House Price Synchronization across the US States: The Role of Structural Oil Shocks

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Abstract

This paper analyzes the impact of disentangled oil shocks on the synchronization in housing price movements across all the US states plus DC. Using a Bayesian dynamic factor model, the house price movements are decomposed into national, regional, and state-specific factors. We then study the impact of oil-specific supply and demand, inventory accumulation, and global demand shocks on the national factor using linear and nonlinear local projection methods. The impulse response analyses suggest that oil-specific supply and consumption demand shocks are most important in driving the national factor. Moreover, as observed from the regime-specific local projection model, these two shocks are found to have a relatively stronger impact in a bearish rather than a bullish national housing market. Our results have important policy implications.

JEL Classifications: C22, C32, E32, Q02, R30.
Keywords: Bayesian dynamic factor model, Housing market synchronization, Local projection method, Structural oil shocks.

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1. Introduction

There exists a large literature (see for example, Balcilar et al., (2015, 2017) for comprehensive reviews) on the impact of oil price and/or oil shocks on stock price and/or returns of the United States (US). Following this line of research, quite a few recent studies have highlighted the significant role of oil price and/or oil shocks on the movements of US house and real estate price and/or growth rate within a single- or multi-country set-up that includes the US (Chan et al., 2011; Breitenfellner et al., 2015; Antonakakis et al., 2016; Nazlioglu et al., 2016, 2020; Agnello et al., 2017; Killins et al., 2017; Aye et al., 2019). Different from these studies, Grossman et al., (2019) investigated the impact of oil price shocks on house prices in the largest urban centers in Texas to show that oil price shocks have limited pass-through to house prices, with the highest effects found among the most oil-dependent cities. Purely from the portfolio perspective of housing as an asset, the growing focus of oil on US real estate prices or its growth rate, over and above stock returns is an important question since residential real estate represents about 83.98% of total household non-financial assets, 30.64% of total household net worth and 26.64% of household total assets (Financial Accounts of the US, First Quarter, 2020).[1] Moreover, given the dominant historical role of oil price in driving real economic activity of the US (see, Gupta and Wohar (2017) and Plakandaras et al., (2017) for detailed reviews), and house price serving as a leading indicator for the macroeconomy as well (Leamer 2007, 2015; Balcilar et al., 2014; Nyakabawo et al., 2015; Emirmahmutoglu et al., 2016), if oil price movements do impact house prices, then the effect of the former on the economy is likely to be prolonged and persistent. Naturally, the relationship between oil and house prices has important implications for policy design.

The above-mentioned studies dealing with oil and house prices highlight at least six channels underlying their relationship. First, the recessionary impact of oil price increases is likely to dampen the demand for housing, and hence, reduce its price. But in the wake of the "Shale Revolution", increases in oil prices are likely to cause a boom in the economy and thus increase housing market activity and house prices from the demand-side. Second, oil price increases, are likely to increase construction and operational building costs, which might push house prices up due to a decline in the supply of housing. Third, tighter monetary policy to curb the pressure induced by oil price increases on headline inflation is likely to reduce liquidity from the housing market and hence, result in a fall in house prices due to a decline in demand for housing. Fourth, if in the wake of inflation, housing is used as a hedge, the inflationary-effect of oil prices might actually end up increasing housing demand and hence, raise its price. Fifth, following oil price hikes, investment opportunities in the oil sector, due to its financialization (Bonato, 2019), might lead to portfolio allocation away from housing, and thus affect its demand and price negatively. Finally, both the oil and housing markets are likely to be driven by common factors such as economic growth. For instance, a booming economy can increase both house and oil price due to higher demand in the respective sectors.

