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The economic drivers of differences in house price inflation rates across MSAs[☆]

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ABSTRACT

This study examines why monetary policy at the national level can have vastly different effects on appreciation rates of single family houses across metropolitan statistical areas (MSAs). The study employs Case/Shiller monthly house price index data for 19 MSAs from 1992:06 to 2014:12 and FHFA quarterly house price index data for 94 MSAs from 1992:3 to 2014:4. We model the importance of MSA-specific demand and supply characteristics through a set of interaction terms between these factors and monetary policy. The empirical analysis is cast in terms of a state-space approach with a stochastic trend component to absorb the impact of omitted variables. Robustness checks use panel data estimators with interaction terms. A lower federal funds rate is associated with home price run-ups in MSAs that are characterized by higher demand and tighter supply conditions.

1. Introduction

The run-up in house prices prior to 2006 was far from evenly distributed across the U.S. Some states and MSAs experienced unprecedented boom times; others were much less affected.[1] Why did we see so very different house price inflation rates across MSAs when all MSAs are subject to the same federal funds rate in a highly

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[1] Wheaton and Nechayev (2008) report that real home prices increased by 74% in Boston, 10% in Los Angeles, 11% in Chicago and decreased by 21% in Dallas and by 38% in Houston from 1980Q1 to 1998Q4. In contrast, from 1999Q1 to 2005Q4 the increases were 83% in Boston, 123% in Los Angeles, 42% in Chicago, but only 12% and 19% in Dallas and Houston, respectively. See also Glaeser et al. (2005) who argue that the dispersion in housing prices has increased substantially since 1970, and mainly in the upper tail of the house price distribution.

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integrated financial market?[2] The key point of this study is to show empirically that the vast differences in home price inflation rates experienced at the MSA level, especially prior to 2006, can be tied to differences in local demand and supply conditions that systematically and predictably cause monetary policy to have rather different consequences at the local level.[3]

We first discuss the demand and supply channels through which monetary policy might affect residential house prices. This helps to clarify how local demand and supply conditions can influence the impact of national interest rate policies at the MSA level. We then provide a novel estimation approach that consists of two independent components, a state-space modeling framework and interaction terms between a time-varying national policy variable, the federal funds rate, and largely time-invariant MSA-level characteristics, such as the percentage of undevelopable land.

The interaction terms *explicitly* incorporate into the estimates characteristics of the MSAs that would ordinarily be captured *implicitly* by MSA-level fixed effects in a typical panel data set-up. The interaction terms allow for a weighted impact of the national policy on individual MSAs without requiring MSA-level variables to be available as continuous time series. This is significant from a practical estimation point of view because continuous time series of MSA-level characteristics may not be available or insufficient variation in their values over time may make estimation difficult.

Compared to the standard panel approach, we employ for estimation a state-space framework of the structural time series or unobserved component type, both in its univariate and multivariate setting. Relative to a panel estimator with deterministic time trends and other non-stochastic components, our approach allows for a far more flexible, data driven way to capture the impact of unobserved or unknown variables that may give rise to stochastic jumps or trends, which may significantly impact the estimates and policy conclusions if left in the residual term. Our results suggest that house price inflation rates react most vigorously to changes in the federal funds rate for MSAs with high population growth and a large percentage of undevelopable land. We show that our results are robust to different estimation approaches.

The remainder of the paper is organized as follows. In the next section, we provide a brief overview of the literature on the relationship between monetary policy and house prices, and the demand and supply conditions in local housing markets through which monetary policy influences house prices. Section 3 describes our identification strategy. Section 4 discusses our data. This is followed in Section 5 by the estimation results and some robustness checks. Section 6 concludes.

