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Paper

The dynamic impact of monetary policy on regional housing prices in the United States

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Abstract

This paper uses a factor-augmented vector autoregressive model to examine the impact of monetary policy shocks on housing prices across metropolitan and micropolitan regions. To simultaneously estimate the model parameters and unobserved factors we rely on Bayesian estimation and inference. Policy shocks are identified using high-frequency suprises around policy announcements as an external instrument. Impulse reponse functions reveal differences in regional housing price responses, which in some cases are substantial. The heterogeneity in policy responses is found to be significantly related to local regulatory environments and housing supply elasticities. Moreover, housing prices responses tend to be similar within states and adjacent regions in neighboring states.

Keywords:	Regional housing prices, metropolitan and micropolitan regions, factor-augmented vector autoregressive model, Bayesian estimation, high-frequency identification
JEL Codes:	C11, C32, E52, R31

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1 Introduction

The housing market is one of the most important, but at the same time most volatile sectors of the economy, and hence of crucial concern for economic policy makers in general, and central banks in particular (Moulton and Wentland, 2018). The notion of a national housing market disregards the fact that housing activities substantially vary across the United States. Moench and Ng (2011) emphasize that of the four regions defined by the United States Census Bureau, the West Region (including California, Nevada and Arizona) and the Northeast Region (including New York and Massachusetts) have, from a historical perspective, shown more active housing markets than the Midwest Region (including Illinois, Ohio and Minnesota) and the South Region (including Florida, Texas and North Carolina). Another factor motivating regional disaggregation of the housing market is the volatility of regional housing markets relative to macroeconomic fluctuations (Fratantoni and Schuh, 2003).

The literature on the impact of monetary policy on housing is fairly limited, in particular at the regional level. Previous work generally relies on two competing approaches. The first uses structural models to analyze the relationship (see Iacoviello and Minetti, 2003; Iacoviello and Neri, 2010; Ungerer, 2015). The major strength of this model-based approach is to provide a theoretically grounded answer to the question of interest. However, such models necessarily strongly impose a priori restrictions on crucial parameters. The second, evidence-based approach, focuses on empirics and relies less directly on economic theory. Microeconomic event studies, for example, provide answers using information on individual transactions to identify causal effects of monetary policy shocks in short-time frames around monetary policy announcements (Moulton and Wentland, 2018). Macroeconomists instead typically use vector autoregressive (VAR) models to measure the impact of monetary policy innovations over longer time horizons, exploiting information contained in macroeconomic time series. Examples include Fratantoni and Schuh (2003), Iacoviello (2005), del Negro and Otrok (2007), Jarocinski and Smets (2008), Iacoviello and Minetti (2008), Vargas-Silva (2008a,b), and Moench and Ng (2011). VAR models are dynamic models of time series that allow the data rather than the researcher, to specify the dynamic structure of the model, and provide a plausible assessment of macroeconomic variables to monetary policy shocks without the need of a fully specified structural model.

This paper lies in the tradition of the second approach, and differs from previous work in terms of both its focus and methodology. Like Fratantoni and Schuh (2003), and del Negro and Otrok (2007), we focus on regional differences in response of housing prices. The coarseness of quarterly state-level observations used in previous research, however, may conceal important variations that is key for researchers to identify cross-regional differences in policy responses. Hence, we use monthly observations on housing prices and provide a comprehensive coverage of the United States at the level of metro- and micropolitan statistical areas,[1] to appropriately identify a monetary policy shock and the associated regional reactions.

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[1]For the definition of metropolitan and micropolitan statistical areas, see subsection 3.1 along with Appendix A.

Similar to Vargas-Silva (2008a), and Moench and Ng (2011), we rely on a factor-augmented vector autoregressive (FAVAR) model to identify the impact of a monetary policy shock on housing prices, but use a fully Bayesian FAVAR model, based on a set of macroeconomic and financial variables, to explore regional housing price responses to a national monetary policy shock. In particular, we apply Markov chain Monte Carlo (MCMC) methods to estimate the model parameters and unobserved factors simultaneously, in contrast to previous approaches. Bayesian inference is advantageous because it directly addresses uncertainty surrounding latent factors and model parameters. Policy shocks are identified using high-frequency surprises around policy announcements as external instrument, where policy surprises are measured within a tight window of 30 minutes around the announcements by the Federal Reserve (see Kuttner, 2001; Gürkaynak et al., 2005; Gertler and Karadi, 2015).

The effects of monetary policy on housing prices in the regions are analyzed using the FAVAR model estimated over the period 1997:04 to 2012:06. Impulse response functions from the estimated model reveal a rich picture about how an expansionary monetary policy shock affects regional housing prices. Differences are evident, and in some cases, substantial. Regions within California, Florida and Nevada are found to be the most sensitive to monetary policy changes, exhibiting effects two times as large as the average response across the country. By contrast, some regions, for example, within Mississippi, Tennessee, Oklahoma and North Carolina are found to be the least responsive, showing no significant impact or even slightly negative responses. By linking the results to the housing supply elasticity literature (Gyourko et al., 2008; Saiz, 2010; Howard and Liebersohn, 2018), this paper provides evidence that the measured cumulative cross-regional differential responses can partly be explained by housing supply elasticities and local regulatory environments.

The remainder of the paper is organized as follows. The next section presents the FAVAR model along with the Bayesian approach for estimation, and specifics about identification of monetary policy shocks. Section 3 describes the data and the sample of regions, and outlines the model specification. The results are presented in Section 4, combined with a brief discussion about the question why housing prices in some regions are more sensitive to monetary policy shocks than others. The final section concludes.

2 Methodology

2.1 The factor-augmented vector autoregressive model

The econometric approach we employ in this study is a FAVAR model, as introduced by Bernanke et al. (2005). In our implementation, we let $\boldsymbol{H}_t$ denote an $R \times 1$ vector of housing prices at time t ($t = 1, \ldots, T$) for R regions. The model postulates that regional housing prices depend on a number of latent factors, monetary and macroeconomic national aggregates and region-specific shocks. This

relationship, henceforth termed the measurement equation, can be written as

$$
\begin{bmatrix} \boldsymbol{H}_t \\ \boldsymbol{M}_t \end{bmatrix} = \begin{bmatrix} \boldsymbol{\Lambda}^F & \boldsymbol{\Lambda}^M \\ \boldsymbol{0}_{K \times S} & \boldsymbol{I}_K \end{bmatrix} \begin{bmatrix} \boldsymbol{F}_t \\ \boldsymbol{M}_t \end{bmatrix} + \begin{bmatrix} \boldsymbol{\epsilon}_t \\ \boldsymbol{0}_{K \times 1} \end{bmatrix},
\tag{1}
$$

where $\boldsymbol{F}_t$ is an $S \times 1$ vector of latent (unobservable) factors which capture co-movement at the regional level. $\boldsymbol{M}_t$ is a $K \times 1$ vector of economic and monetary national aggregates that are treated as observable factors, and $\boldsymbol{\epsilon}_t$ is an $R \times 1$ vector of normally distributed zero mean disturbances with an $R \times R$ variance-covariance matrix $\boldsymbol{\Sigma}_\epsilon = \mathrm{diag}(\sigma_1^2, \ldots, \sigma_R^2)$. These disturbances arise from measurement errors and special features that are specific to individual regional time series. $\boldsymbol{\Lambda}^F$ is an $R \times S$ matrix of factor loadings, while $\boldsymbol{\Lambda}^M$ denotes a coefficient matrix of dimension $R \times K$. The number of latent factors is much smaller than the number of regions, that is, $S \ll R$. Note that the diagonal structure of $\boldsymbol{\Sigma}_\epsilon$ implies that any co-movement between the elements in $\boldsymbol{H}_t$ and $\boldsymbol{M}_t$ stems exclusively from the presence of the latent factors.

The evolution of the factors $\boldsymbol{y}_t = (\boldsymbol{F}_t', \boldsymbol{M}_t')'$ is given by the state equation, governed by a VAR process of order Q,

$$
\boldsymbol{y}_t = \boldsymbol{A} \boldsymbol{x}_t + \boldsymbol{u}_t,
\tag{2}
$$

with $\boldsymbol{x}_t = (\boldsymbol{y}_{t-1}', \ldots, \boldsymbol{y}_{t-Q}')'$ and the associated $(S + K) \times Q(S + K)$-dimensional coefficient matrix $\boldsymbol{A}$. Moreover, $\boldsymbol{u}_t$ is an $(S + K)$-dimensional vector of normally distributed shocks, with zero mean and variance-covariance matrix $\boldsymbol{\Sigma}_u$.

The parameters $\boldsymbol{\Lambda}^F$, $\boldsymbol{\Lambda}^M$ and $\boldsymbol{A}$ as well as the latent dynamic factors $\boldsymbol{F}_t$ are unkown and have to be estimated. To econometrically identify the model, we follow Bernanke et al. (2005) and assume that the upper $S \times S$-dimensional submatrix of $\boldsymbol{\Lambda}^F$ equals an identity matrix $\boldsymbol{I}_S$ while the first S rows of $\boldsymbol{\Lambda}^M$ are set equal to zero. This identification strategy implies that the first S elements in $\boldsymbol{H}_t$ are effectively the factors plus noise.

2.2 A Bayesian approach to estimation

The model described above is highly parameterized, containing more parameters as can reasonably be estimated with the data at hand. In this study, we use a Bayesian estimation approach to incorporate knowledge about parameter values via prior distributions. It is convenient to stack the free elements of the factor loadings in an L-dimensional vector $\boldsymbol{\lambda} = \mathrm{vec}[(\boldsymbol{\Lambda}^F, \boldsymbol{\Lambda}^M)']$ with $L = R(S + K)$, and the VAR coefficients in a J-dimensional vector $\boldsymbol{a} = \mathrm{vec}(\boldsymbol{A})$ with $J = (S + K)^2 Q$.