Given the widespread acceptance that the US housing market is segmented (Apergis and Payne, 2012; Barros et al., 2013; Montañés and Olmos, 2013; Miles, 2015) and hence cannot be examined as a single homogenous market based on aggregate house price (as done by the above-mentioned studies), we analyze the extent of comovement of housing prices across all the US states (plus District of Columbia (DC)), and in turn the role of oil shocks (over and

[1] The reader is referred to https://www.federalreserve.gov/releases/z1/20200611/z1.pdf for further details.

above other standard macroeconomic control variables) in determining this synchronization. The comovement of booms and busts of prices in the housing market and its connections with the macroeconomy (business cycles) has been at the center of discussions among researchers, policymakers, and market participants (Ghent and Owyang, 2010; Christiansen et al., 2019; Sun and Tsang, 2019; Marfatia, 2018), especially in the wake of the Global Financial Crisis, which is known to have its origins in the US subprime mortgage market collapse. For our purpose of studying the nature of synchronization in housing prices across the different states, we use a dynamic factor model (DFM) as discussed in Stock and Watson (1989) to unveil the unobserved forces that lead to the comovement. We use a Bayesian DFM to decompose the movement in real house price growth for all the states in the US plus DC into a national factor which captures the fluctuations that are common across all the states (besides four regional factors which document the common movements in a particular region, and state-specific factors which are unique to each state). This modeling strategy allows us to study the nature of synchronization over time (and the relative importance of each factor in influencing the housing price dynamics in each state). Once we obtain the national housing price factor, realizing that oil price movements impact the economy and asset markets depending on the cause of the oil price change (Kilian, 2009; Kilian and Park 2009; Killins et al., 2017), we analyze the impact of structural oil shocks (oil-specific supply and demand, inventory accumulation, and global demand) rather than oil price per se, on the synchronization of housing prices across the US states by controlling for other important macroeconomic variables. In particular, the four structural oil shocks are used to obtain impulse response functions (IRFs) for the national housing price factor by feeding them into the local projection method (LPM) of Jordà (2005). Understandably, determining the role of oil shocks on the synchronized movements of housing prices in the US is a pertinent question for policymakers in designing their appropriate nationwide response to prevent possible recessionary effect arising due to simultaneous detrimental movements in both oil and the national housing price factor.

To the best of our knowledge, this is the first paper to analyze the role of oil shocks, over and above macroeconomic variables (output growth, inflation and monetary policy), in determining the comovement of housing prices in the US states, based on linear and nonlinear LPM. The nonlinear model allows us to condition the impact of oil shocks on the state of the national factor, and thus captures the possible asymmetry of the shocks across the booms and busts. In the process, our paper builds on the work of Del Negro and Otrok (2007), Marfatia (2018), and Gupta et al., (2020), who too uses a Bayesian DFM to obtain the national factor of house prices associated with the US states, but highlights the role of macroeconomic variables (shocks) in driving the same. The remainder of the paper is organized as follows: Section 2 outlines the data and methodologies involving the Bayesian DFM and the LPM, Section 3 discusses the econometric findings, with Section 4 concluding the paper.

2. Methodologies and Data

In this segment, we briefly discuss the basics of the methodologies of Bayesian DFM and the LPM, as well as the associated data used in the estimation of these two frameworks.

To estimate the unobserved common movement in house prices across states, we decompose the real house price growth rates ($h_{i,t}$) for each i state ($i = 1, \dots, N$) into three latent factors. First, the national factor that is common across all the states. Second, the four regional factors which account for shocks shared by all the states within a census region namely, the Northwest, South, Midwest, and West. Third, the state-specific factor is unique to each state. Note that, in terms of the house price data, we use the seasonally adjusted nominal house price data for the 50 states plus DC derived from the Freddie Mac,[2] with the indices based on an ever-expanding database of loans purchased by either Freddie Mac or Fannie Mae. To obtain the real house prices, the nominal values are deflated by the seasonally adjusted personal consumption expenditures (PCE) deflator derived from the Fred database of the Federal Reserve Bank of St. Louis. To ensure stationarity, required for the estimation of the DFM, we work with month-on-month growth rates of real housing prices.

This decomposition can be represented as follows:

$$h_{i,t} = \beta_i^n f_t^n + \beta_i^r f_t^r + \epsilon_{i,t} \tag{1}$$

where subscript i represents each of the N states. $h_{i,t}$ is the house price in state i at time t. Latent factors, f_t^n and f_t^r, represent the national and regional forces, respectively. The state-specific factor, $\epsilon_{i,t}$, is the idiosyncratic component unique to each state's housing market dynamics. Coefficients β_i^n and β_i^r are the loading of national factor and regional factor, respectively. They show the extent to which each state responds to the national and regional forces. The variable of particular interest used in the application below is the national factor that captures the common movement on house prices across all the states. Following the literature, the three latent factors - f_t^n, f_t^r, and $\epsilon_{i,t}$ - follow an autoregressive (AR) process.

