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The impact of monetary policy on local housing markets: Do regulations matter?

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Abstract This paper shows that monetary policy has uneven impacts on local housing markets, and that the magnitude of the impacts are correlated with housing supply regulations. We apply the linearized present value model, which allows the log rent–price ratio to be decomposed into the expected present values of all future real interests rates, real housing premia, and real rent growth, to the housing markets in 23 US metropolitan statistical areas. Based on the indirect inference bias-corrected VAR estimates, we find that MSAs that are more regulated have (i) a higher variance in the log rent–price ratio, (ii) a larger share of the variance explained by real interest rate, and (iii) a stronger impulse response of house price to the real interest rate shock.

Keywords Present value model · Rent–price ratio · Housing supply regulations

JEL Classification E31 · G12 · R31

1 Introduction

Why does monetary policy have an uneven impact on different local housing markets? We show in this paper that the magnitude of the response in each market is highly correlated with its housing regulations. The more regulated the housing market, the larger is the response to a change in monetary policy.

The approach of this paper is straightforward. For each local housing market, we use the linearized present value framework (see Campbell and Shiller 1988) to decom-

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pose the log rent–price ratio into its fundamental components. Then, we look at how the estimated model is related to two different indices of housing supply regulations. There are three major findings in this paper. First, MSAs that have more supply regulations also have a higher variance in the log rent–price ratio. Second, in the variance decomposition of the log rent–price ratio, a larger share of the variance is explained by real interest rate for more regulated MSAs. Third, house prices in more regulated MSAs have a stronger impulse response to the real interest rate shock.

Several studies have suggested that differences in the level and volatility of house price across metropolitan areas are due to differences in regulations (see Mayer and Somerville 2000; Glaeser et al. 2005; Paciorek 2013). Furthermore, the monetary policy transmission to the housing markets also depends on regional heterogeneities, especially in the housing supply elasticity. To quantify the importance of regional heterogeneity in housing markets for the efficacy of monetary policy, Fratantoni and Schuh (2003) construct a heterogeneous-agent VAR in which the parameters and, therefore, impulse responses are time varying. They show that regional housing markets exhibit significant variations in the responses to monetary shocks. By estimating a multi-region dynamic stochastic general equilibrium model, Leung and Teo (2011) find that differences in the price elasticity of housing supply can be related to the regional differences in the monetary propagation mechanism; a region with a higher adjustment cost in housing, i.e., low supply elasticity, responds more to monetary shocks. In this paper, we examine the relationship between housing supply regulations and the efficacy of a monetary policy in affecting the house price. In a work more directly related to this paper, Himmelberg et al. (2005) argue that house price is typically more sensitive to changes in interest rates in cities where housing supply is relatively inelastic. We extend and strengthen their conclusion by providing empirical evidence from the present value framework.

The linearized present value model has been applied to the housing market. The log rent–price ratio is decomposed as an expected value of all future real interest rates, housing premia, and rent growth rates. Each expected component is then estimated through a vector autoregression (VAR) that consists of real interest rate, excess housing return, and rent growth, as well as a set of macroeconomic variables (see Campbell et al. 2009; Fairchild et al. 2015; Ambrose et al. 2013). Since interest rates are highly persistent, traditional maximum likelihood (ML) estimator of such models is likely to suffer from serious small sample bias so that the persistence in interest rates will be spuriously under-estimated, and the impulse responses and variance decompositions can be misleading; see Bauer et al. (2012) who employ the indirect inference estimator (Smith 1993; Gourieroux et al. 1993) for bias-corrected VAR estimates. By utilizing the indirect inference estimator, this paper revisits the application of the linearized present value model in 23 local housing markets and accounts for the volatility of the log rent–price ratio over the period 1978–2014.

2 The linearized present value model

We start with writing real house price at time t as P_t and real rent as R_t and defining the log of gross real return to housing over the period from t to $t + 1$ as:

$$\phi_{t+1} \equiv \ln\left(\frac{P_{t+1} + R_{t+1}}{P_t}\right). \tag{1}$$

By using a first-order Taylor approximation as in Campbell and Shiller (1988), we are able to decompose the log of rent–price ratio at time t, $rp_t \equiv \ln(R_t/P_t) = \ln(R_t) - \ln(P_t) \equiv r_t - p_t$, into two separately identifiable components beyond a constant—the expected present value of all future real rates of housing return and the expected present value of all future real growth in housing rents (see "Appendix 1" for details):

$$rp_t \simeq k + \mathbb{E}_t\left[\sum_{j=0}^{\infty} \rho^j \phi_{t+1+j} - \sum_{j=0}^{\infty} \rho^j \Delta r_{t+1+j}\right]. \tag{2}$$

Here, ϕ_t is the log of gross real return to housing, and Δr_t is the growth rate of real rent. The parameter ρ is a discount factor that is defined as $(1+e^{\overline{rp}})^{-1}$, where $\overline{rp}$ is the long-run log rent–price ratio. The constant k is equal to $(1-\rho)^{-1}[\ln(\rho)+(1-\rho)\ln(1/\rho-1)]$.

By further defining real housing return, ϕ_t, as the sum of real risk-free interest rate, i_t, and real housing premium over that rate, π_t, we can rewrite the log of rent–price ratio as:

$$rp_t \simeq k + \mathbb{E}_t \sum_{j=0}^{\infty} \rho^j i_{t+1+j} + \mathbb{E}_t \sum_{j=0}^{\infty} \rho^j \pi_{t+1+j} - \mathbb{E}_t \sum_{j=0}^{\infty} \rho^j \Delta r_{t+1+j}, \tag{3}$$

or

$$rp_t \simeq k + \mathcal{I}_t + \Pi_t - \mathcal{G}_t, \tag{4}$$

where $\mathcal{I}_t$, Π_t, and $\mathcal{G}_t$ represent the expected present values of all future real interest rates, all future real housing premia, and all future real rent growth, respectively. It is worth noting that Eqs. (2)–(4) do not hold with exact equality, since the second- and higher-order moments have been ignored through a first-order Taylor approximation.

The expectation components, $\mathcal{I}_t$, Π_t, and $\mathcal{G}_t$, can be obtained from estimating a VAR model that consists of real interest rate i_t (a national variable), local real housing premium π_t, local real rent growth Δr_t, as well as national housing premium π_t^{US} and national real rent growth Δr_t^{US}:

$$\mathbf{Z}_t = \Sigma_0 + \Sigma_1 \mathbf{Z}_{t-1} + \Sigma_2 \mathbf{Z}_{t-2} + \epsilon_t, \tag{5}$$

where $\mathbf{Z}_t = (i_t, \pi_t, \Delta r_t, \pi_t^{\text{US}}, \Delta r_t^{\text{US}})'$ is a vector of $K = 5$ state variables. Σ_0 is a column vector of dimension K, each of Σ_1 and Σ_2 is a K-by-K matrix, ϵ_t is an error term.[1]

[1] Engsted et al. (2012) argue that a properly specified VAR for return decomposition should include the log rent–price ratio, rp_t, as one of the state variables together with either real housing return or real rent growth, since log real house price p_t, hence rp_t, is in the time t information set. Given the approximate identity of Eq. (2), a VAR that contains ϕ_t, rp_t, and a set of other state variables is equivalent to a VAR that contains Δr_t, rp_t, and the same set of other variables. As a result, one of the expectations at the right-hand side of Eq. (2) can be directly derived and the other expectation is backed out residually through the approximate identity. Moreover, as long as the VAR is properly specified, i.e., the log rent–price ratio

The VAR(2) model in Eq. (5) can be rewritten in the form of a VAR(1):

$$\begin{pmatrix} \mathbf{Z}_t \\ \mathbf{Z}_{t-1} \end{pmatrix} = \begin{pmatrix} \Sigma_0 \\ \mathbf{0} \end{pmatrix} + \begin{pmatrix} \Sigma_1 & \Sigma_2 \\ \mathbf{I} & \mathbf{0} \end{pmatrix} \begin{pmatrix} \mathbf{Z}_{t-1} \\ \mathbf{Z}_{t-2} \end{pmatrix} + \begin{pmatrix} \epsilon_t \\ \mathbf{0} \end{pmatrix}, \tag{6}$$

or

$$\mathbb{Z}_t = \Gamma_0 + \Gamma \mathbb{Z}_{t-1} + \xi_t, \tag{7}$$

where $\mathbb{Z}_t = (\mathbf{Z}_t', \mathbf{Z}_{t-1}')'$, $\xi_t = (\epsilon_t', \mathbf{0}')'$. Given parameter estimates $\widehat{\Gamma}_0$ and $\widehat{\Gamma}$, the fitted values of $\mathcal{I}_t$, Π_t, and $\mathcal{G}_t$ are the first three elements of $(1-\rho)^{-1}(\mathbf{I} - \rho\widehat{\Gamma})^{-1}\widehat{\Gamma}_0 + (\mathbf{I} - \rho\widehat{\Gamma})^{-1}\widehat{\Gamma}\mathbb{Z}_t$, i.e.,

$$\widehat{\mathcal{I}}_t = e_1' \left[(1-\rho)^{-1}(\mathbf{I} - \rho\widehat{\Gamma})^{-1}\widehat{\Gamma}_0 + (\mathbf{I} - \rho\widehat{\Gamma})^{-1}\widehat{\Gamma}\mathbb{Z}_t \right], \tag{8}$$

$$\widehat{\Pi}_t = e_2' \left[(1-\rho)^{-1}(\mathbf{I} - \rho\widehat{\Gamma})^{-1}\widehat{\Gamma}_0 + (\mathbf{I} - \rho\widehat{\Gamma})^{-1}\widehat{\Gamma}\mathbb{Z}_t \right], \tag{9}$$

$$\widehat{\mathcal{G}}_t = e_3' \left[(1-\rho)^{-1}(\mathbf{I} - \rho\widehat{\Gamma})^{-1}\widehat{\Gamma}_0 + (\mathbf{I} - \rho\widehat{\Gamma})^{-1}\widehat{\Gamma}\mathbb{Z}_t \right], \tag{10}$$

where $e_i, i = 1, 2, 3$, is a column vector of dimension $2K$ with one as the ith element, and zeros otherwise.