Prior distributions for the state equation

For the VAR coefficients a_j $(j = 1, \ldots, J)$ we impose the Normal-Gamma shrinkage prior proposed in Griffin and Brown (2010, 2017), and applied in a VAR framework by Huber and Feldkircher (2017),

$$
a_j | \xi_a, \tau_{aj}^2 \sim \mathcal{N}\left(0, 2\, \xi_a^{-1} \tau_{aj}^2\right),
\tag{3}
$$

that is controlled by Gamma priors on τ_{aj}^2 $(j = 1, \ldots, J)$ and ξ_a,

$$\xi_a \sim \mathcal{G}(d_0, d_1), \tag{4}$$

$$\tau_{aj}^2 \sim \mathcal{G}(\vartheta_a, \vartheta_a), \tag{5}$$

with hyperparameters d_0, d_1, and ϑ_a, respectively. ξ_a operates as global shrinkage parameter, and τ_{aj}^2 as local scaling parameter. This hierarchical prior shows two convenient features. First, ξ_a applies to all J elements in $\boldsymbol{a}$. Higher values of ξ_a yield stronger global shrinkage towards the origin whereas smaller values induce only little shrinkage. Second, the local scaling parameters τ_{aj}^2 place sufficient prior mass of a_j away from zero in the presence of strong overall shrinkage involved by large values for ξ_a, in cases where the likelihood suggests non-zero values.

The hyperparameter ϑ_a in Eq. (5) controls the excess kurtosis of the marginal prior,

$$p(a_j|\xi_a) = \int p(a_j|\xi_a, \tau_{aj}^2)d\tau_{aj}^2, \tag{6}$$

obtained after integrating over the local scales. Lower values of ϑ_a generally place increasing mass on zero, but at the same time lead to heavy tails, allowing for large deviations of a_j from zero, if necessary. The hyperparameters d_0 and d_1 in Eq. (4) are usually set to rather small values to induce heavy overall shrinkage (see Griffin and Brown, 2010, for more details).

For the variance-covariance matrix $\boldsymbol{\Sigma}_u$ we use an inverted Wishart prior,

$$\boldsymbol{\Sigma}_u \sim \mathcal{IW}(v, \underline{\boldsymbol{\Sigma}}), \tag{7}$$

with v denoting prior degrees of freedom, while $\underline{\boldsymbol{\Sigma}}$ is a prior scaling matrix of dimension $(S + K) \times (S + K)$.

Prior distributions for the observation equation

For the factor loadings λ_ℓ $(\ell = 1, \ldots, L)$ we employ a Normal-Gamma prior similar to the one used for the VAR coefficients in $\boldsymbol{a}$. The set-up follows Kastner (2016) with a single global shrinkage parameter ξ_λ that applies to all free elements λ_ℓ in the factor loadings matrix. Specifically, we impose a hierarchical Gaussian prior on λ_ℓ that depends on Gamma priors for $\tau_{\lambda\ell}^2$ $(\ell = 1, \ldots, L)$ and ξ_λ,

$$\lambda_\ell|\xi_\lambda, \tau_{\lambda\ell}^2 \sim \mathcal{N}\left(0, 2\,\xi_\lambda^{-1}\tau_{\lambda\ell}^2\right), \tag{8}$$

$$\xi_\lambda \sim \mathcal{G}(c_0, c_1),$$

$$\tau_{\lambda\ell}^2 \sim \mathcal{G}(\vartheta_\lambda, \vartheta_\lambda).$$

The hyperparameters c_0, c_1, and ϑ_λ control the tail behavior and overall degree of shrinkage of the prior. For the measurement error variances σ_r^2 $(r = 1, \ldots, R)$ we rely on a sequence of

independent inverted Gamma priors,

$$\sigma_r^2 \sim \mathcal{G}^{-1}(e_0, e_1), \tag{9}$$

where the hyperparameters e_0 and e_1 are typically set to small values to reduce prior influence on σ_r^2.

Estimation of the model parameters and the latent factors is based on the MCMC algorithm described in Appendix B. More specifically, we use Gibbs sampling to simulate a chain consisting of 20,000 draws, where we discard the first 10,000 draws as burn-in. It is worth noting that the MCMC algorithm shows fast mixing and satisfactory convergence properties.

2.3 Identification of monetary policy shocks

The standard approach to identify monetary policy shocks in a VAR framework involves imposing a set of zero restrictions via a Cholesky identification scheme. This approach relies on the assumption that macroeconomic quantities in the system react to changes in the monetary policy instrument with a time lag. Timing restrictions on the impact of the policy indicator may be reasonable for the interactions between the funds rate and macroeconomic variables, but becomes problematic if financial variables are present in addition. Policy shifts not only influence financial quantities, but may also respond to them, directly or indirectly (Gertler and Karadi, 2015). To circumvent the problem of simultaneity, we follow Gertler and Karadi (2015) and use high-frequency surprises as external instrument to identify monetary policy shocks.

The high-frequency variant of the external instruments identification approach employed in this paper is based on surprises in the prices of three-months-ahead futures contracts of the federal funds rate that reflect expectations on interest rate movements further into the future, measured within a 30 minutes time window surrounding announcements by the Federal Open Market Committee (FOMC), the governing council of the Federal Reserve (Kuttner, 2001; Gürkaynak et al., 2005; Gertler and Karadi, 2015). The tight time frame around these announcements is chosen to reduce the likelihood of other events affecting prices of the futures contracts.

Financial markets internalize the behavior of the Federal Reserve (Fed) by anticipating changes in the policy instrument based on predicted movements in key macroeconomic quantities. For instance, facing a weakening economic outlook, federal funds rates futures would decline in advance of the policy announcement by the Fed. Depending on the specific monetary policy action conducted by the central bank, futures markets may either correctly predict the enacted policies, or react to unexpected changes in the policy rate precisely around official announcements. Gürkaynak et al. (2005) provide evidence that the adjustment of the prices of futures contracts happens almost instantaneously, in contrast to fully anticipated changes that do not cause observable reactions. A convenient by-product of this approach is that it also reflects Fed information shocks in the context of forward guidance.

For illustrative purposes, the evolution of the effective federal funds rate over the observation period 1997:04 to 2012:06 is shown in Fig. 1 (upper panel) along with the corresponding policy surprises around announcements (lower panel). The dashed red line refers to the zero line, while the light blue shaded vertical bars represent the recessions dated by the Business Cycle Dating Committee of the National Bureau of Economic Research. Large monetary policy surprises tend to occur in recessionary economic episodes, evidenced by unexpected innovations for both the period between 2001 and 2002, as well as during the Great Recession. Notice that decreases in the federal funds rate not necessarily reflect expansionary shocks. In June 2001, for instance, markets expected the Fed to further decrease the target rate, while the rate was decreased only slightly, translating into a contractionary monetary policy shock. The contrary is observable in the first half of 1997 or June 2006. Here, the Fed left the target rate unchanged while markets expected further increases, resulting in expansionary monetary policy shocks.
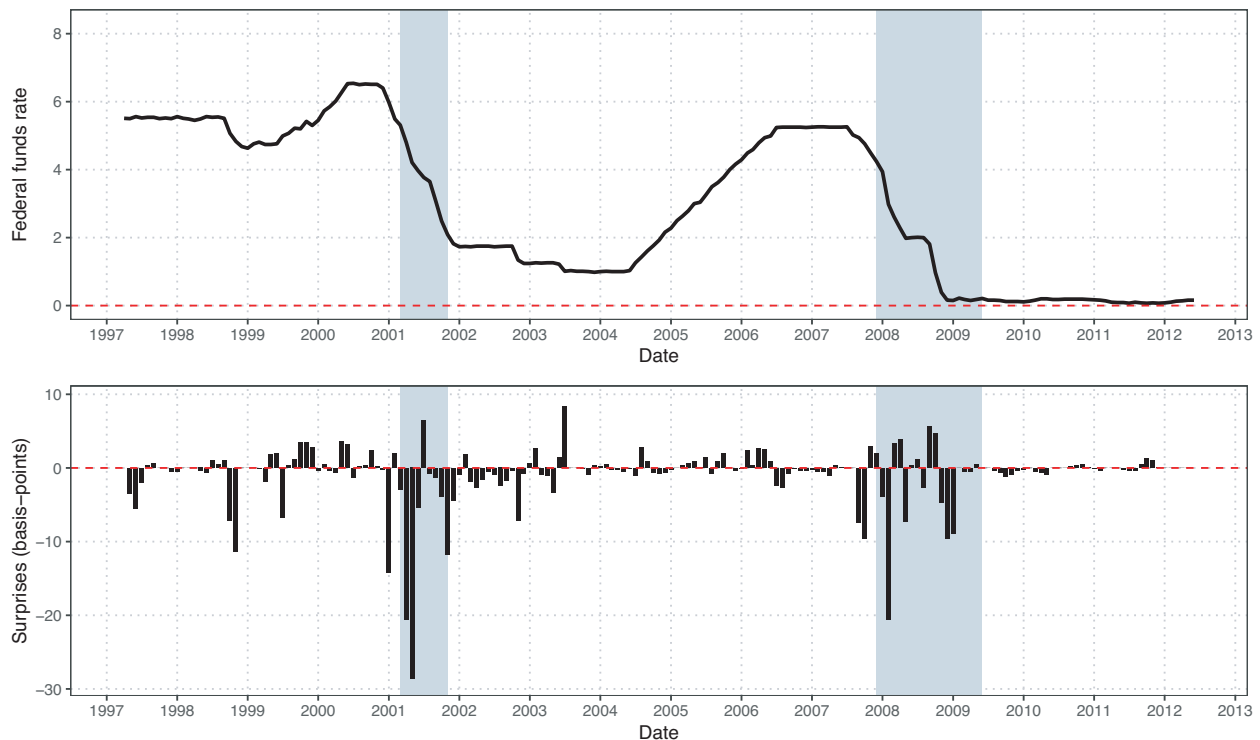

Fig. 1: The federal funds rate and exogenous monetary policy surprises.