2. Monetary policy and house prices: a review

In one of the first studies on the economics of interest rates and housing Porterba (1984) argues that the relationship between rents and prices is determined by the costs of borrowing money. As a consequence, house prices can strongly react to changes in interest rates. Leamer (2007) emphasizes that attempts to control the business cycle need to focus on residential investment and that housing is an important channel through which monetary policy affects the economy directly or indirectly.[4] The user cost of capital is a direct channel through which monetary policy affects the housing market. As an important component of housing demand it consists of several factors and is defined as

$$UC = P_h\left[(1-t)i - \triangle P_h^e + \delta\right],$$

where P_h is the relative price for a new single-family home, i is the nominal mortgage rate, which is assumed to be deductable by the marginal tax rate t. The cost of capital decreases with the expected appreciation in house prices $\triangle P_h^e$ and rises with house depreciation δ.

To show how the housing market responds to monetary policy, we refer to the structural model of the housing sector (see, e.g., DiPasquale and Wheaton (1994) and McCarthy and Peach (2002)). Note that this simple model only illustrates the proposed mechanism, but does not describe our empirical specification. The demand function expresses the relationship between the equilibrium house price P_h^{d*} and the current stock of housing S, permanent household income Inc, population Pop, and the user cost of capital UC,

$$\begin{aligned} P_h^{d*} &= \alpha_1 S + \alpha_2 Inc + \alpha_3 Pop + \alpha_4 UC \\ &= \alpha_1 S + \alpha_2 Inc + \alpha_3 Pop + \alpha_4\left(P_h\left[(1-t)i - \triangle P_h^e + \delta\right]\right), \end{aligned}$$

with the corresponding response parameters $\alpha_1, \alpha_4 < 0$ and $\alpha_2, \alpha_3 > 0$. If additions to the housing stock (C) are equal to its depreciation (δS), the housing stock is constant in the steady state, i.e. $\triangle S = C - \delta S = 0$. In such scenario, more economic activity and the accompanying increase in attractive job offers (and/or amenities) increases households' income, which, in turn, makes housing more affordable to them. Simultaneously, the regional economy might

[2] For instance, Landier et al. (2013) document increasing correlation of house price growth across U.S. states due to geographic integration of banking markets. However, the level of price changes differ significantly among local housing markets. Similarly, Kallberg et al. (2013) as well as Cotter et al. (2015) find that comovements among 14 MSAs significantly increased from 1992 to 2008. They attribute this increase to underlying systematic real and financial factors, which are responsible for greater fundamental integration of those markets.

[3] The mid-2000s U.S. episode of rapidly rising house prices was closely related to aggressive mortgage lending practices and relaxed mortgage requirements (Dell'Ariccia et al., 2009; Pavlov and Wachter, 2010). The traditional banking model became less profitable and the banking system transformed from "originate and hold" to "originate and distribute." At the same time, the supply of asset backed securities (ABS) and the demand for alternatives to insured deposits led to strong growth of the shadow banking system. In addition, capital requirements were effectively removed for investment banks in 2004 for their securitization business (Calomiris et al., 2010). Fiscal policy interventions, in particular the Bush tax cuts, may also have had some effect on home prices. However, this study focuses on the impact of monetary policy and its interaction with house market related demand and supply drivers.

[4] Other than through the user cost of capital, monetary policy has a direct impact on house prices through house price expectations and new house construction. Monetary policy indirectly influences the housing market and the overall economy by the wealth effect and by the credit channel effect on consumption and housing demand, as discussed, for example, by Mishkin (2007).

attract more people, which further increases the demand for housing. Both effects lead to an outward shift of the demand curve. If the demand reacts strongly to changes in income (α_2 is large), house prices increase. This effect is reinforced by a decreasing user cost of capital due to a lower mortgage rate. Simultaneously, population growth drives up rents and a lower interest rate decreases the yield, which again leads to higher prices. Similarly, if stock is highly inelastic as a result of zoning restrictions or natural limitations, i.e. due to undevelopable land, house price inflation is more pronounced, when expansive monetary policy triggers higher demand.