According to Eq. (4), the fundamental log rent–price ratio follows

$$\widehat{rp_t} = k + \widehat{\mathcal{I}}_t + \widehat{\Pi}_t - \widehat{\mathcal{G}}_t. \tag{11}$$

The difference between actual log rent–price ratio and the fundamental value is a pricing error (or forecast discrepancy) $\widehat{e}_t$:

$$\widehat{e}_t = rp_t - \widehat{rp_t}. \tag{12}$$

In this paper, we treat the pricing error independently instead of combining it either with the expected future real rent growth as in Campbell et al. (2009) or with the expected future housing premia as in Fairchild et al. (2015).[2]

Footnote 1 continued
is included as a state variable, the return variance decompositions are independent of which component is treated as a residual. However, if all three variables, rp_t, ϕ_t, and Δr_t, are included in the VAR system, the model becomes redundant and there would be a problem of multicollinearity, since knowing any two of the three equations for rp_{t+1}, ϕ_{t+1}, and Δr_{t+1}, one can infer the third, apart from the approximation error. Then, the VAR estimates would be meaningless. Here, in the present work we exclude rp_t from the VAR but include both ϕ_t and Δr_t (of course, real housing return ϕ_t has been split into real interest rate i_t and real housing premium π_t). This exercise does not violate the argument of Engsted et al. (2012) that p_t is in the information set of time t and should be included in some form for the VAR to be legitimate, since the information in p_t has been included in ϕ_t. However, our method is fundamentally different from that of Engsted et al. (2012) in the sense that we are directly estimating the two expectations on the right-hand side of Eq. (2) without arbitrarily assuming that the first-order Taylor approximation-based linearized present value model holds exactly. Over our sample period, the US housing markets experienced large fluctuations both in 1980s and in the recent financial crisis. Ignoring the pricing error that comes from omitting the second- and higher-order moments is problematic. Indeed, as we show in Sects. 3 and 4, the pricing error is sizeable and it accounts for a large fraction of overall volatility of log rent–price ratio.

[2] Campbell et al. (2009) follow the finance literature and treat the present value of future real rent growth as a residual. They attribute most of the variation in log rent–price ratio to changes in expected future real

3 VAR estimation

In this section, we estimate the VAR model in Eq. (7) for each MSA. As Bauer et al. (2012) argue, due to the high persistence in interest rates, the conventional ML estimator of such a model likely suffers from serious small sample bias and tends to display less time-series persistence than does the true process. To improve on the performance of the ML estimator in small samples, they employ the indirect inference estimator that is proposed by Smith (1993) and Gourieroux et al. (1993) (see also Gourieroux et al. 2000).

3.1 Indirect inference estimator

We begin with a brief discussion of the indirect inference estimator. The ML estimator of Γ can be obtained by applying OLS to each equation in the VAR system. Let $\widehat{\Gamma}$ denote the OLS estimator. The value of Γ which leads to a mean of the OLS estimator across a number of residual bootstrapping samples equal to $\widehat{\Gamma}$ is defined as the indirect inference estimator, $\widetilde{\Gamma}$, i.e.,

$$\widetilde{\Gamma} = \underset{\Gamma}{\operatorname{argmin}} \left\| \widehat{\Gamma} - \frac{1}{H} \sum_{h=1}^{H} \widehat{\Gamma}^h(\Gamma) \right\|, \tag{13}$$

where $\widehat{\Gamma}^h(\Gamma)$, $h = 1, \ldots, H$, is a set of OLS estimator if the data are generated under Γ.

Given the presence of high time-series persistence in real interest rate, we adopt the indirect inference estimator for the estimation of VAR models in this paper. In order to find a parameter matrix $\widetilde{\Gamma}$ that satisfies the condition in Eq. (13), we iterate over the bootstrap algorithm provided in Bauer et al. (2012) for 5000 times, discarding the first 500, using 100 bootstrap replications in each iteration and an adjustment parameter of 0.5.

One potential problem with the indirect inference bias correction procedure is that bias-corrected VAR estimates tend to exhibit explosive roots much more frequently than do OLS estimates. Since the VAR is assumed to be stationary, we need to ensure that all eigenvalues of $\widetilde{\Gamma}$ are less than one in modulus. Once the bias-corrected estimates have eigenvalues higher than one in modulus, we shrink the bias estimate toward zero until this restriction is satisfied.

3.2 Data description

The data we use are at the semi-annual frequency, ranging from the second half of 1978 (1978H2) to the second half of 2014 (2014H2). We use the house price index

Footnote 2 continued
rent growth over the period 1997–2007. However, this phenomenon is mostly driven by the behavior of the forecast discrepancy. Fairchild et al. (2015) treat the residual as part of the future real housing premia instead, and they find that the housing premia account for most variation in the rent–price ratio. Attributing the pricing error either to rent growth or housing premium is arbitrary. Based on our discussion in "Appendix 3", this discrepancy should exist and a significant part of it is caused by the existence and the time variation of the second moment of the log rent–price ratio.

published by the Federal Housing Finance Agency (FHFA) as the measure of house prices. House price data are collected at the quarterly frequency and converted to the semi-annual frequency to match other variables. Housing rents come from the rent of primary residence published by the Bureau of Labor Statistics (BLS).[3] The national CPI excluding shelter from BLS is used for obtaining real house price, P_t, and real housing rent, R_t. In order to obtain values of ρ and k in Eq. (2) for each MSA, we use microdata from the 2000 Decennial Census of Housing (DCH) to benchmark the rent–price ratio in 2000; see Davis et al. (2008) and Campbell et al. (2009) for a detailed procedure. Real interest rate, i_t, is the nominal 10-year Treasury yield less the median reading of 10-year inflation expectations from professional forecasters published by Blue Chip Economic Indicators and Livingston Survey. Real housing premium, π_t, is defined as the difference between real return to owner-occupied housing, $\phi_t \equiv \ln[(R_t + P_t)/P_{t-1}]$, and real interest rate, i_t.

Several measures of housing supply regulation have been constructed in the literature. One popular measure is the Wharton Residential Land Use Regulation Index (WRLURI) based on a 2005 survey; see Gyourko et al. (2008) and Saiz (2010). Another comprehensive measure is the index of housing supply regulation created by Saks (2008) for the late 1970s and 1980s. Both WRLURI and Saks-index are standardized to have a mean of zero and a standard deviation of one and are increasing in the degree of regulation. A community with an index value of positive one is one standard deviation above the national mean. Both regulation measures have data available for all the 23 MSAs in our sample, as shown in Table 1. These two measures have a positive correlation of around 0.6.

The WRLURI for each MSA is calculated as the average across communities within that MSA, and therefore, it is possible to be influenced by a few number of observations. For example, the unique observation within Honolulu (HI) makes it the most regulated MSA in our sample, whose regulation level is surprisingly higher than that of New York (NY). Another advantage of the Saks-index relative to WRLURI in our case is that it is based on the information in the first several years of our sample, whereas the later one from a survey in 2005 might be endogenously determined. Moreover, the Saks-index not only accounts for land use regulations. Instead, this combined index is constructed based on a lot of information beyond land use regulations, such as city-level environmental regulations, the importance of imposing controls on new construction as a method of limiting population growth. We show results using both indices.

3.3 Estimation results

We summarize the indirect inference estimation results in Table 2. The left panel shows the estimates of the first-order coefficient matrix, and the right panel shows the second-order coefficient estimates. Rather than reporting the point estimates for each local market, we report the 25th percentile, the median, and the 75th percentile of

[3] Recent work by Ambrose et al. (2015) argues that the BLS rent index fails to adequately capture changes in housing service flow prices and suggests to use a weighted repeat rent index instead. Unfortunately, since the construction of the repeat rent index requires detailed information on rent contracts, available data only cover 11 large MSAs and range from 2003 to 2009 for most of these MSAs.

Table 1 Summary statistics of regulation indices by MSA

MSA	WRLURI	Saks-index	MSA	WRLURI	Saks-index	MSA	WRLURI	Saks-index
Atlanta	0.04	−0.77	Honolulu	2.30	0.88	Philadelphia	1.03	0.47
Boston	1.54	0.86	Houston	−0.33	−0.52	Pittsburgh	0.07	0.26
Chicago	0.07	−1.01	Kansas City	−0.80	−0.95	Portland	0.30	0.94
Cincinnati	−0.55	0.16	Los Angeles	0.52	1.21	San Diego	0.51	1.60
Cleveland	−0.14	−0.25	Miami	0.78	0.47	San Francisco	0.87	2.10
Dallas	−0.33	−1.18	Milwaukee	0.28	0.19	Seattle	0.98	1.48
Denver	0.87	−0.68	Minneapolis	0.33	−0.16	St. Louis	−0.72	−0.66
Detroit	0.10	−0.69	New York	0.65	2.21			

Table 2 Summary of VAR estimation results

Dependent variable	Coefficient on the 1st lag of					Coefficient on the 2nd lag of					$\overline{R}^2$
	i	π	Δr	π^{US}	Δr^{US}	i	π	Δr	π^{US}	Δr^{US}	
i											
25th percentile	1.411	–	–	0.071	−0.084	−0.412	–	–	−0.044	0.025	0.881
Median	1.411	–	–	0.071	−0.084	−0.412	–	–	−0.044	0.025	0.881
75th percentile	1.411	–	–	0.071	−0.083	−0.412	–	–	−0.044	0.025	0.881
π											
25th percentile	−1.719	0.262	−0.225	–	–	0.055	0.208	−0.111	–	–	0.294
Median	−0.742	0.379	0.202	–	–	0.950	0.317	0.042	–	–	0.395
75th percentile	−0.279	0.543	0.349	–	–	1.572	0.372	0.228	–	–	0.468
Δr											
25th percentile	−0.245	−0.040	0.292	–	–	0.007	−0.008	−0.021	–	–	0.094
Median	−0.146	0.000	0.380	–	–	0.228	0.073	0.140	–	–	0.192
75th percentile	0.085	0.032	0.477	–	–	0.518	0.101	0.194	–	–	0.255
π^{US}											
25th percentile	−1.358	–	–	0.228	0.379	1.407	–	–	0.615	−0.433	0.325
Median	−1.357	–	–	0.228	0.379	1.408	–	–	0.615	−0.433	0.325
75th percentile	−1.356	–	–	0.229	0.379	1.409	–	–	0.615	−0.433	0.325
Δr^{US}											
25th percentile	−0.414	–	–	−0.211	0.729	0.547	–	–	0.215	−0.261	0.183
Median	−0.413	–	–	−0.211	0.729	0.547	–	–	0.215	−0.261	0.183
75th percentile	−0.413	–	–	−0.211	0.729	0.548	–	–	0.215	−0.261	0.183
Largest autoregressive root (median across 23 MSAs): 0.988											