$$f_t^n = \phi_1^n f_{t-1}^n + \ldots + \phi_p^n f_{t-p}^n + v_t^n \qquad v_t^n \sim i.i.d.N(0, \sigma_n^2) \tag{2}$$

$$f_t^r = \phi_1^r f_{t-1}^r + \ldots + \phi_p^r f_{t-p}^r + v_t^r \qquad v_t^r \sim i.i.d.N(0, \sigma_r^2) \tag{3}$$

$$\epsilon_{i,t} = \phi_{i,1}\epsilon_{i,t-1} + \ldots + \phi_{i,q}\epsilon_{i,t-q} + v_{i,t} \qquad v_{i,t} \sim i.i.d.N(0, \sigma_i^2) \tag{4}$$

We undertake above decomposition using the identifying assumption that the shocks are orthogonal contemporaneously as well as at all leads and lags, that is, $E(v_t^n, v_{t-s}^n) = E(v_t^r, v_{t-s}^r) = E(v_{i,t}, v_{i,t-s}) = 0$. We normalize the sign and scale following the strategy established in the literature (Kose, et al., 2003; 2008).[3]

Note that since the factors are latent, the usual regression apparatus is unavailable for estimating the model. Hence, we follow the Bayesian procedure developed by Otrok and Whiteman (1998). We use Markov chain Monte Carlo (MCMC) procedure to successively draw from a series of conditional distributions the complete posterior distribution of all the parameters together with the latent factors. We use a very standard specification for priors, similar to Kose et al., (2003).[4]

We measure the role of the three latent factors in house price movements by variance decomposition estimated from the coefficients. The fraction of variance due to the national (θ_i^n), regional (θ_i^r), and state-specific (θ_i^s) factors are computed as:

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[2] http://www.freddiemac.com/research/indices/house-price-index.page.

[3] In particular, for sign identification, national factor for Alaska is restricted to be positive, whereas the sign restriction on regional factor loadings are chosen arbitrarily. To achieve scale normalizations, we follow Del Negro and Otrok (2007) and restrict σ_n^2 and σ_r^2 to one.

[4] The prior for idiosyncratic state-specific shocks follows an inverse-gamma distribution with parameters 6 and 0.001. The prior for the AR polynomial follows normal distribution with tighter centering on zero (at the geometric rate of 0.5). The prior for factor loadings are standard normal.

$$\theta_i^n = \frac{(\beta_i^n)^2 var(f_t^n)}{var(h_{i,t})}, \qquad \theta_i^r = \frac{(\beta_i^r)^2 var(f_t^r)}{var(h_{i,t})}, \qquad \theta_i^s = \frac{var(\epsilon_{i,t})}{var(h_{i,t})} \tag{5}$$

The variance decomposition shows the proportion of variance in national, regional, and state-specific factor relative to the variance in house price movement of each state.

Next, to examine the impact of various oil shocks on the national factor of real housing price growth rates of the US, we employ the LPM approach of Jordà (2005). The model for computing LPM-based IRFs is as follows:

$$f_{t+s}^n = \alpha_s + \beta_s Oil\ Shock_t + \gamma_s(L) X_{t-1} + \epsilon_{t+s}, \text{ for } s = 0,1,2, \ldots h \tag{6}$$

where s is forecast horizon, h is the maximum length of the forecast horizons,[5] $Oil\ Shock_t$ represents an identified oil shock at time t, X is a vector of control variables, $\gamma_s(L)$ is a polynomial in the lag operator, with a lag-length of 1 chosen by the Akaike Information Criterion (AIC). Our vector of control variables X contains month-on-month growth of the seasonally-adjusted industrial production index, month-on-month PCE deflator-based inflation, and a measure of monetary policy, as well as lags of f_t^n to control for any serial correlation in the variable. The monetary policy decisions are mainly captured by the federal funds rate, but replace it with the Wu and Xia (2016) shadow short rate from 2009 to 2015 to account for the zero lower bound and for the stimulus to the economy provided by the unconventional monetary policy actions that followed the Great Recession. While industrial production and federal funds rate are derived from the FRED database, the shadow short rate is available from the website of Professor Jing Cynthia Wu.[6] The values of the four structural oil-shocks, i.e., the oil supply shock (OSS), economic activity shock (EAS), oil-specific consumption demand shock (OCDS) and oil inventory demand shock (OIDS) are considered one at a time in the model, as part of the oil shock component of equation (6). As far as the data on the four structural oil-shocks are concerned, these are obtained from the structural vector autoregressive (SVAR) model of Baumeister and Hamilton (2019),[7] who formulate a less restrictive framework, than what has been traditionally used in the literature following Kilian (2009), by incorporating uncertainty about the identifying assumptions of the SVAR. In other words, the obtained oil shocks can be considered to be relatively more accurately estimated, with each of them capturing distinct aspects regarding the demand and supply sides of the oil market, i.e., the shocks do not contain overlapping information.