The supply function mirrors the construction industry, where the house price represents the replacement costs of real estate,

$$P_h^{s*} = \beta_1 + \beta_2\left(\frac{C}{S}\right) + \beta_3 CC,$$

with β_1 representing the minimum value per unit space that is required to get construction underway. The higher the investment rate, $C/S = \triangle S + \delta$, the stronger will be the increase in the housing stock, which causes house prices to decrease. By contrast, construction bottlenecks, land scarcity, or zoning restrictions limit the housing supply. Furthermore, construction costs (CC) include costs for the production factors material, labor, and land. With increasing legal and natural building restrictions, new construction becomes less profitable. Amenities and regions of extraordinary high quality of life drive up land prices as well. Furthermore, higher short-term interest rates and the scarcity of construction financing will lower the level of construction, and thus, the housing stock. Hence, if supply is inelastic and financing costs are high, the impact on house prices is reinforced, i.e. either house prices increase to remain at a profitable level or supply does not increase. In equilibrium it must hold that $P_h^{d*} = P_h^{s*} = P_h^*$ and the effect of interest rates on house prices is conditional upon regional demand and supply characteristics.

If a strong connection exists between interest rates and house prices, loose monetary policy may be tied to housing bubbles. This view is supported by Taylor (2007) and Allen and Carletti (2009), who consider monetary policy a key factor in pushing housing activity after the collapse of the technology bubble and the subsequent recession in 2001. Gordon (2009) shows that the Fed maintained short-term interest rates too low compared to the Taylor Rule and, therefore, indirectly contributed to the U.S. house price bubble. Calomiris (2009) agrees that the Fed departed substantially from the Taylor rule during the period 2002–2005 and that lax lending practices fueled house price run-ups in the U.S. and other countries, such as Ireland, Spain, and the U.K. In a similar vein, Bjønland and Jacobsen (2010) find that house prices in Norway, Sweden, and the U.K. react immediately and significantly to monetary policy shocks.

While previous studies argue that monetary policy is an important source of house price inflation, there is a strand of the literature which finds only a moderate impact of interest rates on house prices. For instance, Glaeser et al. (2010) provide evidence that interest rates can only explain about one-fifth of the increase in house price appreciation from 1996 to 2006. Skepticism of the strong role of monetary policy is also raised by Bernanke (2010), who suggests that the rising use of innovative mortgage instruments and the corresponding relaxation of underwriting standards triggered the house price bubble. Hence, regulatory and supervisory policies rather than monetary policies should be held responsible for house price inflation.

In line with the observation by Fratantoni and Schuh (2003) that economic sensitivity to monetary policy varies across regions, Christidou and Konstantinou (2011) demonstrate that the transmission of monetary policy to house prices is heterogeneous across U.S. states and that regional housing market conditions respond differently to a common monetary policy shock. However, no reasons for the differences in the responses are explicitly estimated. Del Negro and Otrok (2007) study whether such heterogeneous increases in house prices reflect a national phenomenon or constitute local bubbles driven by local factors. For the period from 2001 to 2005, the authors find that the increase in house prices is a national phenomenon, while in previous periods house prices were mainly driven by local components. The local effects of monetary policy are also studied by Francis et al. (2011), who find significant variation among MSA regions in the response of employment to monetary policy shocks. Vansteenkiste (2007) studies interest rate shocks on regional U.S. house prices as well as spillovers of house price shocks. She finds that shocks are state-dependent and occur in states with low land supply elasticity. Similar to Saks (2008) and Vansteenkiste (2007), looks into the causes of heterogeneity in house price appreciations, although in a more systematic way. Saks (2008) considers both national and local changes in economic conditions and their interaction. As such it is clearly the study closest to ours. Saks (2008) is restricted to local variables available at the time, which includes per capita income and industry composition, but excludes variables that have become available only since, such as housing supply elasticities, percentages of developable land, quality of life, etc. We also note that the work is based on annual data, ends in 2006, and uses basic regression techniques, for which issues of unobserved variables and underlying non-deterministic trends may play a role.