The dash symbol implies a constraint of a relevant coefficient of zero imposed on the VAR system

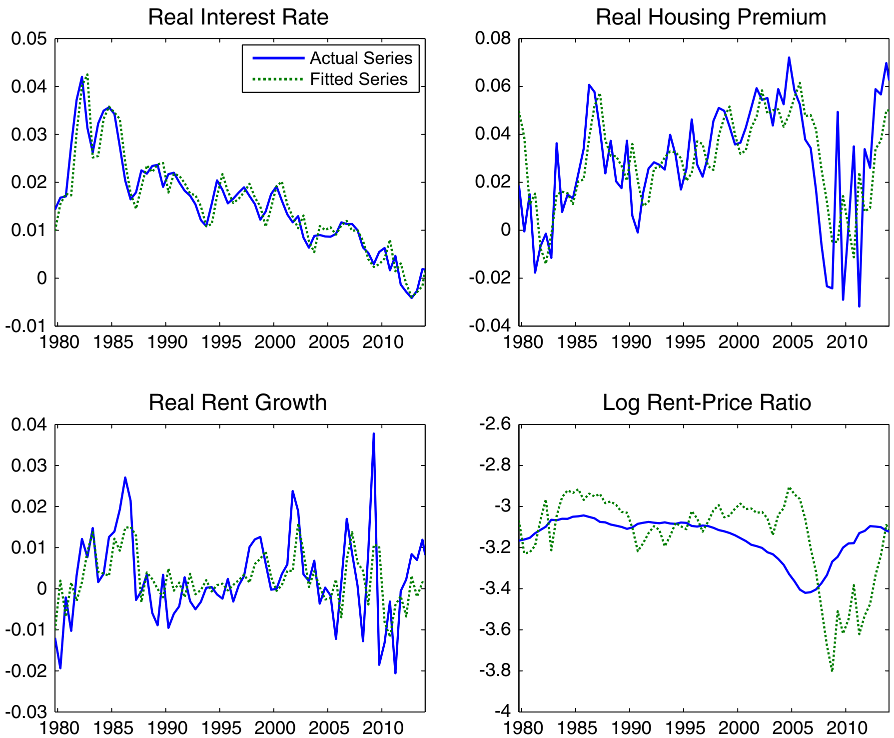

Fig. 1 Actual versus fitted series in the US national market

each parameter estimate across the 23 metropolitan areas. The adjusted R^2 for each equation is listed in the last column.

Since national-level variables i_t, π_t^{US}, and Δr_t^{US} are specified to depend on their own lags only, their parameter estimates are identical across local markets, so that the 25th percentile, the median, and the 75th percentile are all equal (the slight discrepancy is a result of shrinking when the bias-corrected estimates exhibit explosive roots). The indirect inference parameter estimates are considerably different from the ML estimates in Table 7 ("Appendix 2"). The former estimator yields much higher persistence in the VAR system than the later estimator. In particular, the largest autoregressive root has a median of 0.988 versus 0.832. In addition, the indirect inference estimator provides a higher $\overline{R}^2$ for each equation.[4]

In Fig. 1, we plot both the actual and the fitted series of real interest rate, real housing premium, real rent growth, and log rent–price ratio in the US national market.

[4] Campbell et al. (2009) include a set of macroeconomic conditions, including population growth, employment growth, and real personal income growth, in the VAR model. However, macroeconomic variables at MSA-level are only observed at annual frequency and they have to be converted into semi-annual frequency by assuming that their growth rates are constant throughout a given year. To avoid such an arbitrary assumption, we do not include macroeconomic conditions in this paper. In fact, in earlier attempts we find that macroeconomic conditions have little additional explanatory power to the housing variables, once the lags of the housing variables are included.

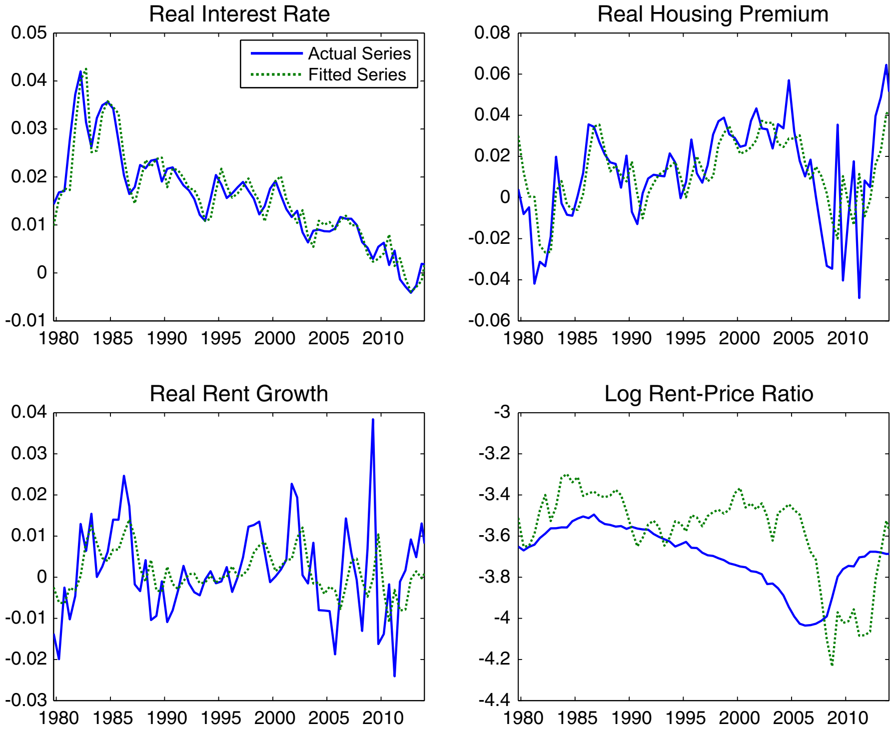

Fig. 2 Actual versus fitted series in the median MSA market

Figure 2 shows an analogous plot for the median metropolitan area. The VAR model with indirect inference bias correction fits the historical data of state variables very well. The fitted log rent–price ratio is slightly larger than the actual ratio on average, i.e., the pricing error is negative. The existence of this negative pricing error is consistent with the fact that the second- and higher-order terms in the Taylor approximation sum to a positive number; see "Appendix 1". Similar plots based on ML estimation results are shown in Figs. 3 and 4. The ML estimates yield a much larger discrepancy (in magnitude) between actual log rent–price ratio and the fitted value.[5]

While the log rent–price ratio implied by the ML estimates is much less volatile than the actual log rent–price ratio, the indirect inference estimator implies a much more volatile fitted log rent–price ratio. Notice that the VAR model is constructed to fit historical patterns of state variables in the system, rather than the VAR-computed log rent–price ratio. We compare the performance of indirect inference estimator versus ML estimator in terms of fitting the historical data of state variables and the log rent–price ratio (rp_t), in the upper panel of Table 3 for the US national market and in the lower panel for the median metropolitan area. The first row of each panel displays the

[5] In stock markets, Campbell and Shiller (1988) reject the null hypothesis that the fitted log dividend–price ratio statistically equals the actual counterpart. Instead, they observe substantial unexplained variation in the log dividend–price ratio.

Table 3 Indirect inference estimator and maximum likelihood estimator

Standard deviation	i_t	π_t	Δr_t	rp_t
USA				
Actually observed	0.998	2.495	1.076	9.974
Implied by IIE	0.992	1.835	0.592	20.320
Implied by MLE	0.920	1.466	0.545	4.230
Metro median				
Actually observed	0.998	3.253	1.425	17.198
Implied by IIE	0.992	2.452	0.832	22.853
Implied by MLE	0.920	2.220	0.800	6.584

All values reported in this table have been multiplied by 100

actually observed standard deviation. The standard deviations of fitted series implied by these two estimators are presented in the second and third row, respectively. The indirect inference estimator implies a standard deviation that is closer to the actual counterpart on all state variables both at the national level and the city level. This comparison suggests that the indirect inference estimator substantially outperforms the ML estimator in the sense that it captures a larger fraction of the variation in state variables and, therefore, yields much more reliable inferences on the impulse response functions in Sect. 5.

4 Volatility decomposition of log rent–price ratio

Given the bias-corrected estimates, $\widehat{\Gamma}_0$ and $\widehat{\Gamma}$, we compute the expected present value of all future real interest rates, $\widehat{\mathcal{I}}_t$, the expected present value of all future housing premia, $\widehat{\Pi}_t$, and the expected present value of all future real rent growth, $\widehat{\mathcal{G}}_t$, according to Eqs. (8)–(10). The pricing error $\widehat{e}_t$ is obtained through Eq. (12). In this section, we examine how each of the four components determines the overall volatility of log rent–price ratio.