The coefficient β_s measures the response of the f_t^n at time $t + s$ to a one unit increase in the identified oil price shock at time *t*. The IRFs can be constructed as a sequence of β_s estimated in a series of single regressions for each horizon (s). It must be pointed out that, the impulse responses can be computed without specification and estimation of the underlying multivariate dynamic system. The central idea consists in estimating local projections at each period of interest rather than extrapolating into increasingly distant horizons from a given model, as it is done within the context of a vector autoregressive (VAR) model. In other words, the analysis of the impact on f_t^n to the oil shocks does not require identification based on a certain scheme, say for example the Cholesky decomposition.

Besides the benchmark LPM, we use a nonlinear version of the same, as developed by Ahmed and Cassou (2016), characterized by a smooth transition function $F(z_t)$ so that we can capture

[5] h is set to 12, which corresponds to 12-month forecast horizons.
[6] https://sites.google.com/view/jingcynthiawu/shadow-rates?authuser=0.
[7] The data is downloadable from the website of Professor Christiane Baumeister at: https://sites.google.com/site/cjsbaumeister/research.

the high (h)- and low (l)-growth regimes of f_t^n, capturing the observed episodes of booms and bust of the housing prices across the US states over our sample period, while analysing the impact of the oil shocks. The regime-switching model is specified as follows:

$$f_{t+s}^n = \left(1 - F(z_t)\right)\left[\alpha_s^{f^n h} + \beta_s^{f^n h} Oil\,Shock_t + \gamma_s^{f^n h}(L)X_{t-1}\right] + F(z_t)\left[\alpha_s^{f^n l} + \beta_s^{f^n l} Oil\,Shock_t + \gamma_s^{f^n l}(L)X_{t-1}\right] + \epsilon_{t+s}, \text{ for } s = 0,1,2, \dots h \tag{7}$$

$$F(z_t) = \exp(-\gamma z_t)/1 + \exp(-\gamma z_t)\,, \gamma > 0, \tag{8}$$

where z_t is a switching variable (i.e., the national factor of real housing growth rate) that is normalised to have unit variance and zero mean, with positive (negative) z_t indicating high (low) growth periods. Values of $F(z_t)$ close to 0 correspond to periods of high common growth of real housing prices, while values close to 1 is associated with periods of low common growth of the same.

3. Empirical Results

Figure 1 shows the behavior of the national factor over time. We find that in the 1979-1981 period the national factor dived down sharply with a quick recovery in the next four years. This is followed by another housing cycle in the 1982-1990 period. From 1990-2005, the national factor rose steadily until the onset of the financial crisis which had its roots in the housing markets. This pattern of national factor mimics the well-known housing boom of 2005, the following crash in the 2005-2008 period, and slow recovery thereafter (2011-2017).

[INSERT TABLE 1]

The estimates of variance decomposition of the national factor are shown in Table 1. Results show that national factor plays a big role in New Jersey and Pennsylvania in the Northeast; District of Columbia and Delaware in the South; Nebraska, Illinois, Michigan, and Missouri in the Midwest; and Arizona, California, and Nevada in the West. The national factor explains nearly 40-50% of the variation in house prices in these states. These results imply that national-level forces significantly impact coastal America and parts of the Midwest which has some of the biggest financial hubs in the country. In contrast, mountain and central states are less linked with the national forces, and more associated with the regional and state-specific dynamics. Overall, the national factor explains 34% of the real house price growth rates of the Northeast and West census regions states, while for the South this number stands at 38% and the lowest explanatory power is found for the Midwest at 32%. Finally, for the overall US involving the 50 states plus DC, the national factor explains 35% of the variation.

