocks are (almost) unchanged when the hyperparameter that controls the tightness of the VAR coefficients is increased to 2.

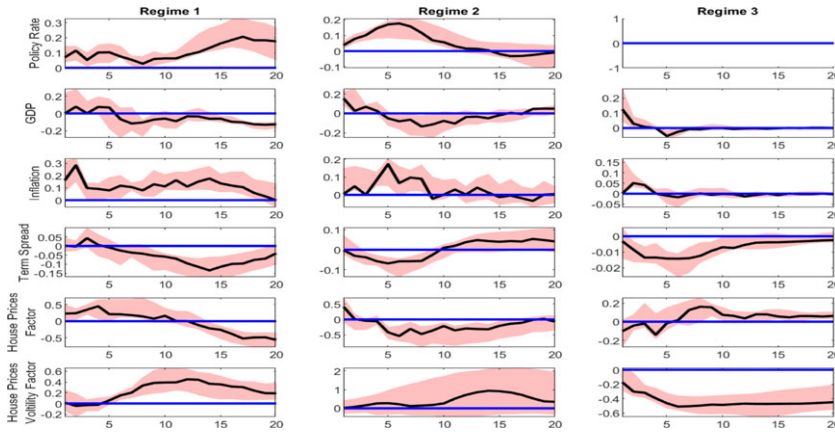


Figure 20. Impulse responses: demand shock.

Notes: The solid (black) line represents the (pointwise) median, while the shaded area captures the 16% – 84% percentiles of the posterior distribution. The shock has been normalized to increase GDP growth by 1 percentage point in the second quarter.

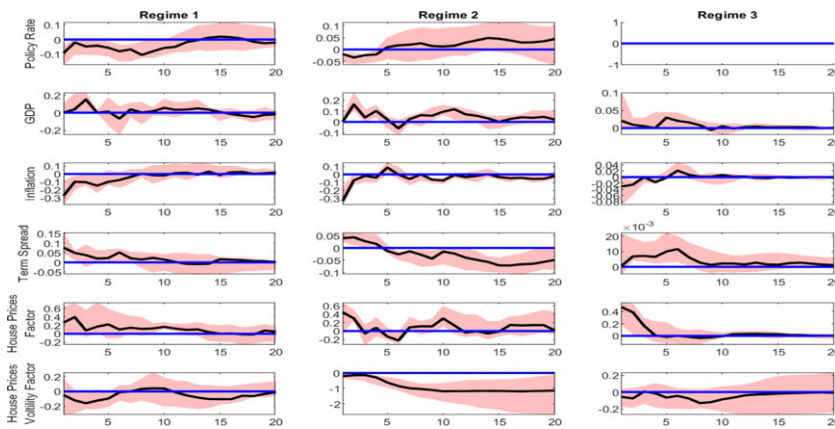


Figure 21. Impulse responses: supply shock.

Notes: The solid (black) line represents the (pointwise) median, while the shaded area captures the 16% – 84% percentiles of the posterior distribution. The shock has been normalized to increase GDP growth by 1 percentage point in the second quarter.

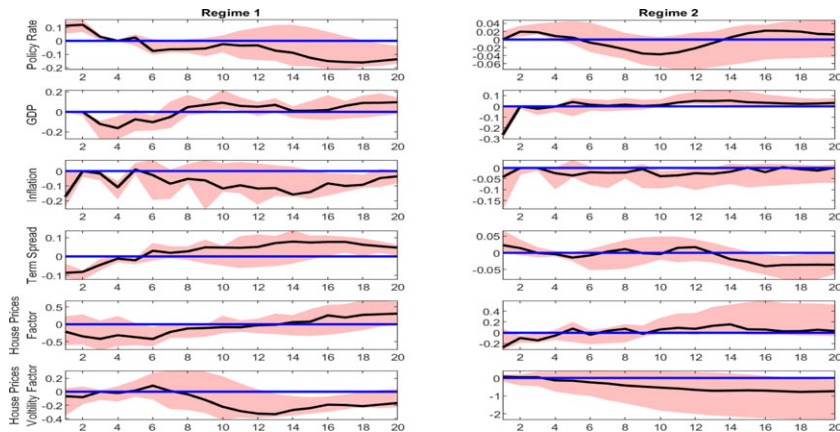


Figure 22. Impulse responses: policy shock.
 Notes: The solid (black) line represents the (pointwise) median, while the shaded area captures the 16% – 84% percentiles of the posterior distribution. The shock has been normalized to increase GDP growth by 1 percentage point in the second quarter.

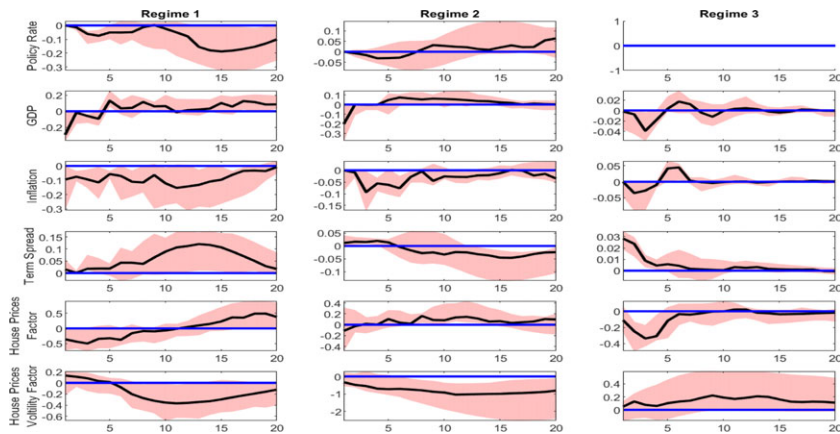


Figure 23. Impulse responses: slope shock.
 Notes: The solid (black) line represents the (pointwise) median, while the shaded area captures the 16% – 84% percentiles of the posterior distribution. The shock has been normalized to increase GDP growth by 1 percentage point in the second quarter.