4.1 Volatility decomposition and regulations

The linearized present value model discussed in Sect. 3 decomposes the actual log rent–price ratio into four components (ignoring the constant term k henceforth):

$$rp_t = \left[\widehat{\mathcal{I}}_t \quad \widehat{\Pi}_t \quad -\widehat{\mathcal{G}}_t \quad \widehat{e}_t\right]\iota_4, \tag{14}$$

where ι_4 is a 4-by-1 column vector of ones. Notice that, since $\widehat{\mathcal{I}}_t$, $\widehat{\Pi}_t$, $\widehat{\mathcal{G}}_t$, and $\widehat{e}_t$ are correlated with one another, it is meaningless to attribute the volatility of log rent–price ratio to these four components by comparing variations in each single component with variations in the log rent–price ratio. Indeed, as shown in Campbell et al. (2009), the total variations in these four components are more than twice of the variations in the log rent–price ratio over the period 1975–1996, while the covariances among them dampen the fluctuations.

Let $\widehat{\Omega}$ denote the covariance matrix of the above four components. A simple Cholesky decomposition allows us to rewrite the log rent–price ratio as the sum of four orthogonal components:

$$\begin{aligned} rp_t &= \left[\widehat{\mathcal{I}}_t' \quad \widehat{\Pi}_t' \quad -\widehat{\mathcal{G}}_t' \quad \widehat{e}_t'\right] P\iota_4, \\ &= \left[\widehat{\mathcal{I}}_t' \quad \widehat{\Pi}_t' \quad -\widehat{\mathcal{G}}_t' \quad \widehat{e}_t'\right] [P_1 \quad P_2 \quad P_3 \quad P_4]', \end{aligned} \tag{15}$$

where P is a 4-by-4 upper triangular matrix which satisfies $P'P = \widehat{\Omega}$, and P_i, $i = 1, \ldots, 4$, is the sum of all elements in row i of matrix P. Thus,

$$\mathrm{var}(rp_t) = P_1^2 \mathrm{var}\left(\widehat{\mathcal{I}}_t'\right) + P_2^2 \mathrm{var}\left(\widehat{\Pi}_t'\right) + P_3^2 \mathrm{var}\left(\widehat{\mathcal{G}}_t'\right) + P_4^2 \mathrm{var}\left(\widehat{e}_t'\right). \tag{16}$$

Notice that each of the orthogonalized terms, $\widehat{\mathcal{I}}_t'$, $\widehat{\Pi}_t'$, $-\widehat{\mathcal{G}}_t'$ and $\widehat{e}_t'$, has a standardized variance of one. Hence, P_i^2, $i = 1, \ldots, 4$, stands for the variation of log rent–price ratio that is attributable to the ith component.

The decomposition results are presented in the left panel of Table 4 in which MSAs are ordered by their Sakes-index for a better expository purpose. We also conduct a similar decomposition for the fitted log rent–price ratio and present the results in the right panel. The bottom rows of the table show the correlations of variances and variance shares with both regulation indices.[6]

At the national level, the pricing error accounts for about 82% of the volatility of log rent–price ratio. Expected future real interest rates accounts for 16% and the other two expectation components do not contribute much. At the metropolitan level, the fraction of variation in log rent–price ratio that is attributable to the pricing error is between 35 and 93% across the 23 MSAs, with a median of 69% (see "Appendix 3" for a discussion on pricing error). Expected future real interest rates is the second largest source and accounts for 23% of the overall volatility.

The variation in log rent–price ratio exhibits a significantly positive correlation with both regulation indices, which is in line with Mayer and Somerville (2000), Glaeser et al. (2005), and Paciorek (2013). In more regulated markets, expected future real interest rates accounts for a significantly larger fraction of volatility of log rent–price ratio and the pricing error accounts for a smaller fraction. Apart from the pricing error, most of the variation in the *fitted* log rent–price ratio is accounted for by the expected future real interest rates, which contributes 70% at the national level and 85% at the metropolitan level. This fraction is much higher than what previous literature suggests (which does not correct for the bias in the VAR). Again, MSAs with more regulations have a more volatile fitted rent–price ratio, and real interest rate also contributes more to the variance.

[6] The result of Cholesky decomposition depends on the ordering of the variables. In our framework, $\widehat{\mathcal{I}}_t$ is the estimate of a national-level variable $\mathcal{I}_t$ which does not depend on any local conditions, and $\widehat{e}_t$ is a pricing error which is supposed to depend on all other three components. As a result, we fix $\widehat{\mathcal{I}}_t$ as the first variable and $\widehat{e}_t$ as the last one, and change the ordering of $\widehat{\Pi}_t$ and $\widehat{\mathcal{G}}_t$.

Table 4 Volatility decomposition of the log rent–price ratio

	Variance	Variance shares (%)						Variance	Variance shares (%)				
	rp_t	$\widehat{\mathcal{I}}_t$	$\widehat{\Pi}_t(1)$	$\widehat{\Pi}_t(2)$	$\widehat{\mathcal{G}}_t(1)$	$\widehat{\mathcal{G}}_t(2)$	$\widehat{e}_t$	$\widehat{rp}_t$	$\widehat{\mathcal{I}}_t$	$\widehat{\Pi}_t(1)$	$\widehat{\Pi}_t(2)$	$\widehat{\mathcal{G}}_t(1)$	$\widehat{\mathcal{G}}_t(2)$
USA	0.010	15.992	1.297	1.507	0.246	0.036	82.465	0.041	69.361	30.478	23.795	0.161	6.845
Dallas	0.006	4.125	3.458	1.791	0.925	2.592	91.492	0.011	74.747	24.436	3.776	0.817	21.477
Chicago	0.016	11.430	1.769	6.635	5.256	0.390	81.545	0.111	85.502	14.460	1.603	0.038	12.895
Kansas City	0.007	2.759	3.252	2.195	0.255	1.313	93.733	0.004	11.222	83.508	87.072	5.270	1.706
Atlanta	0.008	10.788	0.020	5.488	5.800	0.332	83.391	0.007	3.574	92.475	22.434	3.951	73.992
Detroit	0.044	0.423	1.721	10.555	12.142	3.309	85.713	0.186	74.919	25.065	0.766	0.016	24.315
Denver	0.019	33.807	1.826	1.204	0.540	1.162	63.826	0.005	0.008	85.217	40.596	14.775	59.396
St. Louis	0.016	41.399	0.831	0.993	3.661	3.499	54.109	0.083	95.453	4.393	4.458	0.153	0.088
Houston	0.010	0.004	8.933	0.725	0.474	8.682	90.589	0.029	95.518	2.681	3.875	1.800	0.606
Cleveland	0.009	0.277	3.431	0.477	3.337	6.291	92.956	0.030	94.230	5.727	1.825	0.044	3.946
Minneapolis	0.032	26.241	0.071	0.007	6.539	6.603	67.149	0.058	78.431	20.889	19.495	0.680	2.074
Cincinnati	0.007	9.787	3.625	0.043	7.309	10.891	79.280	0.026	96.287	3.533	3.325	0.180	0.388
Milwaukee	0.025	36.893	4.514	8.702	6.994	2.806	51.599	0.054	91.368	8.383	6.286	0.250	2.346
Pittsburgh	0.012	54.381	4.877	6.463	5.425	3.838	35.318	0.036	95.888	3.673	3.207	0.439	0.905
Miami	0.053	19.118	2.271	13.938	24.944	13.277	53.668	0.031	51.104	48.096	15.976	0.800	32.920
Philadelphia	0.030	55.182	1.588	2.635	1.225	0.178	42.006	0.147	92.278	7.607	3.341	0.115	4.381
Boston	0.047	25.958	0.875	1.870	2.456	1.462	70.711	0.587	94.498	5.470	0.368	0.032	5.133
Honolulu	0.053	51.317	7.285	2.857	6.022	10.451	35.375	0.015	92.955	6.446	1.938	0.600	5.107
Portland	0.065	47.671	2.285	6.589	4.348	0.044	45.696	0.113	73.764	26.117	8.680	0.119	17.557

Table 4 continued

	Variance	Variance shares (%)						Variance	Variance shares (%)				
	rp_t	$\widehat{\mathcal{I}}_t$	$\widehat{\Pi}_t(1)$	$\widehat{\Pi}_t(2)$	$\widehat{\mathcal{G}}_t(1)$	$\widehat{\mathcal{G}}_t(2)$	$\widehat{e}_t$	$\widehat{rp}_t$	$\widehat{\mathcal{I}}_t$	$\widehat{\Pi}_t(1)$	$\widehat{\Pi}_t(2)$	$\widehat{\mathcal{G}}_t(1)$	$\widehat{\mathcal{G}}_t(2)$
Los Angeles	0.046	23.059	7.598	0.067	0.663	8.195	68.679	0.103	34.433	65.010	13.416	0.557	52.150
Seattle	0.059	46.763	9.261	2.053	0.737	7.945	43.240	0.071	87.742	11.739	8.138	0.519	4.120
San Diego	0.040	15.560	1.438	5.090	3.688	0.037	79.313	0.135	62.100	36.683	20.391	1.217	17.509
San Francisco	0.059	40.552	0.389	5.018	14.683	10.054	44.376	0.049	30.336	67.886	46.418	1.778	23.247
New York	0.040	17.811	5.015	0.100	2.281	7.195	74.893	1.231	93.715	6.271	1.561	0.013	4.723
Metro median	0.030	23.059	2.285	2.195	3.688	3.499	68.679	0.054	85.502	14.460	4.458	0.519	5.107
Corr. w . Saks-index	0.747	0.443	0.224	−0.037	0.126	0.357	−0.490	0.476	0.131	−0.110	−0.093	−0.292	−0.113
	[0.000]	[0.017]	[0.152]	[0.434]	[0.283]	[0.047]	[0.009]	[0.011]	[0.276]	[0.309]	[0.337]	[0.088]	[0.304]
Corr. w . WRLURI	0.697	0.537	0.126	0.087	0.135	0.191	−0.569	0.236	0.049	−0.054	−0.180	0.016	0.101
	[0.000]	[0.004]	[0.283]	[0.347]	[0.270]	[0.192]	[0.002]	[0.139]	[0.413]	[0.404]	[0.205]	[0.471]	[0.323]

(1) and (2) correspond to the two types of ordering. p values in brackets

5 House price volatility and the monetary shock

In this section, we examine the impact of a shock to real interest rate on housing markets and the local heterogeneity in the transmission of a monetary policy.