[INSERT FIGURE 1]

In Figure 2, we present the impact of the four structural oil shocks on f_t^n. The figure track the responses calculated by local linear projections to the disaggregated oil shocks on the future path of f_t^n for 1 to 12-month-ahead, along with the 95% confidence bands. Resutls show that f_t^n rises following positive aggregate supply shock, and declines due to a positive global economic activity, oil-specific consumption demand and oil inventory demand shocks. The sign of the effects is generally in line with intuition. A positive aggregate supply shock, which implies an increase in oil production and a decline in oil price enhances the domestic economic activity and increases the national housing price factor due to increased demand. The effect is statistically significant until 5-month-ahead from the point of impact and then from 9-month-ahead and beyond. At the same time, an expansion in global economic activity, which drives oil prices higher, negatively influences the national factor, though the effect is significant only at the 4- and 9-month-ahead forecast horizons. The mild negative effect seems a bit counterintuitive, as this shock is associated with a booming world economy. But the decline in the national housing factor when the global economy is in an upturn could be an indication of portfolio reallocation of investors away from housing into riskier assets or even into oil to derive profit from its increased prices.

As far as the oil-specific consumption demand and inventory demand shocks are concerned, these two oil market innovations are associated with oil price increases and capture precautionary and speculative behaviour in the oil market respectively. These shocks result in a decline in the national real housing price factor due to economic agents considering the two shocks as negative news that adversely affects economic activity and pulls down nationwide housing price due to reduced housing demand. Note that the decline in the housing factor due to slowing down of the economy, could actually result from the Federal reserve's response of an interest rate hike to control the inflationary impact of higher oil prices due to oil-specific consumption demand and inventory demand shocks. But it must be noted, while the negative effect due to oil-specific consumption demand shock is statistically significant till 4-month-ahead and then at the end of the forecast horizon, the same holds true for the inventory demand shock briefly at the 7th month after the shock. Overall, the two most important shocks that seem to drive the national real housing price factor are the oil supply and oil-specific consumption demand shocks. Gupta et al., (2020) in a recent study highlights the important role of the oil supply and oil-specific consumption demand shocks in reducing and increasing uncertainty associated with the real estate sector. This could be another possible channel which results in increasing and decreasing the national factor respectively, given the negative relationship between real estate uncertainty and housing prices (Nguyen Thanh et al., 2018).

[INSERT FIGURE 2]

It must be pointed out that our results are not directly comparable with the literature, which primarily deals with the effects of oil price on overall house price and/or its growth rate, barring to some extent the work of Killins et al., (2017), which does analyze the impact of disaggregated oil shocks (oil supply, global economic activity, and oil-specific consumption demand) on overall US housing price growth rate. These authors found that only oil-specific consumption demand shock significantly affects aggregate housing price growth, but unlike us, the effect is positive rather than negative, and is indeed counter-intuitive especially for an oil-importing country, as discussed in detail in Kilian and Park (2009), associated with the analysis of US stock returns. The difference with our findings could be due to the accurate identification of the oil shocks relative to Killian's (2009) approach adopted by Killins et al., (2017), as highlighted by Baumeister and Hamilton (2019).

In Figure 3 presents the IRFs from the nonlinear LPM, which produces regime-specific impacts of oil shocks on the housing factor, with the high and low regimes characterizing booms and busts respectively. In terms of the sign and the significance of the IRFs of the four oil shocks on the national factor, our results from the linear model generally carry over to the regime-based framework, though the strength of the oil supply and oil-specific consumption demand shocks is found to be stronger during the low(l)-, rather than the high(h)-state. As the low-regime of the national factor is generally aligned (barring the one in 2001) with US recessions (as seen from Figure 1), the stronger effect of these shocks in this regime makes sense. In particular, when the nationwide housing sector is in a bearish phase along with an economic slowdown, a positive supply shock which results in lower oil prices is likely to recover the economy and the housing market more strongly than when the economy is booming and house prices are already high due to higher demand. In the same vein, a negative news shock in the form of an oil price shock during a recession and housing market downturn, is likely to depress the economy and house prices more strongly, than when the US economy is experiencing a bullish housing market and economic expansion.