Notes: The dashed red line refers to the zero line, while the light blue shaded vertical bars denote the recessions dated by the Business Cycle Dating Committee of the National Bureau of Economic Research (www.nber.org). Surprises are measured within an half-hour window, starting ten minutes before and ending 20 minutes after release of the FOMC policy statement. The data for monetary policy surprises between 1997:04 and 2012:06 come from Gertler and Karadi (2015).

To implement the approach, we follow Paul (2018) and use high-frequency surprises as a proxy for the monetary policy shock. This is achieved by integrating the surprises into Eq. (2) as an

exogenous variable z_t, to yield

$$y_t = Ax_t + \zeta z_t + u_t. \tag{10}$$

Hereby ζ is a $Q(S+K)$-dimensional vector of regression coefficients that collects the impulses of the shocks. Paul (2018) shows that under mild conditions, the contemporaneous relative impulse responses can be estimated consistently.[2] Note that the impact response of y_t to changes in z_t is given by ζ. Higher order responses are obtained recursively by exploiting the state space representation of the VAR model in Eq. (2).

3 Data and model implementation

3.1 Regions and data

To explore regional differences in the impact of monetary policy on housing prices, we need to define our notion of regions. Throughout the paper, we use $R = 417$ regions, a subsample of the 917 core-based statistical areas.[3] These 417 regions include 263 metropolitan and 154 micropolitan statistical areas. They have been selected based on the availability of the data over time. For the list of regions in the sample, see Appendix A.

Our dataset consists of a panel of monthly time series ranging from 1997:04 to 2012:06. The $R \times 1$ vector of housing prices H_t is constructed using the Zillow Home Value Index.[4] A key advantage of this index is to provide a comprehensive coverage of core-based statistical areas across the country, in contrast to the FHFA (Federal Housing Finance Agency) Index and the Standard & Poor's Case-Shiller Index. The Zillow Home Value Index does not use a repeat sales methodology, but statistical models along with information from sales assessments to generate valuations for all homes (single family houses, town houses, appartments, condos and properties that are typically associated with the residential market) in any given region. These valuations are aggregated to determine the Zillow Home Value Index, measured in US dollars.

We include $K = 7$ variables in the vector of observable national aggregates M_t: three economic variables, namely housing investment (measured in terms of housing starts), the industrial pro-

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[2]Relative impulse responses are obtained by normalizing the absolute impulse responses, that is, the change in y_{t+h} to a change in z_t, by the contemporaneous response of some element in y_t.

[3]A core-based statistical area is a US geographic area – defined by the Office of Management and Budget – that consists of one or more counties anchored by an urban center of at least 10,000 people plus adjacent counties that are socioeconomically tied to the urban center. The term core-based statistical area refers collectively to both metropolitan and micropolitan statistical areas.

[4]The Zillow Home Value Index uses detailed information about hundreds of millions of real estate transactions across the United States to provide a comprehensive coverage of the core-based statistical areas. The set of data we use in this study is available for download at `https://www.zillow.com/research/data/`. Note that no data is available for Maine and South Dakota since these states do not require mandatory disclosure for sale prices. Core-based statistical areas within Montana, Vermont and Wyoming had to be eliminated due to limited availability of time series data. Previous VAR/FAVAR-based studies on monetary transmission via house prices rely on different price indices. Fratantoni and Schuh (2003) use the MSA-level index from the Fannie Mae Repeat Transactions Database, Iacoviello (2005) the Freddie Mac House Price Index, del Negro and Otrok (2007) the FHFA/OFHEO house prices indices, and Jarocinski and Smets (2008) the S&P/Case-Shiller Index.

duction index and the consumer price index. The one-year government bond rate serves as policy indicator of the Fed. The advantage of using this longer rate rather than the federal funds rate is that it incorporates – as Gertler and Karadi (2015) argue – measures of forward guidance and hence remains a valid measure of the monetary policy stance also in situations when the federal funds rate is constrained by the zero lower bound.[5]

The FAVAR model developed in this paper extends a standard macroeconomic autoregressive model with a set of three credit-spreads: the ten-year treasury yield minus the federal funds rate, the prime mortgage spread calculated over ten-year government bond yields, and the Gilchrist and Zakrajšek (2012) excess bond premium. The excess bond premium may roughly be seen as the component of the spread between an index of yields on corporate fixed income securities and a similar maturity government bond rate that is left after removing the component due to default risk (Gertler and Karadi, 2015). Gilchrist and Zakrajšek (2012) show that this variable provides a convenient summary of additional information that may be relevant to economic activity.

The economic variables capture housing, price and output movements. The mortgage spread is relevant to the cost of housing finance, and the excess bond premium to the cost of long-term credit in the business sector, while the term spread measures expectations on short-term interest rates (Gertler and Karadi, 2015). All observable national aggregates are taken from the FRED database (McCracken and Ng, 2016), with the exception of the excess bond premium and the mortgage spread that have been obtained from the dataset provided in Gertler and Karadi (2015). All data series are seasonally adjusted, if applicable, and transformed to be approximately stationary.

3.2   Model implementation

For implementation of the FAVAR, we have to specify the lag order Q of the VAR process and the number of latent factors, S. As is standard in the literature, we pick $Q = 2$ lags of the endogenous variables. To decide on the number of factors, we use the deviance information criterion (Spiegelhalter et al., 2002) where the full data likelihood is obtained by running the Kalman filter and integrating out the latent states. This procedure yields $S = 1$, a choice that is also consistent with traditional criteria, for instance, the Bayesian information criterion or the Kaiser criterion, for selecting the number of factors.

A brief word on hyperparameter selection for the prior setup is in order. We specify $\vartheta_a = \vartheta_\lambda = 0.1$, a choice that yields strong shrinkage but, at the same time, leads to heavy tails in the underlying marginal prior. Recent literature (see, for example, Huber and Feldkircher, 2017) integrates out $\vartheta_a, \vartheta_\lambda$ and finds that, for US data, the posterior is centered on values between 0.10 and 0.15. The hyperparameters on the global shrinkage parameters are set equal to $c_0 = c_1 = d_0 = d_1 = 0.01$, a choice that is consistent with heavy shrinkage towards the origin representing a standard in the literature (Griffin and Brown, 2010). The prior on $\boldsymbol{\Sigma}_u$ is specified to be weakly informative, i.e.

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[5]To support this view, we estimated the model using the federal funds rate as policy indicator for a robustness check. The results – available upon request – suggest similar responses compared to the one-year government bond rate.

$\nu = S + K + 1$ and $\underline{\boldsymbol{\Sigma}} = 10^{-2} \boldsymbol{I}_{S+K}$. Likewise, for the inverted Gamma prior on σ_r^2 $(r = 1, \ldots, R)$ we set $e_0 = e_1 = 0.01$ to render the prior only weakly influential.

4 Econometric results

4.1 The dynamic factor and its loadings

We briefly consider the estimated latent factor and its loadings, with two aims in mind: first, to provide a rough intuition on how the latent factor captures co-movement in regional house price variations, and second, to indicate the relative importance of individual regions shaping the evolution of the common factor. The posterior mean of the negative latent factor (in solid red) shown in Fig. 2 provides evidence that the common factor co-moves with the average growth rate of housing prices (in solid blue, calculated using the arithmetic mean of the individual regional housing prices) nearly perfectly. The figure illustrates that during the 2001 recession, housing price declines have been mild, while being substantial during the Great Recession, with large variations across space. It is worth noting that home prices fell the most during the late 2000s in regions with the largest declines in economic activity (Beraja et al., 2017).
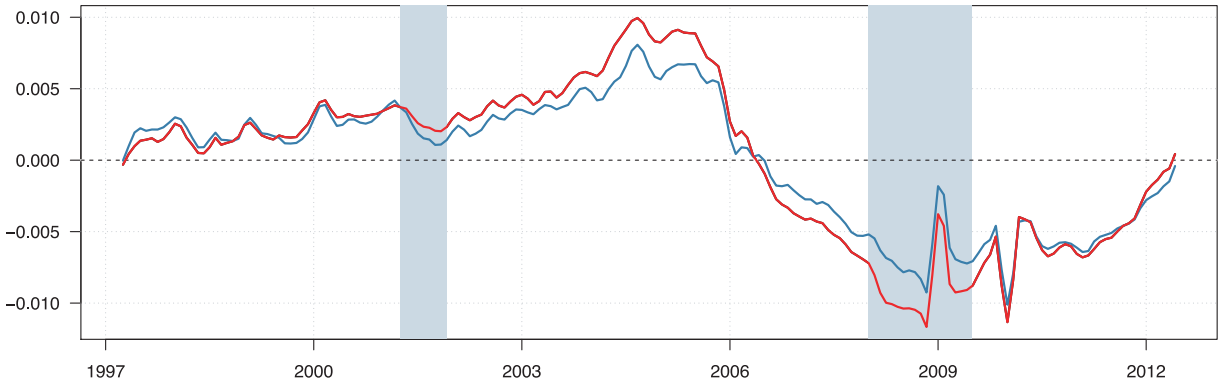

Fig. 2: Co-movement of the negative latent dynamic factor and national housing prices over time.

Notes: The solid red line denotes the posterior mean of the negative latent factor, i.e. $-F_t$, the solid blue line the national housing prices, calculated as mean of the individual regions. The dashed black line refers to the zero line, while the light blue shaded vertical bars represent the recessions dated by the Business Cycle Dating Committee of the National Bureau of Economic Research (www.nber.org). Sample period: 1997:04 – 2012:06. Vertical axis: growth rates. Front axis: months.