We premise our analysis on the idea that expansionary monetary policy raises the demand for houses through at least two channels. First, a lower interest rate reduces the cost of financing a home. Second, the increased availability of credit, which was a major component of the monetary easing after 2001, makes it easier to obtain financing at any interest rate. Rather than trying to determine which of those channels has been more important for the U.S., our focus is on the heterogeneity in the response to monetary expansion, and in particular on the economic reasons for the observed heterogeneity. Given that there has been very significant financial market integration (see Landier et al., 2013), significant differences in house price inflation appear worthy of an explanation. Vansteenkiste (2007) and Saks (2008) have already shown the importance of land supply elasticities and some other factors. We expand on their work.

We contribute to the literature in several directions. First, we identify a number of local demand and supply factors that have not been used, for example by Saks (2008), in the context of explaining the differences in house price appreciations across MSAs in response to a country wide change in monetary policy. This includes in particular factors that do not differ much or at all over time, but that vary widely across MSAs. Second, we expand our data set to after the economic crisis to capture not only the increase in house price inflation, but also its subsequent decrease. This should make our analysis more general as it covers several monetary expansions and contractions. Third, we suggest an estimation methodology that allows us (a) to explicitly incorporate local demand and supply factors via interaction terms, and (b) to capture issues of non-stationarity, pre-existing trends and omitted variables via the specification of a flexible underlying stochastic trend in the context of a state-space estimation approach. Finally, we check our results with two different types of data sets on housing prices to confirm the plausibility of our results.

3. Identification strategy

We propose to identify the reasons why MSAs responded so differently in terms of house price inflation to changes in monetary policy. We utilize both a univariate and a multivariate state-space model, in which we allow the federal funds rate to differ in its impact at the MSA level through a number of interaction terms with local demand and supply conditions that change little or not at all over time. We also provide a number of robustness checks using alternative, more traditional methodologies.

The choice of a state-space model has some advantages. First, it allows us to capture pre-existing trends that do not follow simple deterministic trend patterns of the linear or quadratic type with relative ease. Compared to cointegration methods, no formal pre-testing is needed and issues of unknown structural breaks do not typically weigh heavily on the results. The stochastic trend specification, which is a typical component of state-space models, is not only flexible enough to capture complicated underlying trends, it can also absorb the impact of variables that are unobserved and that result in unexpected jumps of the dependent variable. This is important because in trying to uncover the factors that drive local house price inflation rates one faces two problems that are not atypical for work with regional data: first, the economic theory is far from being fully developed, which makes it difficult to theoretically identify all relevant variables; second, variables that are known to play a role according to theoretical reasoning may not be available for every time period. In either case, the impact of unobserved variables may show up in the residual terms of standard regression approaches and cause endogeneity issues. In the state-space modeling framework that we employ, the impact of these unobserved variables is largely captured by stochastic components, such as stochastic trends, that are explicitly estimated.

3.1. State-space modeling

We utilize two alternative state-space models, a univariate one and a multivariate one. We illustrate our basic estimation approach with the simplest possible multivariate set-up, a model with just one right-hand side variable x. The multivariate model is composed of two matrix equations, one for the observation equation, and one for the state equation. For time period t, the set of observation equations can be written as

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_N \end{bmatrix}_t = \begin{bmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{bmatrix} \mu_t + \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_N \end{bmatrix} x_{t-k} + \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_N \end{bmatrix}_t , \qquad (1)$$

where the dependent variable vector consists of observations on N different MSAs $(i = 1, \ldots, N)$ for each time period t. The right-hand side decomposes the dependent variable into (i) an unobserved stochastic trend (μ_t) that is common to all N MSAs,[5] (ii) an exogenous policy variable that enters with lag k $\left(x_{t-k}\right)$ and that is associated with N MSA-specific reaction coefficients, and (iii) an MSA-specific white-noise error term (w_{it}) with zero mean and constant variance.