5.1 Orthogonal impulse response functions

After obtaining the bias-corrected estimates of Σ_1 and Σ_2, labeled $\widehat{\Sigma}_1$ and $\widehat{\Sigma}_2$, we can derive the responses of $\widehat{\mathbf{Z}}_{t+\tau}$, $\tau \geq 0$, to a one-unit shock in $\mathbf{Z}_t$ as:

$$\widehat{\mathrm{IR}}_{\mathbf{Z},\mathbf{Z},t+\tau} = \frac{\partial \widehat{\mathbf{Z}}_{t+\tau}}{\partial \widehat{\epsilon}_t'} = \begin{cases} \mathbf{I} & \text{if } \tau = 0, \\ \widehat{\Sigma}_1 & \text{if } \tau = 1, \\ \frac{\partial \widehat{\mathbf{Z}}_{t+\tau-1}}{\partial \widehat{\epsilon}_t'} \widehat{\Sigma}_1 + \frac{\partial \widehat{\mathbf{Z}}_{t+\tau-2}}{\partial \widehat{\epsilon}_t'} \widehat{\Sigma}_2 & \text{if } \tau \geq 2, \end{cases} \tag{17}$$

where the three subscripts of the $K \times K$ impulse response matrix ("$\widehat{\mathrm{IR}}$") stand for response variables, impulse variables, and τ-period ahead prediction.

The Cholesky decomposition allows us to focus exclusively on the impact of a shock to one of the state variables, holding all others constant. The orthogonal impulse response functions are obtained by post-multiplying the impulse responses in Eq. (17) with a lower triangular matrix $\widehat{P}$ satisfying $\widehat{\Sigma}_\epsilon = \widehat{P}\widehat{P}'$, where $\widehat{\Sigma}_\epsilon$ is the covariance matrix of the residual, $\widehat{\epsilon}$, i.e.,

$$\widehat{\mathrm{OIR}}_{\mathbf{Z},\mathbf{Z},t+\tau} = \widehat{\mathrm{IR}}_{\mathbf{Z},\mathbf{Z},t+\tau} \widehat{P}. \tag{18}$$

The jth, $j = 1, \ldots, K$, column of the orthogonal impulse response matrix ("$\widehat{\mathrm{OIR}}$") represents the responses of all K state variables to an orthogonal impulse in the jth variable. The responses to an orthogonal impulse in real interest rate are represented by the first column of the orthogonal impulse response matrix and hence can be written as:

$$\widehat{\mathrm{OIR}}_{\mathbf{Z},i,t+\tau} = \widehat{\mathrm{OIR}}_{\mathbf{Z},\mathbf{Z},t+\tau} e_1, \tag{19}$$

the jth, $j = 1, \ldots, K$, row of which represents the response of jth state variable to an orthogonal impulse in real interest rate, e.g.,

$$\widehat{\mathrm{OIR}}_{z_j,i,t+\tau} = e_j' \widehat{\mathrm{OIR}}_{\mathbf{Z},i,t+\tau}, \tag{20}$$

with

$$z_1 = i, z_2 = \pi, z_3 = \Delta r.$$

Here, e_j, $j = 1, 2, 3$, is a column vector of dimension K with one as the jth element, and zeros otherwise.

Based on the response functions of state variables to an orthogonal impulse in real interest rate, we are able to obtain the orthogonal impulse response functions of VAR-computed variables, including the expected future real interest rates $\widehat{\mathcal{I}}_t$, expected future real housing premia $\widehat{\Pi}_t$, expected future real rent growth $\widehat{\mathcal{G}}_t$, VAR-computed log rent–price ratio $\widehat{rp}_t$, log real housing rent $\widehat{r}_t$, and log real house price $\widehat{p}_t$; see "Appendix 4" for a detailed derivation.

The standard error estimates of the orthogonal impulse responses are produced by bootstrapping from 1000 simulated realizations. More specifically, we generate 1000 replications $\widehat{\mathrm{OIR}}^*_{\mathbf{Z},i,t+\tau}$ of the orthogonal impulse response estimates for state variables, conditional on $\widehat{\Gamma}_0$, $\widehat{\Gamma}$, and the covariance matrix of $\widehat{\epsilon}_t$, as though they were the population values. Each bootstrap sample of the residuals is drawn from a joint normal distribution. Replications $\widehat{\mathrm{OIR}}^*_{\mathcal{I},i,t+\tau}$, $\widehat{\mathrm{OIR}}^*_{\Pi,i,t+\tau}$, $\widehat{\mathrm{OIR}}^*_{\mathcal{G},i,t+\tau}$, $\widehat{\mathrm{OIR}}^*_{rp,i,t+\tau}$, $\widehat{\mathrm{OIR}}^*_{r,i,t+\tau}$, and $\widehat{\mathrm{OIR}}^*_{p,i,t+\tau}$ are derived based on Eqs. (28) through (32) in Appendix". It is worth noting that the bootstrapped standard error estimates for VAR-computed variables are usually large due to the presence of uncertainty, both in the coefficient matrices and in the state variables (see Campbell and Shiller 1987; Engsted and Tanggaard 2001; Campbell and Vuolteenaho 2004). As in Campbell and Vuolteenaho (2004), we bootstrap the standard error estimates by generating orthogonal impulse responses for the VAR-computed variables within each simulated realization conditional on the estimated coefficient matrix.[7]

5.2 Impulse responses and regulations

Since we use data at semi-annual frequency, each period stands for half a year. Table 5 shows the 0- to 8-period ahead orthogonal impulse responses of the fitted log real rent and the fitted log real price to a one-standard-deviation real interest rate shock for the US national market and metropolitan areas (with the bootstrapped standard errors in parenthesis). In most markets, the fitted log real rent does not significantly respond to the real interest rate shock, but the fitted log real price responds negatively. The response of log real price has a median of -0.043. Dallas (TX) and Houston (TX) are the only two exceptions where a raise in real interest rate induces a significant increase in house price.[8]

We present the correlation of the impulse responses of log real rent and log real price with housing regulations in Table 6. The impulse responses of log real price exhibit a negative correlation with both regulation indices, indicating that house price is more responsive to a change in real interest rate in more regulated markets. The result is robust when we discard the recent recession and focus particularly on the period 1978H2:2006H2.[9] The intuition of this result is straightforward: Housing regulations

[7] Such standard error estimates do not incorporate full estimation of uncertainty of the impulse responses of VAR-computed variables. In order to capture full estimation uncertainty, one should estimate the VAR and the orthogonal impulse responses separately for each simulated realization.

[8] Dallas (TX) and Houston (TX) are the only two housing markets that experienced a large price fall in 1980s and have not fully recovered. It is reasonable that the linearized present value model fails to capture the sharp fluctuation in these markets, since the model depends on a first-order approximation. If the data for the 1980s are discarded, we are able to obtain more sensible results.

[9] A major difference between the BLS rent index and the repeat rent index suggested by Ambrose et al. (2015) is that the later shows a substantial decrease in rents following the onset of the housing crisis in 2007 while the former does not. The robustness of our result over the non-crisis subsample period 1978H2:2006H2 indicates that the discrepancy between these two rent indexes is not likely to affect the findings of this paper.

Table 5 Orthogonal impulse responses to a real interest rate shock

Response variable Horizon (half a year)	0	1	2	3	4	5	6	7	8
Panel (1): log real rent									
USA	−0.003 (0.001)	−0.004 (0.002)	−0.004 (0.002)	−0.004 (0.003)	−0.003 (0.003)	−0.002 (0.003)	−0.001 (0.004)	0.000 (0.004)	0.001 (0.004)
Dallas	−0.003 (0.002)	−0.004 (0.003)	−0.004 (0.003)	−0.004 (0.004)	−0.003 (0.004)	−0.003 (0.005)	−0.002 (0.005)	−0.002 (0.006)	−0.002 (0.007)
Chicago	−0.002 (0.001)	−0.003 (0.002)	−0.003 (0.003)	−0.002 (0.003)	−0.001 (0.003)	0.000 (0.004)	0.002 (0.004)	0.003 (0.005)	0.005 (0.005)
Kansas City	−0.002 (0.002)	−0.001 (0.003)	0.000 (0.003)	0.002 (0.003)	0.003 (0.004)	0.005 (0.004)	0.007 (0.005)	0.008 (0.005)	0.009 (0.006)
Atlanta	−0.003 (0.002)	−0.005 (0.003)	−0.006 (0.004)	−0.005 (0.005)	−0.004 (0.005)	−0.002 (0.006)	0.000 (0.007)	0.002 (0.007)	0.005 (0.008)
Detroit	−0.002 (0.002)	−0.006 (0.003)	−0.006 (0.003)	−0.007 (0.004)	−0.007 (0.004)	−0.007 (0.005)	−0.006 (0.005)	−0.006 (0.006)	−0.005 (0.006)
Denver	−0.003 (0.002)	−0.003 (0.003)	−0.003 (0.004)	−0.004 (0.005)	−0.004 (0.005)	−0.005 (0.006)	−0.006 (0.007)	−0.007 (0.007)	−0.008 (0.008)
St. Louis	−0.001 (0.002)	−0.001 (0.002)	−0.001 (0.003)	0.000 (0.003)	0.001 (0.004)	0.002 (0.004)	0.003 (0.005)	0.004 (0.005)	0.005 (0.006)
Houston	−0.004 (0.002)	−0.002 (0.003)	−0.001 (0.004)	−0.001 (0.005)	−0.001 (0.005)	−0.003 (0.006)	−0.004 (0.007)	−0.006 (0.007)	−0.008 (0.008)
Cleveland	−0.004 (0.002)	−0.005 (0.003)	−0.005 (0.003)	−0.004 (0.004)	−0.003 (0.004)	−0.001 (0.005)	0.000 (0.005)	0.002 (0.006)	0.003 (0.006)
Minneapolis	−0.003 (0.002)	−0.004 (0.003)	−0.004 (0.003)	−0.004 (0.004)	−0.002 (0.004)	−0.001 (0.005)	0.000 (0.005)	0.001 (0.006)	0.003 (0.006)
Cincinnati	−0.002 (0.002)	−0.005 (0.002)	−0.006 (0.003)	−0.006 (0.003)	−0.006 (0.003)	−0.005 (0.004)	−0.004 (0.004)	−0.003 (0.005)	−0.003 (0.005)
Milwaukee	−0.002 (0.002)	−0.003 (0.002)	−0.002 (0.003)	0.000 (0.003)	0.002 (0.004)	0.004 (0.004)	0.006 (0.005)	0.007 (0.005)	0.009 (0.006)
Pittsburgh	−0.004 (0.002)	−0.007 (0.002)	−0.007 (0.003)	−0.007 (0.003)	−0.006 (0.004)	−0.006 (0.004)	−0.005 (0.005)	−0.004 (0.005)	−0.004 (0.006)
Miami	−0.002 (0.002)	−0.003 (0.003)	−0.006 (0.003)	−0.007 (0.004)	−0.009 (0.004)	−0.011 (0.005)	−0.013 (0.006)	−0.015 (0.006)	−0.016 (0.007)
Philadelphia	−0.001 (0.002)	−0.001 (0.002)	0.000 (0.003)	0.001 (0.003)	0.003 (0.004)	0.005 (0.004)	0.008 (0.005)	0.010 (0.005)	0.012 (0.006)
Boston	−0.002 (0.002)	−0.001 (0.003)	−0.001 (0.003)	0.000 (0.004)	0.001 (0.005)	0.002 (0.005)	0.003 (0.006)	0.004 (0.006)	0.006 (0.007)
Honolulu	−0.002 (0.002)	−0.002 (0.003)	−0.002 (0.004)	−0.001 (0.004)	−0.001 (0.005)	0.000 (0.006)	0.001 (0.006)	0.003 (0.007)	0.004 (0.008)
Portland	−0.003 (0.002)	−0.006 (0.003)	−0.009 (0.003)	−0.011 (0.003)	−0.012 (0.004)	−0.013 (0.005)	−0.013 (0.005)	−0.014 (0.006)	−0.014 (0.006)