Besides the importance of the aggregate supply and the oil-specific consumption demand shock, the global economic activity shock is shown to have a marginally significant impact over the 4- to 5-month-ahead horizon over the low-state only, which is understandably the regime that drives the result for this shock in the linear model. Intuitively, the negative effect as explained above for the linear model based on portfolio allocation away from housing investment is likely to hold when housing price is low and oil price rises due to a positive global economic activity shock. Interestingly, the short-lived mild impact of the inventory demand shock observed under the linear model is no longer detected when nonlinearity in the evolution of the housing factor is considered. The stronger effects of oil shocks during bear-regimes of the housing market and the economy in general are in line with the observations drawn by Balcilar et al., (2015) and Holm-Hadulla and Hubrich (2017), derived while analyzing regime-specific oil-stock prices and oil-economy nexuses.

[INSERT FIGURE 3]

4. Conclusions

This paper examines synchronization in house price movements across the US states and the role of disentangled oil shocks over and above macroeconomic variables in driving the comovement. We first use a Bayesian dynamic factor model (DFM) to decompose the house price movements for each state into a national factor that affects all the states, a regional factor capturing linkages of the housing markets at a regional level, and a state-specific factor which captures the idiosyncratic dynamics. We find that the national factor explains 35% of the variation of real housing price growth rates of the 50 states plus DC. Furthermore, we analyze the impact of oil-specific supply and demand, inventory accumulation, and global demand shocks derived rather than oil price per se, on the synchronization of housing prices across the US states, i.e., the national factor, by controlling for other important macroeconomic variables (output growth, inflation and monetary policy rate). To this end, we undertake impulse response analysis derived from a local projection method (LPM). We observe that out of the four structural shocks, oil-specific supply and consumption demand shocks are most important in driving the national factor. While a positive oil supply shock associated with a decline in oil price positively impacts the national factor, the same declines following an oil price increase resulting from the precautionary nature of the oil-specific consumption demand shock. Moreover, using a nonlinear version of the LPM, which allows us to capture the impact of these shocks conditional on the boom and bust regimes of the national real house price growth factor, we find that these two shocks have a stronger impact in a bearish rather than a bullish national housing market. Our results imply that the strength of expansionary (monetary and/or fiscal) policies that would be required to revive the housing market (and possibly real activity) would need to be regime-specific, especially if negative oil supply and oil-specific consumption demand shocks hit the US economy when the housing market is in a downturn.

As part of future research, it would be interesting to extend our analysis to other developed and emerging countries, contingent on the availability of regional house price data.

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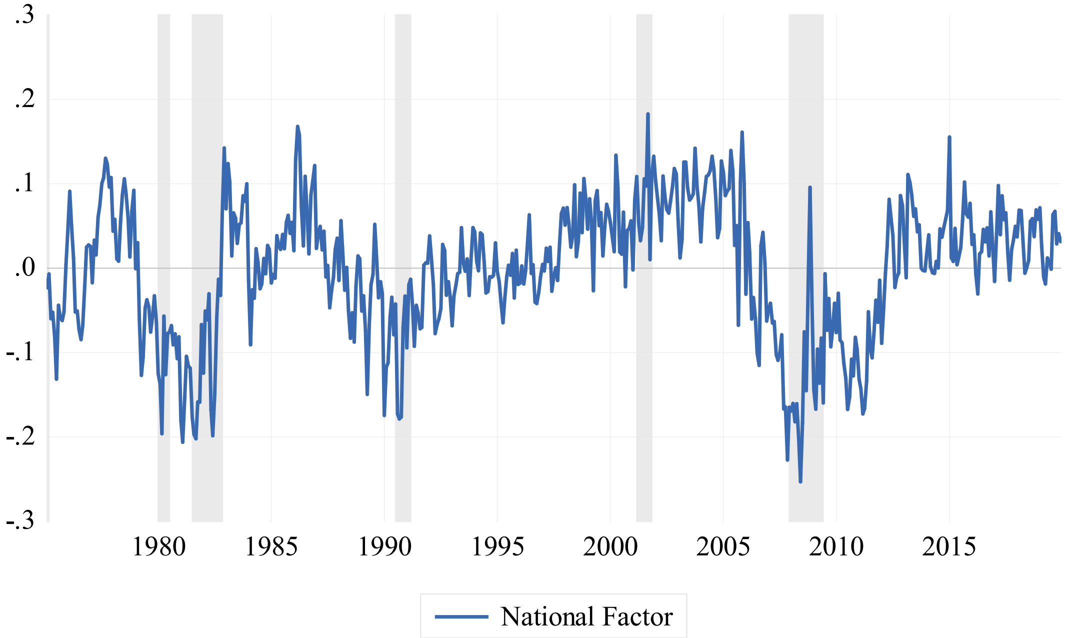
Table 1. Variance Decomposition