The corresponding state equation identifies the evolution of the state variable μ_t over time. We choose a simple random walk to represent μ_t,

$$\mu_t = \mu_{t-1} + v_t, \qquad (2)$$

where v_t is a white-noise error term with zero mean and common variance across the N MSAs. The presence of μ_t in Eq. (1) removes any random-walk like trend from y or x.[6] Given that the dependent variable is an inflation rate, which is a variable without a persistent trend, a random walk specification for the stochastic trend μ_t is likely to be sufficiently flexible. If we wanted to explain a variable with a highly persistent trend, such as house prices as opposed to house price inflation, a simple random walk would not be an appropriate specification, but a model with an explicit growth component would be required. These types of models typically add a slope or drift term to Eq. (2), which itself can evolve as a random walk.[7]

[5] We also note in this context that the stochastic trend is not associated with any coefficient. The parameter to estimate for μ_t is the variance associated with the particular specification of μ_t. This variance is also known as a hyper-parameter. For complicated versions of the trend, there may be more than just one variance (hyper-parameter) that needs estimation.

[6] This can be thought of as akin to an application of the Frisch–Waugh–Lovell theorem to Eq. (1).

[7] These more complex trend specifications are known as local linear trend and smooth trend models. More on these specifications is contained in Harvey (1989) and in Durbin and Koopman (2001). An introduction from a practical estimation perspective is given in Commandeur and Koopman (2007).

We assume a separate variance R_i with $i = 1, \dots, N$ for each of the N MSAs in Eq. (1), with all covariances set to zero,[8]

$$Ew_t w_t' = \begin{bmatrix} R_1 & 0 & 0 & 0 \\ 0 & R_2 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & R_N \end{bmatrix}, \tag{3}$$

where R_i is the observation variance of MSA i. A much stricter assumption would be a variance that is identical across all N MSAs. The corresponding set of restrictions is easily tested with a likelihood ratio test. Because for all models in this study, this restriction is rejected, we will not further consider this case. The stochastic trend specified by Eq. (2) is assumed to have a constant variance across time (Q), which is different from and uncorrelated with those of Eq. (1),

$$Ev_t' v_t = Q. \tag{4}$$

The model consisting of Eqs. (1)–(4) implies that any non-random variation across MSAs in the dependent variable that is tied to variable x is absorbed by the coefficient vector a in Eq. (1). Since the impact of common national trends and events are taken up by the stochastic trend μ_t, any differences in the coefficient vector a across the N MSAs should be due to differences in conditions at the MSA level. Local conditions affecting the dependent variable across the N equations, but not moderated by the policy variable x_{t-k}, enter through the error term w.

Local conditions may consist of a variety of demand and supply factors, some influencing the impact of x, others being independent of x; some varying over time, while others showing little or no time variation. The focus of this paper is on those factors that influence the impact of x on y but that show little or no time variation. In a typical panel data framework these factors, which may differ widely across cross-section units, are accounted for by unit fixed effects, which are typically not made explicit. In Eq. (1), we have a similar issue: we know that differences in the elements of the coefficient vector a across MSAs result from differences in local conditions, but Eq. (1) does not explicitly reveal these factors. To make the local demand and supply factors visible, we amend Eq. (1) with a set of interaction terms to identify the driving forces at the local level.