While Fig. 2 provides intuition on the shape of the latent housing factor, the question on how individual regions are linked to it still needs to be addressed. For this purpose, Fig. 3 reports the posterior mean of the region-specific factor loadings in form of a geographic map in which thinner lines denote the boundaries of the regions, while thicker lines signify US state boundaries. Visualization is based on a classification scheme with equal-interval breaks. We see that the great majority of regions exhibit negative loadings, and only 23 regions show positive values. Eighty regions have zero loadings or loadings where the 16th and 84th credible sets (68 percent posterior coverage) of
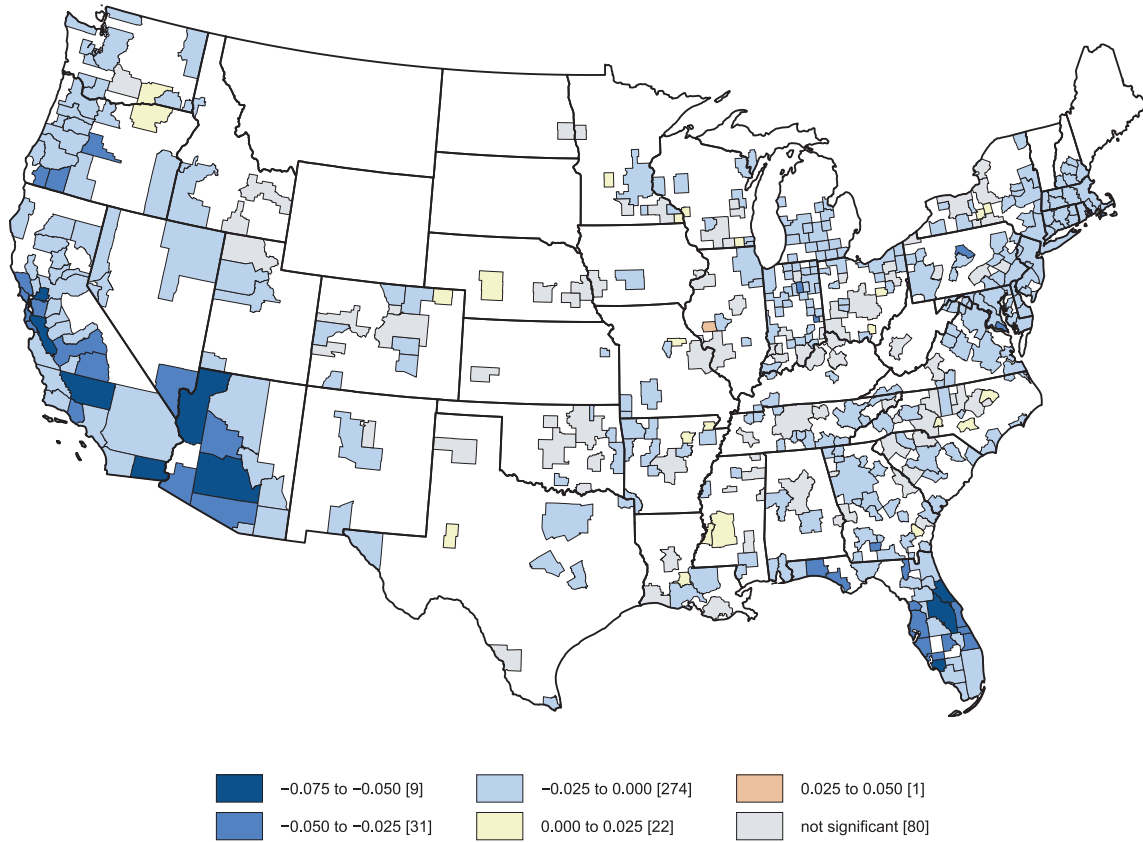
Fig. 3: Region-specific factor loadings.

Notes: Visualization is based on a classification scheme with equal-interval breaks. The Number of regions is allocated to the classes in squared brackets. Thinner lines denote the boundaries of the regions, while thicker lines represent US state boundaries. Results are based on 10,000 posterior draws. Sample period: 1997:04 – 2012:06. For the list of regions see Appendix A.

the respective posterior distributions include zero. The pattern of factor loadings, evidenced by the map, indicates that the latent factor is largely driven by regions located in California, Arizona and Florida. Regions in the rest of the country, with loadings being either small in absolute terms or not significantly different from zero, tend to play only a minor role in shaping national housing prices.

4.2 Impulse responses of macroeconomic quantities

Impulse response functions represent the standard way to summarize the dynamic impact of policy shocks. We first consider the dynamic evolution of the endogenous variables included in M_t in response to a monetary policy shock to illustrate that the results of the model are consistent with established findings in the literature. An expansionary monetary policy shock is modeled by taking the one-year government bond rate as the relevant policy indicator, rather than the federal funds rate that is commonly used in the literature. Gertler and Karadi (2015) show that the one-year
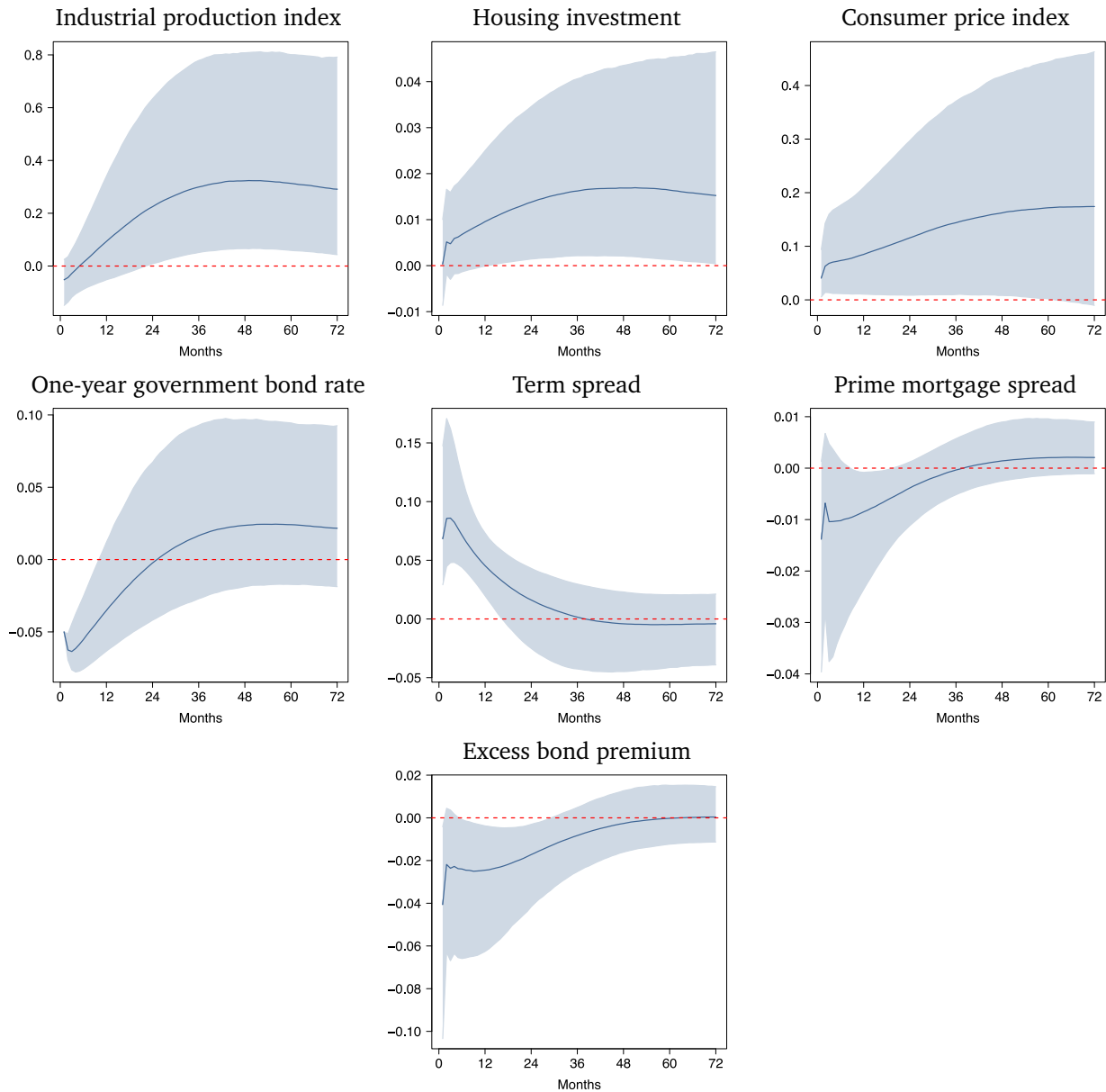
Fig. 4: Impulse responses of macroeconomic fundamentals to a monetary policy shock.

Notes: The solid blue line denotes the median response, the dashed red line the zero line, and the shaded bands (in light blue) the 68 percent posterior coverage interval. Results are based on 10,000 posterior draws. Sample period: 1997:04 – 2012:06. Vertical axis: percentage changes for indices and housing investment; otherwise percentage points. Front axis: months after impact.

bond rate has a stronger impact on market interests than the funds rate does, based on the assertion that forward guidance is more adequately reflected in the longer maturity yield. Normalization is achieved by assuming that a monetary policy shock yields a five basis points decrease in the policy indicator.