State name	National	Regional	State	State name	National	Regional	State
Northeast				Midwest			
Connecticut	0.426	0.057	0.517	Iowa	0.353	0.029	0.618
Massachusetts	0.266	0.004	0.730	Illinois	0.391	0.060	0.548
Maine	0.433	0.027	0.540	Indiana	0.198	0.146	0.655
N. Hampshire	0.251	0.024	0.725	Kansas	0.211	0.002	0.787
New Jersey	0.454	0.018	0.528	Michigan	0.405	0.022	0.572
New York	0.402	0.020	0.578	Minnesota	0.378	0.004	0.618
Pennsylvania	0.023	0.046	0.931	Missouri	0.462	0.002	0.536
Rhode Island	0.440	0.017	0.543	N. Dakota	0.219	0.059	0.721
Vermont	0.386	0.014	0.599	Nebraska	0.506	0.008	0.487
South				Ohio	0.134	0.261	0.605
Alabama	0.402	0.181	0.417	S. Dakota	0.305	0.057	0.639
Arkansas	0.466	0.096	0.438	Wisconsin	0.287	0.068	0.645
DC	0.506	0.195	0.300	West			
Delaware	0.460	0.072	0.468	Alaska	0.444	0.256	0.300
Florida	0.354	0.005	0.641	Arizona	0.516	0.188	0.296
Georgia	0.430	0.067	0.503	California	0.467	0.234	0.300
Kentucky	0.283	0.004	0.713	Colorado	0.417	0.211	0.372
Louisiana	0.433	0.059	0.507	Hawaii	0.386	0.007	0.607
Maryland	0.344	0.004	0.652	Idaho	0.310	0.005	0.685
Mississippi	0.264	0.132	0.604	Montana	0.445	0.027	0.528
N. Carolina	0.435	0.019	0.547	N. Mexico	0.135	0.090	0.774
Oklahoma	0.559	0.002	0.439	Nevada	0.371	0.047	0.582
S. Carolina	0.416	0.006	0.577	Oregon	0.204	0.004	0.792
Tennessee	0.087	0.002	0.911	Utah	0.379	0.033	0.588
Texas	0.353	0.056	0.592	Washington	0.257	0.044	0.698
Virginia	0.375	0.036	0.589	Wyoming	0.107	0.115	0.778
West Virginia	0.345	0.046	0.609				

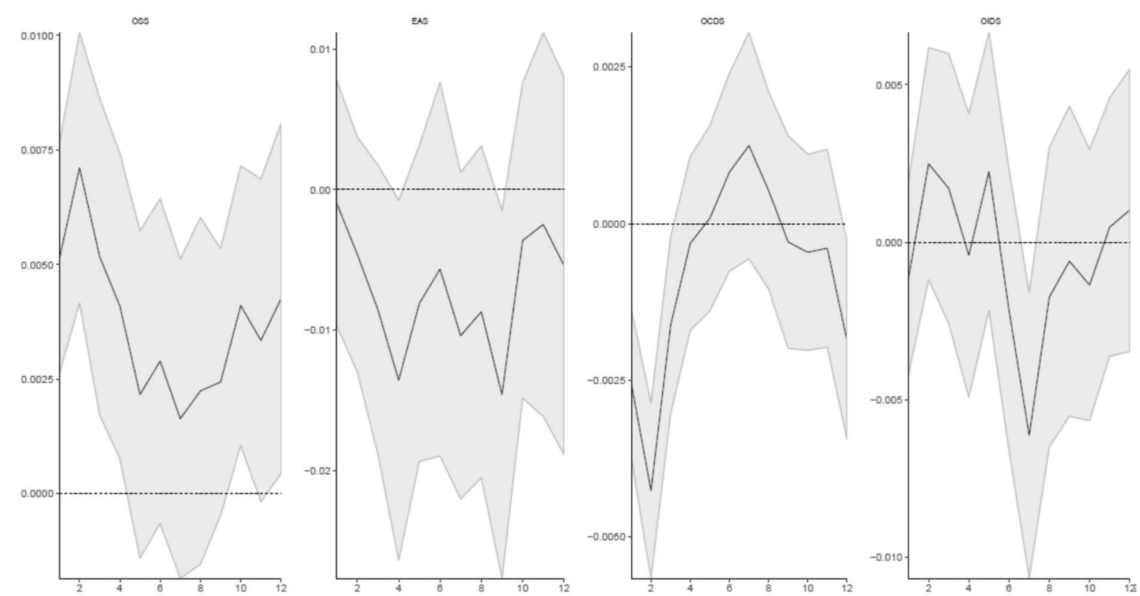
Note: The table reports the variance decomposition of real house price into the national, regional, and state-specific factors.