Consider for that purpose the following modification of Eq. (1),

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_N \end{bmatrix}_t = \begin{bmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{bmatrix} \mu_t + \begin{bmatrix} \beta \\ \beta \\ \vdots \\ \beta \end{bmatrix} x_{t-k} + x_{t-k} \begin{bmatrix} z_{1,1} & z_{2,1} & \cdots & z_{p,1} \\ z_{1,2} & z_{2,2} & \cdots & z_{p,2} \\ \vdots & \vdots & \vdots & \vdots \\ z_{1,N} & z_{2,N} & \cdots & z_{p,N} \end{bmatrix} \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_p \end{bmatrix} + \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_N \end{bmatrix}_t, \tag{5}$$

where we introduce interaction terms between variable x, measured at time $t-k$, and the elements of a matrix z consisting of $N \times p$ elements. In Eq. (5), z consists of p different variables ($i = 1, \dots, p$). We assume that each of the p variables varies across the N MSAs but not over time.[9] In contrast to Eq. (1), the coefficient vector in front of variable x in Eq. (5) consists of a single parameter (β), which does not vary by MSA. The local variation in Eq. (5) is captured by the interaction terms between the p row-elements of z and x. Each of the p variables making up each row of z has its own estimated coefficient (b_i). Taken together, the p row-elements of z are the driving forces behind the different responses of the N MSAs to a change in variable x. Based on estimates of Eq. (5) we can predict to what extent MSAs with different time-invariant characteristics and, therefore, different z values react differently to a change in the policy variable x. The prediction depends for each MSA on the partial derivative of the dependent variable with respect to variable x. This derivative depends for each MSA on β, vector b, and the MSA-specific values taken on by z.

The multivariate model consisting of either Eqs. (1)–(4) or Eqs. (2)–(5) can be estimated only in situations where the number of time series observations T per unit (MSA in our case) is significantly larger than the number of cross-section units N. This applies in the present study for the Case/Shiller data set, which contains close to $T = 300$ monthly observations for $N = 19$ usable MSAs. However, it does not apply for the FHFA data set, which contains less than $T = 100$ quarterly observations for $N = 94$ usable MSAs. If one wants to take advantage of the flexible, stochastic trend specifications of state-space models, the FHFA data set would force a move from a multivariate model to a univariate model. Such a model could be

[8] This assumption implies the estimation of N equations that are related via cross-equation parameter restrictions, but unrelated via the error terms. Ideally, one would want to test the assumption of zero covariances relative to a model with a fully specified covariance matrix. However, for our data set, the number of degrees of freedom is insufficient for reliable estimates.

[9] The model is flexible enough to allow the variables making up z to vary not only by MSA but also over time. But that case is standard and causes no estimation issues.

specified as

$$\begin{bmatrix} y_{1,1} \\ y_{2,1} \\ \vdots \\ y_{T,1} \\ y_{1,2} \\ y_{2,2} \\ \vdots \\ y_{T,2} \\ \vdots \\ y_{T,N} \end{bmatrix} = \begin{bmatrix} \mu_1 \\ \mu_2 \\ \vdots \\ \mu_T \\ \mu_{T+1} \\ \mu_{T+2} \\ \vdots \\ \mu_{2T} \\ \vdots \\ \mu_{NT} \end{bmatrix} + \gamma \begin{bmatrix} 1 \\ 2 \\ \vdots \\ T \\ 1 \\ 2 \\ \vdots \\ T \\ \vdots \\ T \end{bmatrix} + \beta \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_T \\ x_1 \\ x_2 \\ \vdots \\ x_T \\ \vdots \\ x_T \end{bmatrix}$$

$$+ \begin{bmatrix} x_1 z_{1,1} & x_1 z_{2,1} & \cdots & x_1 z_{p,1} \\ x_2 z_{1,1} & x_2 z_{2,1} & \cdots & x_2 z_{p,1} \\ \vdots & \vdots & \vdots & \vdots \\ x_T z_{1,1} & x_T z_{2,1} & \cdots & x_T z_{p,1} \\ x_1 z_{1,2} & x_1 z_{2,1} & \cdots & x_1 z_{p,2} \\ x_2 z_{1,2} & x_2 z_{2,1} & \cdots & x_2 z_{p,2} \\ \vdots & \vdots & \vdots & \vdots \\ x_T z_{1,2} & x_T z_{2,1} & \cdots & x_T z_{p,2} \\ \vdots & \vdots & \vdots & \vdots \\ x_T z_{1,N} & x_T z_{2,N} & \cdots & x_T z_{p,N} \end{bmatrix} \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_p \end{bmatrix} + \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_T \\ w_{T+1} \\ w_{T+2} \\ \vdots \\ w_{2T} \\ \vdots \\ w_{NT} \end{bmatrix}, \quad (6)$$