The impulse response functions of all the endogenous variables to the monetary policy shock are presented in Fig. 4. All plots include the median response (in blue) for 72 months after impact along with 68 percent posterior coverage intervals reflecting posterior uncertainty. An unanticipated decrease in the government bond rate by five basis points causes a significant increase in real activity, with industrial production, housing investment and consumer prices all increasing over the next months after the impact. From a quantitative standpoint, the effects of the monetary shock on industrial production and consumer prices are considerably larger than the impact on housing investment, although uncertainty surrounding the size of impacts is large, and posterior coverage intervals include zero during the first months after impact. Housing investment shows a reaction similar in shape to real activity measured in terms of the industrial production index, suggesting a positive relationship between expansionary monetary policy and housing investment at the national level.

Turning to the responses of financial market indicators, it should be noted that the one-year government bond rate falls by five basis points on impact by construction, then increases significantly before it turns non-significant after about nine months. The term spread reacts adversely on impact, and we find significant deviations from zero that die out after about 16 months. This result points towards an imperfect pass-through of monetary policy on long-term rates, implying that long-term yields display a weaker decline as compared to short-term rates. The prime mortgage spread does not show a significant effect on impact, while responses between ten to 20 months ahead indicate a slightly negative overall reaction to expansionary monetary policy. Consistent with Gilchrist and Zakrajšek (2012), one implication of this finding is that movements in key short-term interest rates tend to impact credit markets, with mortage spreads showing a tendency to decline. The responses of the excess bond premium almost perfectly mirror the reaction of the mortgage spread. The effects, however, are much larger from a quantitative point of view.

To sum up, the results obtained by the impulse response analysis provide empirical support that monetary policy shocks, identified by using high-frequency surprises around policy announcements as external instrument, generate impulse responses of the endogenous variables that are consistent with economic theory and the findings of previous empirical studies.[6]

4.3   Impulse responses of housing prices

Figure 5 displays the impulse response function of the latent factor over 72 months after impact to an expansionary monetary policy shock. The latent factor reacts positively after the shock, but the posterior coverage interval includes zero for the time horizon considered. Nevertheless, sufficient posterior mass is shifted away from zero reflecting positive reactions. This is consistent with economic theory, suggesting decreases in the cost of financing a home purchase via expanding the

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[6]To allay potential concerns of the policy rate reaching the zero lower bound, we conducted various robustness checks (results are available upon request). Using a shadow rate to capture unconventional monetary policy actions leaves the results qualitatively unchanged. The same holds true when using the federal funds rate rather than the one-year government bond rate as policy indicator.

availability of credit, thereby increasing the demand for housing. As a result, real housing prices tend to increase.
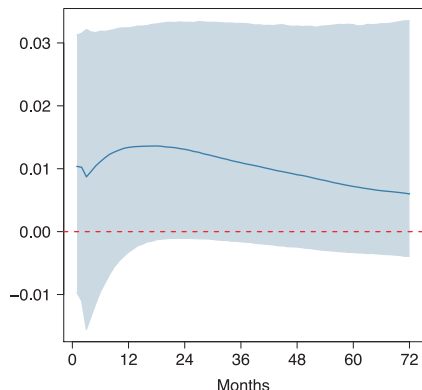

Fig. 5: Reaction of the negative latent factor, following a monetary policy shock.

Notes: The solid blue line denotes the median response, the dashed red line the zero line, and the shaded bands (in light blue) the 68 percent posterior coverage interval. Results are based on 10,000 posterior draws. Vertical axis: percentage points. Front axis: months after impact.

While for reasons of space we do not report the housing price responses of all the 417 regions, we summarize the long-run regional house price responses (i.e., cumulative 72 months responses, expressed in percentage points) in form of a geographic map with a classification scheme that generates class breaks in standard deviation measures (SD=0.61) above and below the mean of 0.71 (see Fig. 6).[7] Again thinner lines denote the boundaries of the regions and thicker lines those of the US states. Some few regions show no significant impact or even negative responses. In more than 91 percent of the regions, however, the cumulative response of housing prices is positive.

Monetary policy shocks affect regions asymmetrically. Differences in policy responses are evident, and in some cases, substantial. The largest response among regions (Las Vegas-Henderson-Paradise, Nevada) exceeds the smallest (Tahlequah, Oklahoma) by 3.2 percentage points. Regions within California, Florida and Nevada – commonly referred to as Sand States – are noticeably more responsive to monetary policy changes. The top ten most responsive regions are dominated by six Californian regions: Riverside-San Bernadino-Ontario, Madera, Merced, Clearlake, Modesto and Bakersfield. The first two slots in the ranking, however, are occupied by Las Vegas-Henderson-Paradise and Fernley, a micropolitan region (both within Nevada). Port St. Lucie, Clewiston and Key West (all Florida) round out the top ten, and bring the coastal eastern regions into picture.

By contrast, certain regions of the country are much less sensitive to monetary policy shocks (± 0.25 standard deviation from zero). These regions are not concentrated in only a few states or areas. Rather, they span 14 states and 24 metro- and micropolitan regions. Given the narrowness of our definition, this emphasizes the point that less responsive regions, in terms of reactions

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[7]The results are robust to an alternative identification scheme based on sign-restrictions (see Appendix C). Concerns on the validity of the identification scheme using external instruments, that may come from the period where interest rates nearly reached zero, are thus alleviated.
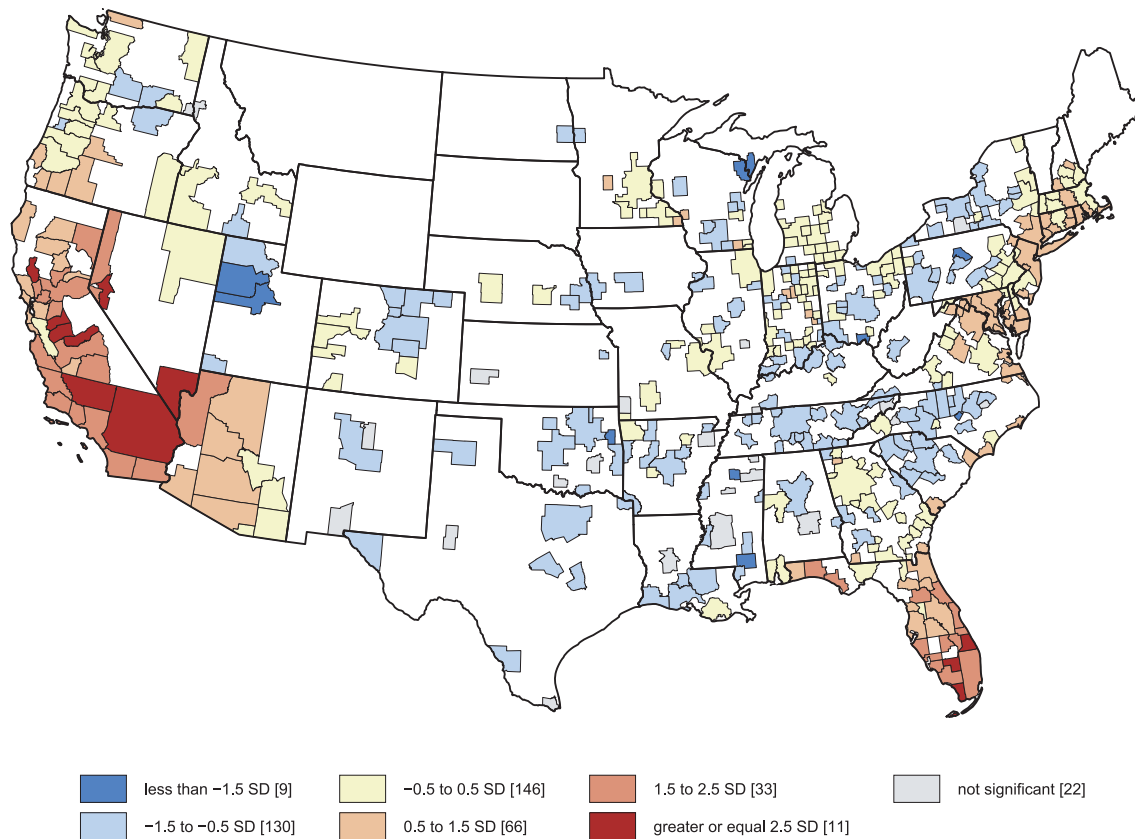
Fig. 6: Long-run responses of regional housing prices to a monetary policy shock, i.e. cumulative 72 months responses.

Notes: Visualization is based on a classification scheme that generates breaks in standard deviation measures (SD = 0.61) above or below the mean of 0.71. Number of regions allocated to the classes in squared brackets. The responses based on 10,000 posterior draws have been accumulated. Thinner lines denote the boundaries of the regions, while thicker lines represent US state boundaries. Sample period: 1997:04 – 2012:06. For the list of regions see Appendix A.

to monetary policy shocks, are spread throughout much of the country. Clarksville (Tennessee-Kentucky), Tulsa, Enid and Bartlesville (Oklahoma), as well as Hickory-Lenoir-Morgenton and Fayetteville (North Carolina), and Baton Rouge (Louisiana) are found to be the least responsive. Note that five percent of the regions do not show significant results, while 3.6 percent (including, e.g., Salt Lake City, Utah) exhibit negative responses.

Metropolitan regions like Chicago-Naperville-Elgin (Illionois-Indiana-Wisconsin), Boston-Cambridge-Newton (Massachusetts-New Hampshire), Portland-Vancouver-Willsborough (Oregon-Washington), Savannah (Georgia) and San Jose-Sunnyvale-Santa Clara (California) respond to monetary policy changes in ways that closely mirror the average dynamic response across the United States (± 0.25 standard deviation).

Figure 6 reveals substantial heterogeneity in the magnitude of the dynamic responses, but also indicates that regional responses tend to be similar within states and adjacent neighboring states.

This spatial autocorrelation phenomenon becomes particularly evident in the case of Californian regions and is most likely due to the importance of new house construction industries, along with the spatial influence the Californian housing market has on regions in neighboring states, especially Nevada and Arizona.