D.2. Unemployment

This section illustrates that agents’ responses to identified macroeconomic shocks are again (almost) unchanged when the unemployment (instead of GDP growth) is used.

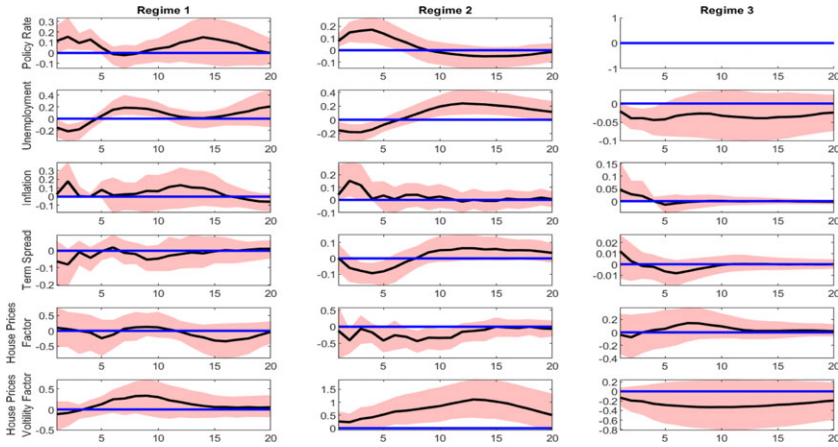


Figure 24. Impulse responses: demand shock.

Notes: The solid (black) line represents the (pointwise) median, while the shaded area captures the 16% – 84% percentiles of the posterior distribution. The shock has been normalized to increase GDP growth by 1 percentage point in the second quarter.

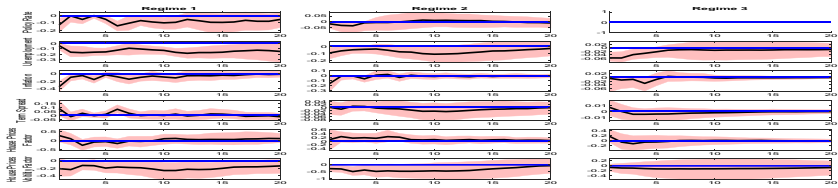


Figure 25. Impulse responses: supply shock.

Notes: The solid (black) line represents the (pointwise) median, while the shaded area captures the 16% – 84% percentiles of the posterior distribution. The shock has been normalized to increase GDP growth by 1 percentage point in the second quarter.

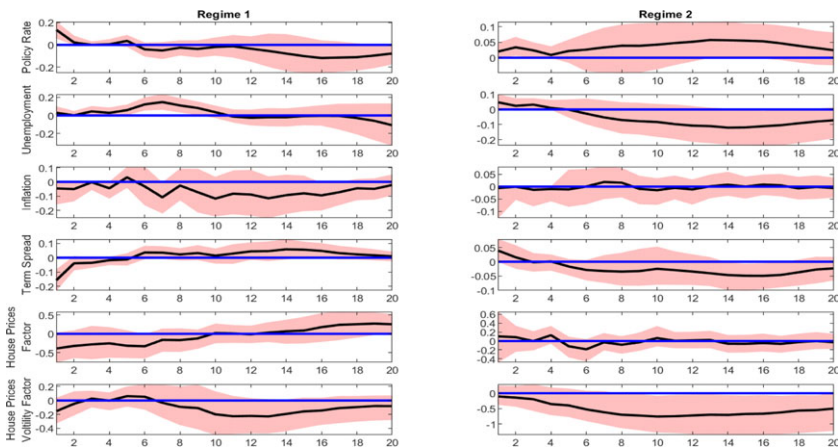


Figure 26. Impulse responses: policy shock.

Notes: The solid (black) line represents the (pointwise) median, while the shaded area captures the 16% – 84% percentiles of the posterior distribution. The shock has been normalized to increase GDP growth by 1 percentage point in the second quarter.

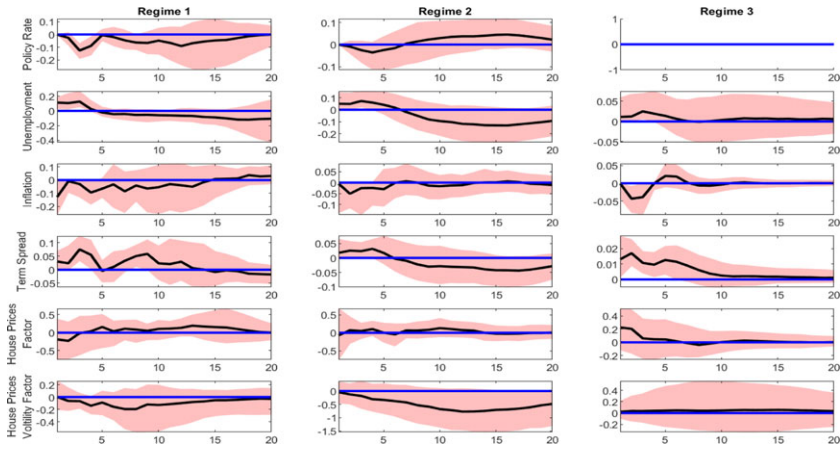


Figure 27. Impulse responses: slope shock.
 Notes: The solid (black) line represents the (pointwise) median, while the shaded area captures the 16% – 84% percentiles of the posterior distribution. The shock has been normalized to increase GDP growth by 1 percentage point in the second quarter.