Figure 1. National Real House Price Growth Factor



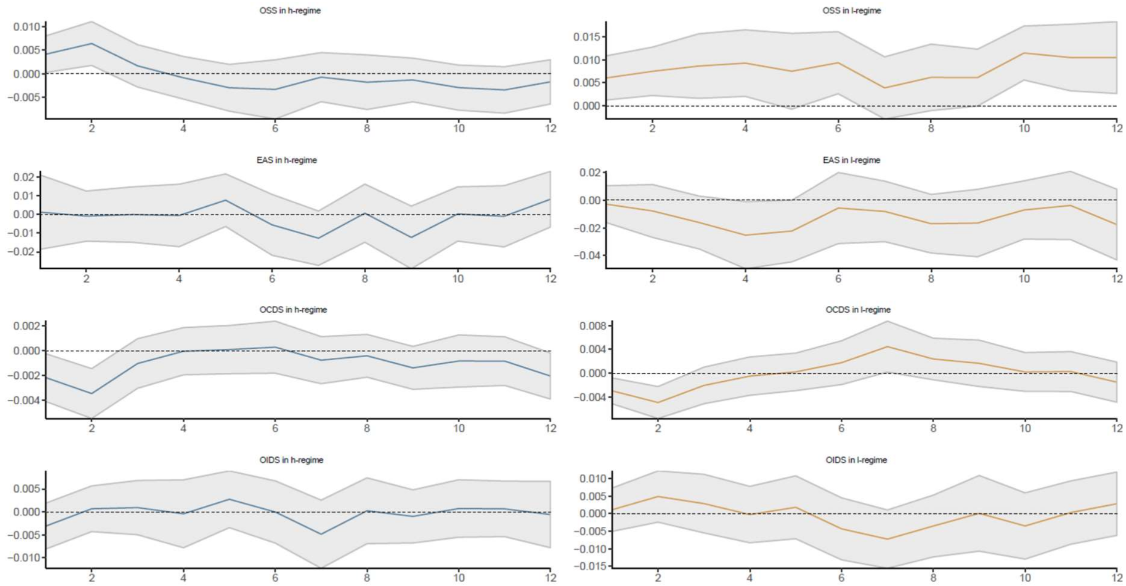
Note: The shaded regions correspond to the NBER recession dates.

Figure 2. Impulse Response Functions of National Factor to Four Structural Oil Shocks using the Linear Local Projection Method



Note: The figures show impulse response of the national factor of real house price growth rates (f_t^n) to a 1 unit increase in disaggregated oil shock. The shaded areas represent the 95% confidence bands; OSS: oil supply shock; EAS: economic activity shock; OCDS: oil-specific consumption demand shock; OIDS: oil inventory demand shock.

Figure 3. Regime-Specific Impulse Response Functions of National Factor to Four Structural Oil Shocks using the Nonlinear Local Projection Method



Note: The figures show impulse response of the national factor of real house price growth rates (f_t^n) to a 1 unit increase in disaggregated oil shock, conditional on the high (h), and low (l)-regime of f_t^n. The shaded areas represent the 95% confidence bands; OSS: oil supply shock; EAS: economic activity shock; OCDS: oil-specific consumption demand shock; OIDS: oil inventory demand shock.