4.4 Explanation for the differential housing price responses

Housing price responses vary substantially over space, with size and modest sign differences among the regions, as evidenced by Fig. 6. This raises the question why housing prices in some regions are more responsive to monetary policy shocks than in others. To address this issue, we link our results to the housing supply elasticity literature (Gyourko et al., 2008; Saiz, 2010; Howard and Liebersohn, 2018), more specifically, to local land use regulation as captured by the Wharton Residential Land Use Regulatory Index (WRLURI), and a measure of housing supply elasticity developed by Howard and Liebersohn (2018).

The WRLURI created by Gyourko et al. (2008) is an index comprised of eleven sub-indices that summarize information on different aspects of the local regulatory environment. The index calculated for our regions shows that much heterogeneity in land use regulatory environments exists across the regions.[8] The two Michigan metropolitan regions, Ann Arbor and Jackson, and the Michigan micropolitan region, Adrian, represent the most heavily regulated markets, with WRLURI scores at least 2.9 standard deviation above the national mean of -0.18. The next most heavily regulated regions, according to the index, are Seattle-Tacoma-Bellevue (Washington), San Diego-Carlsbad and San Francisco-Oakland-Hayward (both within California), being about one standard deviation above the mean. Dallas-Fort Worth-Arlington (Texas) is a typical housing market near the mean in terms of land use regulatory environments. Bartlesville (Oklahoma), Lewiston (Idaho-Washington), Toledo (Ohio) and Tahlequah (Oklahoma) are examples for the least regulated regions, having WRLURI scores that are at least one standard deviation below the mean. All these examples emphasize that local land use regulation is neither uniformly high nor uniform across the country.

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[8]We calculate WRLURI scores for the regions by taking a population-weighted average for all counties within a region. Note that the WRLURI does not provide full coverage for the United States, and systematically undercovers micropolitan regions. Hence, scores are missing for 15 percent of the regions in our sample.
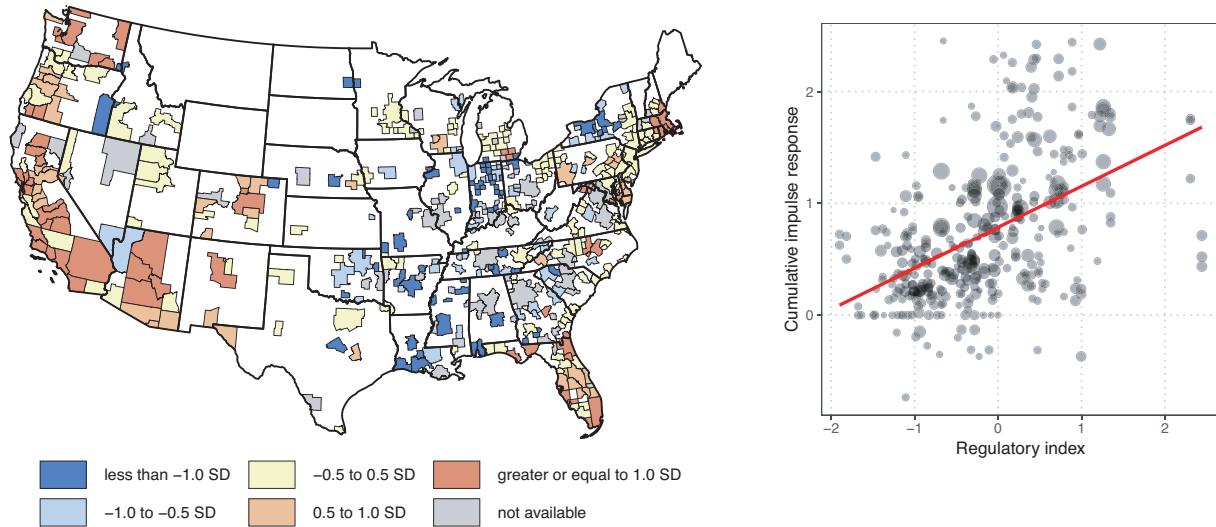
Fig. 7: Estimated local land use regulation, captured by WRLURI, and comparison with the housing price responses.

Notes: The left hand panel presents the estimated local land use regulation (visualized of the geographic map based on a classification scheme with equal-interval breaks around the mean of −0.18), while the right panel shows the correlation between cumulative impulse responses of housing prices and the corresponding WRLURI scores (the circles represent the regions, with their size indicating population density). Thinner lines denote the boundaries of the regions, while thicker lines represent US state boundaries. The solid red line denotes the correlation. For the list of regions see Appendix A.

Figure 7 presents the estimated local land use regulation in form of a geographic map with a classification scheme that generates class breaks in standard deviation (0.82) measures above and below the mean of −0.18 (left panel), while the comparison with the corresponding cumulative impulse responses of housing prices is shown in the right panel. The figure clearly suggests that there exists a positive relationship between the sensitivity of housing price reactions and land use regulation. Regions characterized by tight regulations also tend to feature strong reactions of local housing markets. This can be attributed to the positive relationship between regulatory measures and housing prices that has previously been identified in the literature (see, for instance, Ihlanfeldt, 2007; Glaeser and Ward, 2009). We conjecture that this relationship directly translates into increased responsiveness of housing prices, leading to stronger reactions to national monetary policy shocks.

In the next step, we assess how housing supply elasticity is linked to housing price responses in Fig. 8. We use Howard and Liebersohn's housing supply elasticity measure for commuting zones to construct elasticities for the regions. The elasticity measure estimates the effect of a change in housing units on housing prices, projecting this relationship onto three measures associated with land availability: the WRLURI index, population density and the coastal status (Howard and Liebersohn,

2018).[9] Estimated housing supply elasticities for the regions reveal that San Francisco-Oakland-Hayward, San Diego-Carlsbad, Santa Rosa, Napa and Vallejo-Fairfield (all within California) belong to the top ten most inelastic regions, with elasticities below 0.72. The three Michigan regions Ann Arbor, Adrian and Jackson along with Philadelphia-Camden-Wilmington (Pennsylvania-New Jersey-Delaware-Maryland) and Trenton (New Jersey) complete the top ten list. Housing supply is estimated to be quite elastic (3.73, with a standard deviation of 2.78) for the average region, represented by Salt Lake City (Utah). By contrast, Las Vegas-Henderson-Paradise (Nevada) and Santa Fe (New Mexico) stand out as prominent examples with most elastic housing supply, with at least one standard deviation above the national mean.
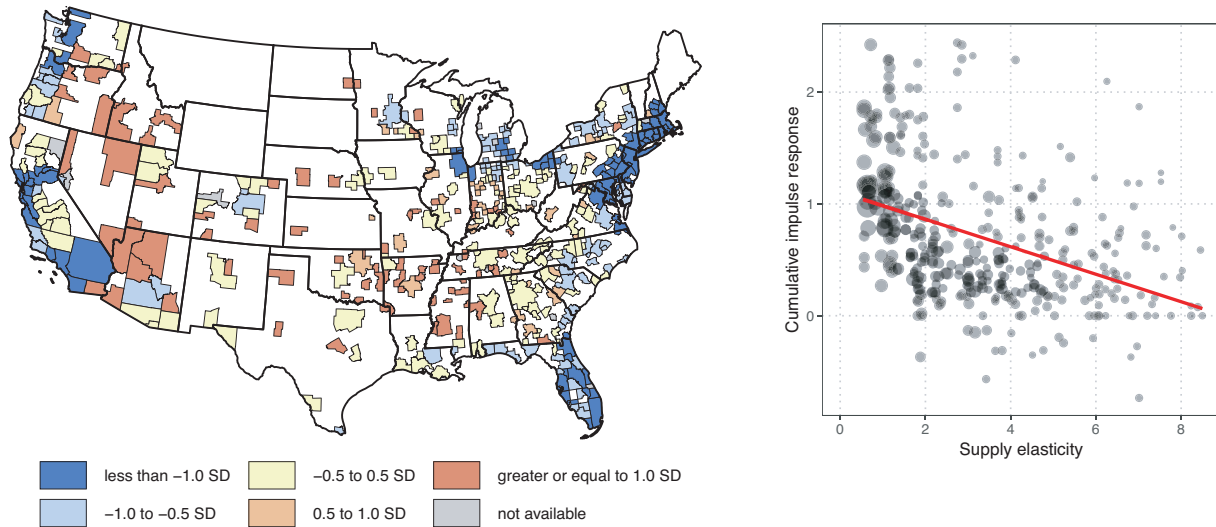

Fig. 8: Estimated elasticities and comparison with the housing price responses.

Notes: The left hand panel presents the estimated housing supply elasticities (visualized of the geographic map based on a classification scheme with equal-interval breaks around the mean of 3.73), while the right panel shows the correlation between cumulative impulse responses of housing prices and the corresponding elasticities (the circles represent the regions, with their size indicating population density). Thinner lines denote the boundaries of the regions, while thicker lines represent US state boundaries. The solid red line denotes the correlation. For the list of regions see Appendix A.

On the right in Fig. 8, one observes a negative relationship between housing supply elasticities and price responses. In our specific example, we find that expansionary monetary policy directly translates into cheaper credit, leading to upward movements in housing demand. This increase in housing demand in face of a rather steep supply curve for housing yields a strong price reaction. This finding corroborates and extends the results in Glaesera et al. (2008), who report a negative relationship between supply elasticities and movements in property prices, especially in the context of excessive increases in housing prices. These results indicate higher effectiveness of monetary

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[9]To classify coastal regions, we used NOAA's (National Oceanic and Athmospheric Administration) definition of coastal counties. Any region that contains a coastal county was coded as coastal.

policy to influence housing prices by the central bank in regions characterized by low levels of supply elasticities.