Table 5 continued

Response variable Horizon (half a year)	0	1	2	3	4	5	6	7	8
Los Angeles	−0.002 (0.002)	−0.003 (0.003)	−0.003 (0.003)	−0.003 (0.004)	−0.002 (0.004)	−0.001 (0.005)	0.000 (0.005)	0.001 (0.006)	0.002 (0.006)
Seattle	−0.003 (0.002)	−0.005 (0.003)	−0.007 (0.003)	−0.010 (0.004)	−0.012 (0.005)	−0.014 (0.005)	−0.015 (0.006)	−0.017 (0.007)	−0.018 (0.007)
San Diego	−0.003 (0.002)	−0.005 (0.003)	−0.006 (0.004)	−0.005 (0.004)	−0.004 (0.005)	−0.002 (0.006)	0.000 (0.006)	0.003 (0.007)	0.006 (0.007)
San Francisco	−0.002 (0.002)	−0.004 (0.003)	−0.005 (0.004)	−0.004 (0.005)	−0.003 (0.005)	−0.001 (0.006)	0.001 (0.007)	0.004 (0.007)	0.006 (0.008)
New York	−0.004 (0.002)	−0.006 (0.002)	−0.007 (0.003)	−0.008 (0.003)	−0.007 (0.004)	−0.007 (0.004)	−0.006 (0.005)	−0.005 (0.005)	−0.003 (0.006)
Metro median	−0.002 (0.002)	−0.004 (0.003)	−0.004 (0.003)	−0.004 (0.004)	−0.003 (0.004)	−0.002 (0.005)	0.000 (0.005)	0.001 (0.006)	0.003 (0.006)
Panel (2): log real price									
USA	−0.017 (0.014)	−0.021 (0.016)	−0.025 (0.012)	−0.028 (0.011)	−0.030 (0.010)	−0.032 (0.010)	−0.033 (0.010)	−0.034 (0.011)	−0.034 (0.011)
Dallas	0.040 (0.006)	0.040 (0.007)	0.038 (0.005)	0.038 (0.005)	0.037 (0.006)	0.036 (0.006)	0.035 (0.007)	0.034 (0.007)	0.033 (0.008)
Chicago	−0.061 (0.023)	−0.066 (0.026)	−0.071 (0.018)	−0.074 (0.016)	−0.077 (0.016)	−0.078 (0.016)	−0.079 (0.017)	−0.079 (0.018)	−0.079 (0.020)
Kansas City	0.007 (0.005)	0.005 (0.007)	0.004 (0.005)	0.003 (0.004)	0.003 (0.004)	0.003 (0.005)	0.003 (0.005)	0.004 (0.005)	0.005 (0.005)
Atlanta	0.014 (0.008)	0.014 (0.008)	0.013 (0.007)	0.014 (0.007)	0.014 (0.007)	0.015 (0.007)	0.015 (0.007)	0.016 (0.007)	0.017 (0.008)
Detroit	−0.074 (0.031)	−0.085 (0.037)	−0.090 (0.028)	−0.098 (0.025)	−0.102 (0.024)	−0.107 (0.025)	−0.109 (0.026)	−0.112 (0.028)	−0.113 (0.029)
Denver	0.010 (0.006)	0.011 (0.007)	0.011 (0.005)	0.011 (0.005)	0.011 (0.005)	0.010 (0.006)	0.009 (0.006)	0.008 (0.007)	0.007 (0.007)
St. Louis	−0.074 (0.020)	−0.078 (0.022)	−0.083 (0.015)	−0.085 (0.013)	−0.087 (0.013)	−0.086 (0.014)	−0.086 (0.015)	−0.084 (0.016)	−0.083 (0.018)
Houston	0.059 (0.011)	0.061 (0.013)	0.063 (0.009)	0.063 (0.008)	0.061 (0.009)	0.059 (0.010)	0.055 (0.011)	0.051 (0.012)	0.047 (0.013)
Cleveland	−0.042 (0.010)	−0.050 (0.012)	−0.055 (0.009)	−0.059 (0.008)	−0.060 (0.008)	−0.060 (0.009)	−0.059 (0.010)	−0.057 (0.011)	−0.055 (0.012)
Minneapolis	−0.043 (0.019)	−0.044 (0.022)	−0.048 (0.016)	−0.050 (0.013)	−0.051 (0.012)	−0.052 (0.013)	−0.053 (0.013)	−0.053 (0.014)	−0.052 (0.014)

Table 5 continued

Response variable Horizon (half a year)	0	1	2	3	4	5	6	7	8
Cincinnati	−0.043 (0.011)	−0.049 (0.012)	−0.053 (0.009)	−0.055 (0.008)	−0.056 (0.008)	−0.056 (0.009)	−0.055 (0.009)	−0.054 (0.010)	−0.052 (0.011)
Milwaukee	−0.049 (0.015)	−0.056 (0.017)	−0.062 (0.012)	−0.066 (0.011)	−0.068 (0.011)	−0.069 (0.011)	−0.069 (0.012)	−0.067 (0.013)	−0.065 (0.014)
Pittsburgh	−0.053 (0.013)	−0.060 (0.015)	−0.066 (0.010)	−0.069 (0.009)	−0.070 (0.009)	−0.069 (0.010)	−0.068 (0.011)	−0.067 (0.012)	−0.065 (0.013)
Miami	−0.025 (0.017)	−0.026 (0.019)	−0.030 (0.011)	−0.032 (0.011)	−0.034 (0.010)	−0.036 (0.011)	−0.038 (0.011)	−0.039 (0.011)	−0.040 (0.011)
Philadelphia	−0.082 (0.024)	−0.090 (0.027)	−0.097 (0.019)	−0.103 (0.017)	−0.106 (0.017)	−0.107 (0.018)	−0.107 (0.019)	−0.106 (0.021)	−0.105 (0.022)
Boston	−0.191 (0.052)	−0.199 (0.057)	−0.205 (0.038)	−0.209 (0.034)	−0.211 (0.033)	−0.212 (0.035)	−0.212 (0.037)	−0.210 (0.040)	−0.208 (0.043)
Honolulu	−0.035 (0.008)	−0.036 (0.009)	−0.040 (0.007)	−0.039 (0.007)	−0.039 (0.007)	−0.037 (0.007)	−0.036 (0.008)	−0.034 (0.009)	−0.032 (0.010)
Portland	−0.059 (0.028)	−0.064 (0.032)	−0.069 (0.022)	−0.072 (0.019)	−0.075 (0.018)	−0.078 (0.018)	−0.080 (0.018)	−0.081 (0.019)	−0.082 (0.020)
Los Angeles	−0.009 (0.034)	−0.010 (0.033)	−0.011 (0.018)	−0.012 (0.016)	−0.013 (0.015)	−0.014 (0.015)	−0.015 (0.015)	−0.016 (0.016)	−0.017 (0.016)
Seattle	−0.071 (0.021)	−0.075 (0.023)	−0.079 (0.015)	−0.082 (0.014)	−0.084 (0.014)	−0.085 (0.015)	−0.086 (0.016)	−0.086 (0.017)	−0.085 (0.019)
San Diego	−0.051 (0.030)	−0.053 (0.032)	−0.056 (0.020)	−0.059 (0.018)	−0.062 (0.017)	−0.065 (0.017)	−0.067 (0.018)	−0.068 (0.019)	−0.069 (0.020)
San Francisco	0.003 (0.021)	0.000 (0.022)	−0.001 (0.013)	−0.002 (0.011)	−0.004 (0.010)	−0.007 (0.009)	−0.009 (0.009)	−0.011 (0.009)	−0.012 (0.009)
New York	−0.272 (0.076)	−0.281 (0.086)	−0.289 (0.060)	−0.296 (0.052)	−0.300 (0.051)	−0.303 (0.052)	−0.305 (0.056)	−0.306 (0.060)	−0.306 (0.064)
Metro median	−0.043 (0.019)	−0.050 (0.022)	−0.055 (0.013)	−0.059 (0.011)	−0.060 (0.011)	−0.060 (0.011)	−0.059 (0.012)	−0.057 (0.013)	−0.055 (0.014)