5   Closing remarks

This paper uses a Bayesian FAVAR model to examine the impact of monetary policy shocks on housing prices across the United States. Bayesian inference is advantageous because it directly addresses uncertainty surrounding latent factors and model parameters. Monetary policy shocks are identified making use of high-frequency surprises around policy announcements as external instrument. Impulse response functions reveal that monetary policy shocks affect regions asymmetrically. There is substantial heterogeneity in the magnitude of the regional housing price responses. The largest response exceeds the smallest by 3.2 percentage points. Regions within California, Florida and Nevada are noticeably more responsive than others. By contrast, the least responsive regions are spread throughout much of the country.

This heterogeneity in responses may be due to varying sensitivity of housing to interest rates across space, and regional differences in housing markets such as different local regulatory environments and supply elasticities. The paper links the results to the housing supply elasticity literature and provides evidence that the variation in housing responses across space can be explained partly by different supply elasticities and regulatory environments.

Finally, it is worth noting that our analysis is confined to a linear setting, implying the underlying transmission mechanism to be constant over time. This assumption simplifies the analysis, but may be overly simplistic in turbulent economic times such as the collapse of the housing market around the Great Recesssion. Hence, an extension of the linear setting to allow for non-linearities – in the spirit of Huber and Fischer (2018) – might be a promising avenue for future research.

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Appendix A   Regions used in the study

Regions in this study are defined as core-based statistical areas (CBSA) that – by definition of the United States Office of Management and Budget – are based on the concept of a core area of at least 10,000 population, plus adjacent counties having at least 25 percent of employed residents of the county who work in the core area. Core-based statistical areas may be categorized as being either metropolitan or micropolitan. The 917 core-based statistical areas include 381 metropolitan statistical areas which have an urban core population of at least 50,000, and 536 micropolitan statistical areas which have an urban core population of at least 10,000 but less than 50,000. In this study we use 263 metropolitan and 154 micropolitan statistical areas, due to limited availability of data. These 417 regions represent contiguous states (excluding Maine, Montana, South Dakota, Vermont and Wyoming) plus the District of Columbia, and Hawaii.

Table A.1: The list of metropolitan statistical areas used.

State (Census Bureau Region)	**Region**
Alabama (South)	Birmingham-Hoover, Daphne-Fairhope-Foley, Mobile, Montgomery, Tuscaloosa
Arizona (West)	Flagstaff, Lake Havasu City-Kingman, Phoenix-Mesa-Scottsdale, Prescott, Sierra Vista-Douglas, Tucson, Yuma
Arkansas (South)	Fayetteville-Springdale-Rogers*, Fort Smith*, Hot Springs, Jonesboro, Little Rock-North Little Rock-Conway
California (West)	Bakersfield, Chico, El Centro, Fresno, Hanford-Corcoran, Los Angeles-Long Beach-Anaheim, Madera, Merced, Modesto, Napa, Oxnard-Thousand Oaks-Ventura, Redding, Riverside-San Bernardino-Ontario, Sacramento–Roseville–Arden-Arcade, Salinas, San Diego-Carlsbad, San Francisco-Oakland-Hayward, San Jose-Sunnyvale-Santa Clara, San Luis Obispo-Paso Robles-Arroyo Grande, Santa Cruz-Watsonville, Santa Maria-Santa Barbara, Santa Rosa, Stockton-Lodi, Vallejo-Fairfield, Visalia-Porterville, Yuba City
Colorado (West)	Boulder, Colorado Springs, Denver-Aurora-Lakewood, Fort Collins, Grand Junction, Greeley, Pueblo
Connecticut (Northeast)	Bridgeport-Stamford-Norwalk, Hartford-West Hartford-East Hartford, New Haven-Milford, Norwich-New London
Delaware (South)	Dover
District of Columbia (South)	Washington-Arlington-Alexandria*
Florida (South)	Cape Coral-Fort Myers, Crestview-Fort Walton Beach-Destin, Deltona-Daytona Beach-Ormond Beach, Gainesville, Homosassa Springs, Jacksonville, Lakeland-Winter Haven, Miami-Fort Lauderdale-West Palm Beach, Naples-Immokalee-Marco Island, North Port-Sarasota-Bradenton, Ocala, Orlando-Kissimmee-Sanford, Palm Bay-Melbourne-Titusville, Panama City, Pensacola-Ferry Pass-Brent, Port St. Lucie, Punta Gorda, Sebastian-Vero Beach, Sebring, Tallahassee, Tampa-St. Petersburg-Clearwater, The Villages
Georgia (South)	Albany, Athens-Clarke County, Atlanta-Sandy Springs-Roswell, Augusta-Richmond County*, Columbus*, Dalton, Gainesville, Hinesville, Macon, Savannah, Valdosta, Warner Robins
Hawaii (West)	Kahului-Wailuku-Lahaina, Urban Honolulu
Idaho (West)	Boise City, Idaho Falls, Lewiston*
Illinois (Midwest)	Bloomington, Chicago-Naperville-Elgin*, Davenport-Moline-Rock Island*, Kankakee, Springfield

Indiana (Midwest)	Bloomington, Elkhart-Goshen, Evansville*, Fort Wayne, Lafayette-West Lafayette, Muncie, South Bend-Mishawaka*, Terre Haute
Iowa (Midwest)	Des Moines-West Des Moines
Kansas (Midwest)	Lawrence
Kentucky (South)	Lexington-Fayette, Louisville-Jefferson County*
Louisiana (South)	Alexandria, Baton Rouge, Houma-Thibodaux, Lafayette, Lake Charles
Maryland (South)	Baltimore-Columbia-Towson, California-Lexington Park, Cumberland*, Hagerstown-Martinsburg*, Salisbury*
Massachusetts (Northeast)	Barnstable Town, Boston-Cambridge-Newton*, Pittsfield, Springfield, Worcester*
Michigan (Midwest)	Ann Arbor, Battle Creek, Bay City, Grand Rapids-Wyoming, Jackson, Lansing-East Lansing, Midland, Monroe, Muskegon, Saginaw
Minnesota (Midwest)	Mankato-North Mankato, Minneapolis-St. Paul-Bloomington*, Rochester
Mississippi (South)	Hattiesburg, Jackson
Missouri (Midwest)	Columbia, Joplin, Springfield, St. Louis*
Nebraska (Midwest)	Grand Island, Lincoln, Omaha-Council Bluffs*
Nevada (West)	Las Vegas-Henderson-Paradise, Reno
New Hampshire (Northeast)	Manchester-Nashua
New Jersey (Northeast)	Ocean City, Trenton, Vineland-Bridgeton
New Mexico (West)	Albuquerque, Las Cruces, Santa Fe
New York (Northeast)	Albany-Schenectady-Troy, Binghamton, Elmira, Glens Falls, Ithaca, Kingston, New York-Newark-Jersey City*, Rochester, Syracuse, Watertown-Fort Drum
North Carolina (South)	Asheville, Burlington, Charlotte-Concord-Gastonia*, Durham-Chapel Hill, Fayetteville, Greensboro-High Point, Hickory-Lenoir-Morganton, Raleigh, Rocky Mount, Wilmington, Winston-Salem
North Dakota (Midwest)	Fargo*
Ohio (Midwest)	Akron, Canton-Massillon, Cincinnati*, Cleveland-Elyria, Columbus, Dayton, Lima, Springfield, Toledo, Youngstown-Warren-Boardman*
Oklahoma (South)	Oklahoma City, Tulsa
Oregon (West)	Albany, Bend-Redmond, Corvallis, Eugene, Grants Pass, Medford, Portland-Vancouver-Hillsboro*, Salem
Pennsylvania (Northeast)	Allentown-Bethlehem-Easton*, Altoona, Erie, Harrisburg-Carlisle, Lancaster, Philadelphia-Camden-Wilmington*, Pittsburgh, Reading, Scranton–Wilkes-Barre–Hazleton, State College, York-Hanover
Rhode Island (Northeast)	Providence-Warwick*
South Carolina (South)	Columbia, Florence, Greenville-Anderson-Mauldin, Hilton Head Island-Bluffton-Beaufort, Myrtle Beach-Conway-North Myrtle Beach*, Spartanburg
Tennessee (South)	Chattanooga*, Clarksville*, Cleveland, Jackson, Johnson City, Kingsport-Bristol-Bristol*, Knoxville, Nashville-Davidson–Murfreesboro–Franklin
Texas (South)	Amarillo, Brownsville-Harlingen, College Station-Bryan, Dallas-Fort Worth-Arlington, El Paso, Killeen-Temple, Laredo, Midland, Texarkana*
Utah (West)	Ogden-Clearfield, Provo-Orem, Salt Lake City, St. George
Virginia (South)	Charlottesville, Harrisonburg, Richmond, Roanoke, Staunton-Waynesboro, Virginia Beach-Norfolk-Newport News*, Winchester*
Washington (West)	Bellingham, Kennewick-Richland, Longview, Olympia-Tumwater, Seattle-Tacoma-Bellevue, Spokane-Spokane Valley, Walla Walla, Yakima
West Virginia (South)	Charleston
Wisconsin (Midwest)	Appleton, Eau Claire, Fond du Lac, Janesville-Beloit, La Crosse-Onalaska*, Madison, Oshkosh-Neenah, Racine

Note: Asterisks indicate that the metropolitan area lies mainly in the indicated state, but parts of it cross state borders.

Table A.2: The list of microplitan statistical areas used.