Table 6 Correlation between impulse responses and regulations

Sample period	Response variable	Regulation index	Horizon (half a year) 0	1	2	3	4	5	6	7	8
78H2:14H2	Log real rent	Saks-index	−0.183	−0.252	−0.348	−0.356	−0.337	−0.285	−0.223	−0.162	−0.106
			[0.202]	[0.123]	[0.052]	[0.048]	[0.058]	[0.094]	[0.154]	[0.230]	[0.315]
		WRLURI	0.033	0.156	0.018	−0.033	−0.081	−0.083	−0.074	−0.054	−0.034
			[0.441]	[0.239]	[0.468]	[0.441]	[0.356]	[0.354]	[0.368]	[0.403]	[0.440]
	Log real price	Saks-index	−0.487	−0.480	−0.476	−0.472	−0.474	−0.476	−0.481	−0.485	−0.489
			[0.009]	[0.010]	[0.011]	[0.011]	[0.011]	[0.011]	[0.010]	[0.010]	[0.009]
		WRLURI	−0.318	−0.308	−0.307	−0.300	−0.299	−0.297	−0.297	−0.296	−0.296
			[0.070]	[0.076]	[0.077]	[0.082]	[0.083]	[0.084]	[0.084]	[0.085]	[0.085]
78H2:06H2	Log real rent	Saks-index	0.257	0.000	−0.180	−0.224	−0.209	−0.162	−0.105	−0.049	0.005
			[0.118]	[0.500]	[0.206]	[0.152]	[0.169]	[0.229]	[0.317]	[0.413]	[0.490]
		WRLURI	0.297	0.346	0.143	0.029	−0.047	−0.073	−0.077	−0.064	−0.047
			[0.085]	[0.053]	[0.257]	[0.447]	[0.415]	[0.371]	[0.364]	[0.386]	[0.415]
	Log real price	Saks-index	−0.246	−0.263	−0.289	−0.314	−0.358	−0.402	−0.447	−0.481	−0.496
			[0.129]	[0.113]	[0.091]	[0.072]	[0.047]	[0.029]	[0.016]	[0.010]	[0.008]
		WRLURI	−0.043	−0.072	−0.094	−0.111	−0.134	−0.157	−0.180	−0.196	−0.203
			[0.423]	[0.371]	[0.334]	[0.307]	[0.271]	[0.237]	[0.206]	[0.185]	[0.176]

p values in brackets

lower the price elasticity of housing supply so that house price becomes more sensitive to an interest rate shock.

Previous literature finds that supply-side regulations play an important role in housing markets (see the discussion in the introduction); observed regulations can explain a large fraction of differences in the volatility of house price between a highly regulated city and a relatively unregulated city, even when they face identical demand shocks. Using the real interest rate shock as the common demand shock to all local housing markets, our results are consistent with this argument.

6 Conclusion

We find that the uneven impacts of monetary policy are highly correlated with the supply regulations in the local housing markets. The more regulated the housing market, the larger its response to a real interest rate shock. While it is reasonable to assume that regulations are exogenously determined within our empirical framework, a strong correlation does not imply causality. We have not showed that housing supply elasticity is the only factor behind the uneven impacts of monetary policy. Also, within the linearized Campbell–Shiller framework, we have not considered how regulations can contribute to the second-order movements of the log rent–price ratio. We leave these issues for future research.

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Appendix 1: Campbell–Shiller decomposition

Starting from the realized log gross return to housing defined in Eq. (1) and using lowercase letters for logs, we have

$$\begin{aligned}\phi_{t+1} &= \ln(P_{t+1} + R_{t+1}) - \ln(P_t),\\ &= p_{t+1} + \ln\left(1 + \frac{R_{t+1}}{P_{t+1}}\right) - p_t,\\ &= p_{t+1} - p_t + \ln(1 + \exp(r_{t+1} - p_{t+1})).\end{aligned} \tag{21}$$

Applying a Taylor approximation to the function $f(x) = \ln(1 + \exp(x))$ around $x = \overline{r - p}$ yields

$$\ln(1 + \exp(r_{t+1} - p_{t+1})) = \sum_{n=0}^{\infty} \frac{f^{(n)}(\overline{r-p})}{n!}(r_{t+1} - p_{t+1} - \overline{r-p})^n, \tag{22}$$

or equivalently,

$$\ln(1+\exp(r_{t+1}-p_{t+1})) = [-\ln(\rho)-(1-\rho)\ln(1/\rho-1)] \\ +(1-\rho)(r_{t+1}-p_{t+1})+O((r_{t+1}-p_{t+1})^2), \tag{23}$$

where $\rho=(1+\exp(\overline{r-p}))^{-1}\in(0,1)$. The last term $O((r_{t+1}-p_{t+1})^2)$ is positive, since its sign is determined by the second-order derivative of $f(x)$,

$$f^{(2)}(x)=\frac{\exp(x)}{(1+\exp(x))^2}>0,$$

Substituting Eqs. (23) into (21) yields:

$$\phi_{t+1} = p_{t+1}-p_t+[-\ln(\rho)-(1-\rho)\ln(1/\rho-1)] \\ +(1-\rho)(r_{t+1}-p_{t+1})+O((r_{t+1}-p_{t+1})^2), \tag{24}$$

and

$$p_t = \rho p_{t+1}+[-\ln(\rho)-(1-\rho)\ln(1/\rho-1)]+(1-\rho)r_{t+1} \\ -\phi_{t+1}+O((r_{t+1}-p_{t+1})^2). \tag{25}$$

Iterating Eq.(25) forward yields:

$$p_t = \frac{-\ln(\rho)-(1-\rho)\ln(1/\rho-1)}{1-\rho}+\sum_{j=0}^{\infty}\rho^j((1-\rho)r_{t+1+j}-\phi_{t+1+j}) \\ +\frac{O((r_{t+1}-p_{t+1})^2)}{1-\rho}, \tag{26}$$

and

$$r_t-p_t = \frac{\ln(\rho)+(1-\rho)\ln(1/\rho-1)}{1-\rho}+\sum_{j=0}^{\infty}\rho^j(\phi_{t+1+j}-\Delta r_{t+1+j}) \\ -\frac{O((r_{t+1}-p_{t+1})^2)}{1-\rho}, \tag{27}$$

which gives Eq. (2) with a negative approximation bias under rational expectations.

Appendix 2: Estimation without bias correction

See Table 7 and Figs. 3 and 4.

Table 7 Summary of ML estimation results

Dependent variable	Coefficient on the 1st lag of					Coefficient on the 2nd lag of					$\overline{R}^2$
	i	π	Δr	π^{US}	Δr^{US}	i	π	Δr	π^{US}	Δr^{US}	
i											
25th percentile	1.163	–	–	0.009	−0.025	−0.266	–	–	−0.002	−0.060	0.875
Median	1.177	–	–	0.011	−0.006	−0.254	–	–	0.002	−0.049	0.876
75th percentile	1.187	–	–	0.020	0.015	−0.241	–	–	0.005	−0.031	0.877
π											
25th percentile	−1.449	0.269	−0.205	–	–	−0.487	0.150	−0.089	–	–	0.258
Median	−0.719	0.399	−0.009	–	–	0.587	0.214	0.157	–	–	0.398
75th percentile	−0.147	0.476	0.265	–	–	1.455	0.304	0.354	–	–	0.461
Δr											
25th percentile	−0.374	0.006	0.208	–	–	0.124	−0.001	0.011	–	–	0.044
Median	−0.115	0.031	0.306	–	–	0.373	0.056	0.128	–	–	0.176
75th percentile	0.051	0.045	0.350	–	–	0.663	0.077	0.207	–	–	0.236
π^{US}											
25th percentile	−0.779	–	–	0.372	−0.293	0.121	–	–	0.122	0.023	0.258
Median	−0.509	–	–	0.472	−0.091	0.361	–	–	0.196	0.149	0.273
75th percentile	−0.386	–	–	0.541	0.048	0.565	–	–	0.269	0.279	0.298
Δr^{US}											
25th percentile	−0.346	–	–	−0.112	0.356	0.396	–	–	0.087	−0.131	0.106
Median	−0.301	–	–	−0.082	0.455	0.519	–	–	0.108	−0.071	0.133
75th percentile	−0.202	–	–	−0.060	0.544	0.567	–	–	0.129	−0.029	0.145

Largest autoregressive root (median across 23 MSAs): 0.832

The dash symbol implies a constraint of a relevant coefficient of zero imposed on the VAR system

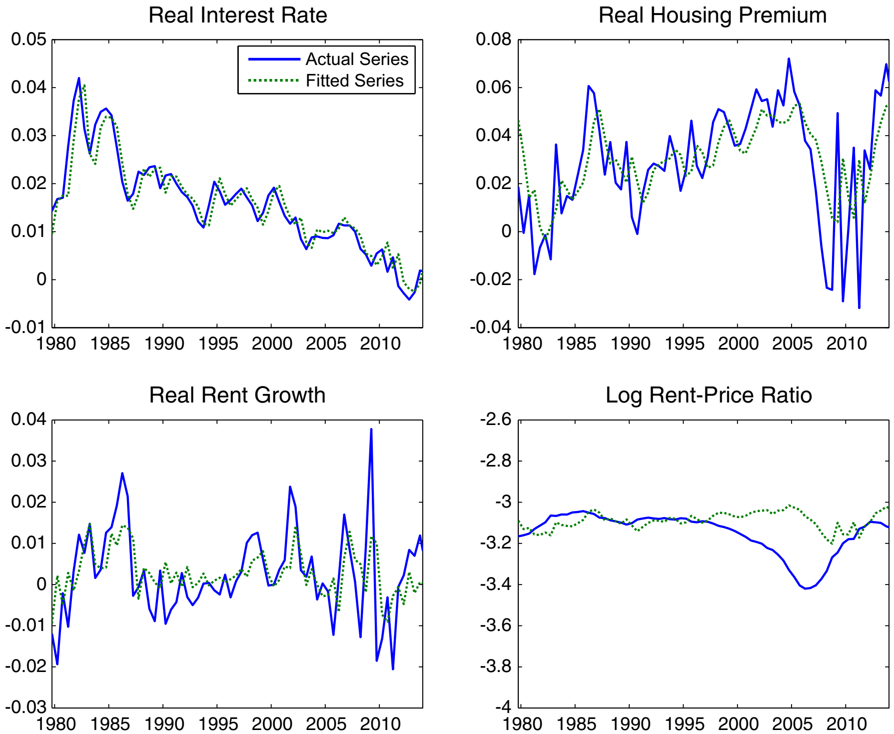

Fig. 3 Actual versus predicted series in the US national market, ML estimation results

Appendix 3: Sources of the pricing error

There are two potential sources of error in $\widehat{e}_t$: (1) The VAR-computed $\widehat{\mathcal{I}}_t$, $\widehat{\Pi}_t$, and $\widehat{\mathcal{G}}_t$ might not be good estimates of $\mathcal{I}_t$, Π_t, and $\mathcal{G}_t$ under rational expectations and (2) the linearized present value model ignores the second- and higher-order moments. We deal with the first source of error by utilizing the indirect inference estimator, and it turns out that the bias correction procedure considerably reduces the pricing error; see a comparison between Figs. 1 and 3 and between Figs. 2 and 4. In order to investigate the pricing error that comes from the second source, we conduct a Monte Carlo experiment for the US national market by repeating the following steps 1000 times:

1. We keep i_t and Δr_t as in the original sample and construct a new series of log rent–price ratio with small fluctuations around its sample mean, $rp'_t = \overline{rp} + \nu_t$, where $\nu_t \sim \mathcal{N}(0, \sigma_\nu^2)$. Then, using rp'_t we back out the relevant housing premium π'_t.
2. We estimate the VAR with $\mathbf{Z}_t = (i_t, \pi'_t, \Delta r_t)$ and compute the pricing error, $\widehat{e'_t} = rp'_t - \widehat{rp'_t}$.

Figure 5 compares the average absolute value of the pricing error over 1000 repetitions when σ_ν takes on different values. The black line shows that, when σ_ν equals one tenth of the standard error of the actually observed log rent–price ratio, the pricing

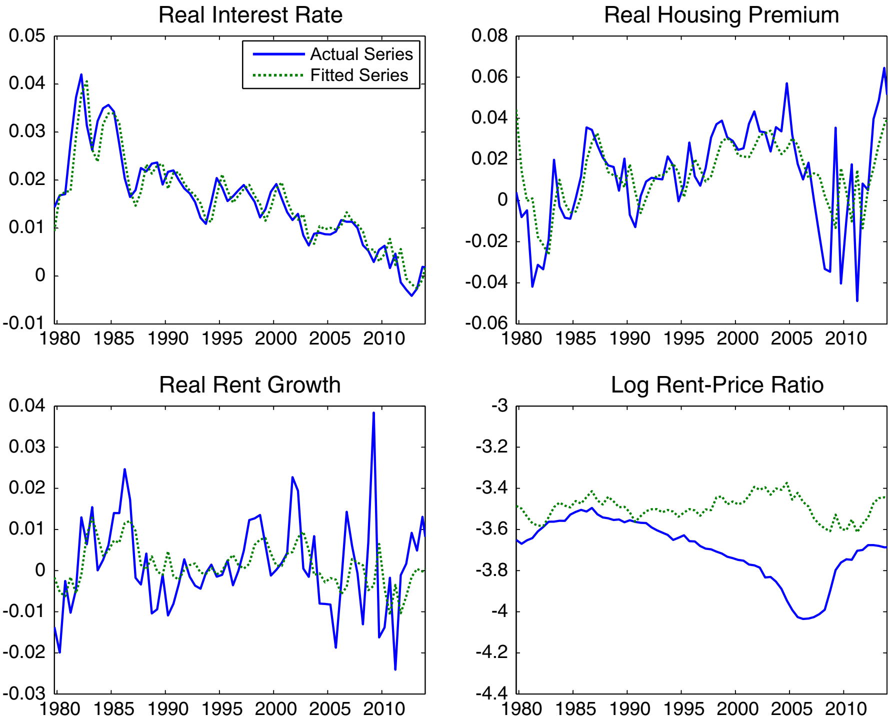

Fig. 4 Actual versus predicted series in the median MSA market, ML estimation results

error is small and relatively stable. When we increase σ_ν to one half of the observed standard error (the purple line), the pricing error becomes larger in magnitude and the series starts to vary over time. As the log rent–price ratio becomes as volatile as the observed series (the blue line), both the first and the second moments of the pricing error increase dramatically.

However, the constant standard error can hardly replicate the model-implied pricing error. Therefore, we assign different standard errors to the simulated log rent–price ratio for the earlier period 1978H2:1999H2 and the later period 2000H1:2014H2. As the red line shows, the pricing error shoots up once the simulated log rent–price ratio becomes more volatile.

This simulation exercise suggests that both the presence and the time variation of the second moment in the log rent–price ratio contribute to a sizeable pricing error. A necessary condition for the Campbell–Shiller decomposition, which utilizes a first-order Taylor approximation around the steady-state log rent–price ratio, to fit the data well, is that the log rent–price ratio is relatively stable over time. In the data, however, the log rent–price ratio experienced large fluctuations between 2000 and 2012, during which period the fitted log rent–price ratio largely deviates from the actual counterpart; see Fig. 1.

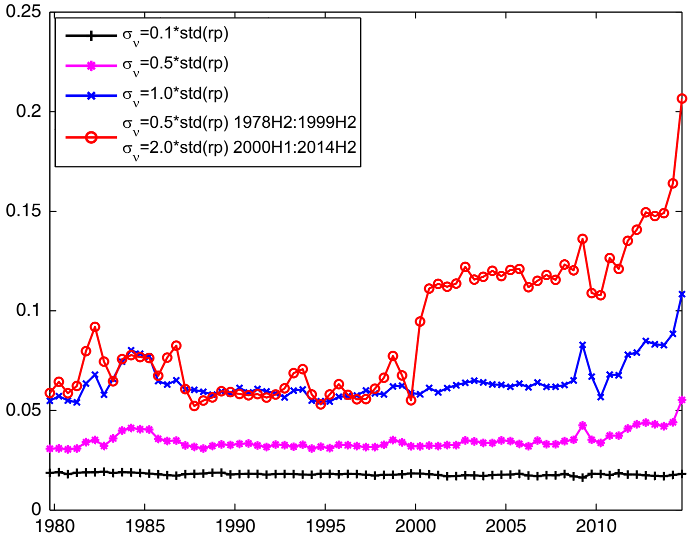

Fig. 5 Simulated pricing errors

Appendix 4: Orthogonal impulse response functions

Given the response functions of state variables to an orthogonal impulse in real interest rate, those for VAR-computed $\widehat{\mathcal{I}}_t$, $\widehat{\Pi}_t$, and $\widehat{\mathcal{G}}_t$ are readily available via a linear combination. According to Eqs. (8)–(10), the responses of $\widehat{\mathcal{I}}_t$, $\widehat{\Pi}_t$, and $\widehat{\mathcal{G}}_t$ to an orthogonal impulse in real interest rate are:

$$\widehat{\mathrm{OIR}}_{\mathfrak{z}_j,i,t+\tau} = \begin{cases} e_j'(\mathbf{I}-\rho\widehat{\Gamma})^{-1}\widehat{\Gamma}\left[\widehat{\mathrm{OIR}}_{\mathbf{Z},i,t+\tau}' \quad \mathbf{0}\right]' & \text{if } \tau = 0, \\ e_j'(\mathbf{I}-\rho\widehat{\Gamma})^{-1}\widehat{\Gamma}\left[\widehat{\mathrm{OIR}}_{\mathbf{Z},i,t+\tau}' \quad \widehat{\mathrm{OIR}}_{\mathbf{Z},i,t+\tau-1}'\right]' & \text{if } \tau > 0, \end{cases} \tag{28}$$

with $\mathfrak{z}_1 = \mathcal{I}$, $\mathfrak{z}_2 = \Pi$, and $\mathfrak{z}_3 = \mathcal{G}$, which infer the response of the VAR-computed log rent–price ratio to an orthogonal impulse in real interest rate as,

$$\widehat{\mathrm{OIR}}_{rp,i,t+\tau} = \widehat{\mathrm{OIR}}_{\mathcal{I},i,t+\tau} + \widehat{\mathrm{OIR}}_{\Pi,i,t+\tau} - \widehat{\mathrm{OIR}}_{\mathcal{G},i,t+\tau}. \tag{29}$$

Given the log real rent at time $t-1$, r_{t-1}, the τ-period ahead prediction of log real rent with $\tau \geq 0$ can be expressed as:

$$\widehat{r}_{t+\tau} = r_{t-1} + \sum_{s=0}^{\tau} \widehat{\Delta r}_{t+s}, \tag{30}$$

and τ-period prediction of log real price takes the following form:

$$\widehat{p}_{t+\tau} = \widehat{r}_{t+\tau} - \widehat{rp}_{t+\tau}. \tag{31}$$

Then, we are able to obtain the τ-period ahead responses of the predicted log real rent and the predicted log real price to an orthogonal interest rate shock at time t,

$$\widehat{\mathrm{OIR}}_{r,i,t+\tau} = \sum_{s=0}^{\tau} \widehat{\mathrm{OIR}}_{\Delta r,i,t+s}, \tag{32}$$

$$\widehat{\mathrm{OIR}}_{p,i,t+\tau} = \sum_{s=0}^{\tau} \widehat{\mathrm{OIR}}_{\Delta r,i,t+s} - \widehat{\mathrm{OIR}}_{rp,i,t+\tau}. \tag{33}$$

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