State (Census Bureau Region)	Region
Arizona (West)	Nogales, Payson, Safford
Arkansas (South)	Batesville, Harrison, Paragould, Russellville, Searcy
California (West)	Clearlake, Eureka-Arcata-Fortuna, Red Bluff, Susanville, Truckee-Grass Valley
Colorado (West)	Durango, Glenwood Springs, Montrose, Sterling
Connecticut (Northeast)	Torrington
Florida (South)	Clewiston, Key West, Lake City, Okeechobee, Palatka
Georgia (South)	Bainbridge, Calhoun, Cedartown, Dublin, Jesup, Moultrie, St. Marys, Thomaston, Tifton, Vidalia, Waycross
Hawaii (West)	Hilo
Idaho (West)	Burley
Illinois (Midwest)	Effingham, Jacksonville
Indiana (Midwest)	Angola, Auburn, Bedford, Connersville, Crawfordsville, Decatur, Frankfort, Greensburg, Huntington, Jasper, Kendallville, Logansport, Madison, Marion, New Castle, North Vernon, Peru, Plymouth, Richmond, Seymour, Vincennes, Wabash, Warsaw, Washington
Kansas (Midwest)	Garden City
Kentucky (South)	Danville, Murray
Louisiana (South)	Opelousas
Maryland (South)	Cambridge, Easton
Massachusetts (Northeast)	Greenfield Town, Vineyard Haven
Michigan (Midwest)	Adrian, Hillsdale, Holland, Ionia, Ludington, Owosso
Minnesota (Midwest)	Owatonna, Willmar, Winona
Mississippi (South)	Cleveland, Columbus, Corinth, Grenada, Laurel, Oxford, Picayune, Tupelo, Vicksburg
Missouri (Midwest)	Mexico
Nebraska (Midwest)	North Platte
Nevada (West)	Elko, Fernley, Gardnerville Ranchos
New Hampshire (Northeast)	Concord, Keene, Laconia
New York (Northeast)	Amsterdam, Batavia, Corning, Cortland, Gloversville, Hudson, Olean, Oneonta, Plattsburgh, Seneca Falls
North Carolina (South)	Albemarle, Morehead City, Sanford, Wilson
Ohio (Midwest)	Ashtabula, Coshocton, Defiance, Findlay, Jackson, New Philadelphia-Dover, Portsmouth, Sandusky, Urbana, Wooster
Oklahoma (South)	Ardmore, Bartlesville, Durant, Enid, Marion, McAlester, Tahlequah
Oregon (West)	Coos Bay, Hermiston-Pendleton, Klamath Falls, Ontario*, Roseburg, The Dalles
Pennsylvania (Northeast)	Indiana, Lock Haven, Oil City, Pottsville
South Carolina (South)	Orangeburg
Tennessee (South)	Cookeville, Lawrenceburg, Lewisburg, Martin, Paris, Sevierville, Shelbyville, Tullahoma-Manchester
Virginia (South)	Danville, Martinsville
Washington (West)	Oak Harbor, Port Angeles, Shelton
Wisconsin (Midwest)	Baraboo, Marinette*, Whitewater-Elkhorn

Note: Asterisks indicate that the micropolitan area lies mainly in the indicated state, but parts of it cross state borders.

Appendix B   The MCMC algorithm

We estimate the model by running an MCMC algorithm. The full conditional posterior distributions are available in closed form implying that we can apply Gibbs sampling to obtain draws from the joint posterior distribution. More specifically, our MCMC algorithm involves the following steps:

(i) Simulate the VAR coefficients a_j $(j = 1, \ldots, J)$ conditional on the factors and remaining model parameters from a multivariate Gaussian distribution that takes a standard form (see, for instance, George et al., 2008, for further information).

(ii) Simulate the latent factors $\boldsymbol{F}_t$ by using forward filtering backward sampling (Carter and Kohn, 1994; Frühwirth-Schnatter, 1994).

(iii) The error variance-covariance matrix $\boldsymbol{\Sigma}_u$ is simulated from an inverted Wishart posterior distribution with degrees of freedom equal to $\nu = v + T$ and scaling matrix equal to $\boldsymbol{P} = \sum_{t=1}^{T}(\boldsymbol{y}_t - \boldsymbol{A}\boldsymbol{x}_t)'(\boldsymbol{y}_t - \boldsymbol{A}\boldsymbol{x}_t) + \underline{\boldsymbol{\Sigma}}$.

(iv) Simulate the factor loadings λ_ℓ $(\ell = 1, \ldots, L)$ from Gaussian posteriors (conditioned on the remaining parameters and the latent factors) by running a sequence of $(R - S)$ unrelated regression models.

(v) The measurement error variances σ_r^2 for $r = S + 1, \ldots, R$ are simulated independently from an inverse Gamma distribution $\sigma_r^2 | \Xi \sim \mathcal{G}^{-1}(\alpha_r, \beta_r)$ with $\alpha_r = \frac{1}{2}T + e_0$ and $\beta_r = \frac{1}{2}\sum_{t=1}^{T}(H_{rt} - \boldsymbol{\Lambda}_{r\bullet}^F\boldsymbol{F}_t - \boldsymbol{\Lambda}_{r\bullet}^M\boldsymbol{M}_t)^2 + e_1$. The notation $\boldsymbol{\Lambda}_{r\bullet}^F$ indicates that the rth row of the matrix concerned is selected and Ξ stands for conditioning on the remaining parameters and the data.

(vi) Simulate τ_{aj}^2 $(j = 1, \ldots, J)$ from a generalized inverted Gaussian distributed posterior distribution with

$$\tau_{aj}^2 | \Xi \sim \mathcal{GIG}\left(\vartheta_a - \frac{1}{2}, a_j^2, \vartheta_a\xi_a\right). \tag{B.1}$$

(vii) Draw ξ_a from a Gamma distributed posterior given by

$$\xi_a | \Xi \sim \mathcal{G}\left(c_0 + \vartheta_a J, c_1 + \frac{1}{2}\vartheta_a \sum_{\ell=1}^{L} \tau_{a\ell}^2\right). \tag{B.2}$$

(viii) Simulate the posterior of $\tau_{\lambda\ell}^2$ $(\ell = 1, \ldots, L)$ from a generalized inverted Gaussian distribution,

$$\tau_{\lambda\ell}^2 | \Xi \sim \mathcal{GIG}\left(\vartheta_\lambda - \frac{1}{2}, \lambda_\ell^2, \vartheta_\lambda\xi_\lambda\right). \tag{B.3}$$

(ix) Finally, the global shrinkage parameter ξ_λ associated with the prior on the factor loadings is simulated from a Gamma distribution,

$$\xi_\lambda | \Xi \sim \mathcal{G}\left(d_0 + \vartheta_\lambda L, d_1 + \frac{1}{2}\vartheta_\lambda \sum_{\ell=1}^{L} \tau_{\lambda\ell}^2\right). \tag{B.4}$$

Steps described above are iterated for 20,000 cycles, where we discard the first 10,000 draws as burn-in.

Appendix C Robustness check – comparing with an identification scheme imposing sign-restrictions

To assess the sensitivity of our results with respect to identification of the monetary policy shock, we use an alternative strategy based on contemporaneous sign restrictions (see Uhlig, 2005; Dedola and Neri, 2007). Technical implementation is achieved by adopting the algorithm proposed in Arias et al. (2014) that collapses to the procedure outlined in Rubio-Ramirez et al. (2010) in the absence of zero restrictions. For each iteration of the MCMC algorithm we draw a rotation matrix and assess whether the following set of sign restrictions is satisfied. Consistent with economic common sense, output (measured in terms of the industrial production index), housing investment (measured in terms of housing starts) and consumer prices (measured in terms of the consumer price index) are bound to increase on impact. Moreover, we assume that the term-spread also widens on impact. Finally, consistent with the normalization adopted when using an external instrument, we assume that the one-year yield declines. If this is the case, we keep the rotation matrix and store the associated structural coefficients, while if the sign restrictions are not met, we reject the draw and repeat the procedure.

The results are displayed in form of a geographic map with a classification scheme that generates class breaks in standard deviation measures above and below the mean, see Fig. C.1. A comparison with Fig. 6 provides evidence of the robustness of our results.
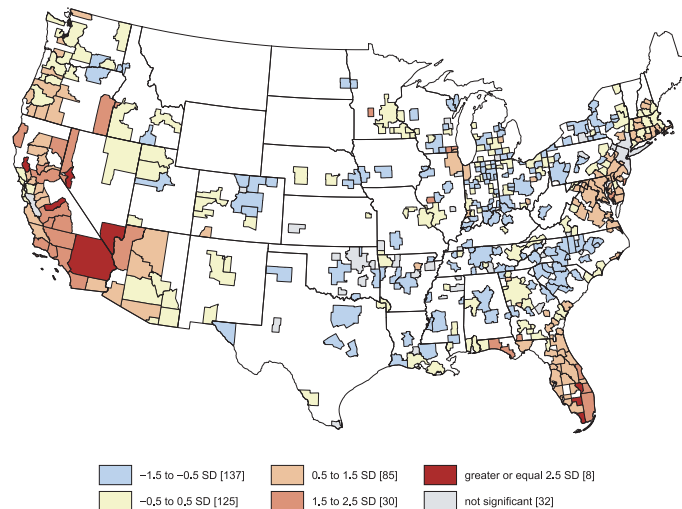

☐ −1.5 to −0.5 SD [137]	☐ 0.5 to 1.5 SD [85]	☐ greater or equal 2.5 SD [8]
☐ −0.5 to 0.5 SD [125]	☐ 1.5 to 2.5 SD [30]	☐ not significant [32]

Fig. C.1: Robustness check: Cumulative responses of regional housing prices to a monetary policy shock identified using sign restrictions.

Notes: Visualization is based on a classification scheme that generates breaks in standard deviation measures. The number of regions is allocated to the classes in squared brackets. The responses based on 10,000 posterior draws have been accumulated. Thinner lines denote the boundaries of the regions, while thicker lines represent US state boundaries. Sample period: 1997:04–2012:06. For the list of regions see Appendix A.