where variables x and z and the stochastic terms z and w have the same meaning as in Eq. (5).[10] Variable x varies over time, but not by MSA; variables z_j do not vary over time, but by MSA. What makes Eq. (6) different from Eqs. (1) and (5) is the fact that the model is reduced from N equations to just one. In particular, the first T observations belong to MSA 1, the next T observations to MSA 2, and so forth. As in a common panel data format, the dependent variable consists of N stacked cross-sections, each with T observations, for a total of $T \times N$ observations. In the multivariate format, by contrast, the total number of observations equals T. The key difference between Eq. (6) and a standard panel data set-up is the presence of a flexible, stochastic trend.[11] Eq. (6) assumes a common variance for the stochastic trend μ_t across all N cross-section units, which is the same assumption as that for the multivariate models. The stacking into one $T \times N$ vector increases the number of observations on which to estimate the variance parameter Q of Eq. (2) by an order of magnitude. But it also adds the complication that the first time series value of μ_t of cross-section unit j refers back to the last time series observation of cross-section unit $j-1$ by the assumption that μ_t follows a random walk. We address this complication by adding a deterministic time trend to Eq. (6). This time trend is a standard $T \times N$ vector with estimated parameter γ. It can be thought of as deterministically resetting the stochastic time trend at the beginning of each new cross-section. We note that, compared to the multivariate model consisting of Eqs. (2)–(5), the univariate model centered on Eq. (6) contains only one estimated variance for the $T \times N$ error term w. This is equivalent to the restriction $R_1 = R_2 = \cdots = R_N$ in Eq. (3).

3.2. Robustness checks

Given that the approach encapsulated by Eqs. (1), (5) and (6) is uncommon, we offer two sensitivity checks, which should corroborate the importance of the variables contained in z. As a first plausibility check, we estimate the model made up by Eqs. (1)–(4) and analyze to what extent the elements of vector a vary by known characteristics of the N MSAs. This is accomplished by running simple least squares regressions of the type

$$a_i = \delta_0 + \sum_{j=1}^{p} \delta_j z_{j,i} + \varepsilon_i, \quad (7)$$

where the elements of a_i in Eq. (1) are explained by the p variables contained in z that vary by MSA i but not over time. Due to the fact that the variation in the values of a_i are systematically related to the variables in z, the estimated coefficients δ_j should be empirically consistent with the estimates of b_i in Eqs. (5) and (6). To the extent that the number of MSAs (N) and, therefore, the number of observations in Eq. (7) is small, we can only expect a rough approximation of the results obtained from Eqs. (5) and (6).

A more elaborate robustness check makes use of a panel data approach equivalent to that of Eq. (6). Consistent with a traditional panel data estimator, the stochastic trend μ_t is replaced by unit fixed-effects (λ_N) and a second-order time trend,

$$\begin{bmatrix} y_{1,1} \\ y_{2,1} \\ \vdots \\ y_{T,1} \\ y_{1,2} \\ y_{2,2} \\ \vdots \\ y_{T,2} \\ \vdots \\ y_{T,N} \end{bmatrix} = \begin{bmatrix} \lambda_1 \\ \lambda_1 \\ \vdots \\ \lambda_1 \\ \lambda_2 \\ \lambda_2 \\ \vdots \\ \lambda_2 \\ \vdots \\ \lambda_N \end{bmatrix} + \vartheta \begin{bmatrix} 1 \\ 2 \\ \vdots \\ T \\ 1 \\ 2 \\ \vdots \\ T \\ \vdots \\ T \end{bmatrix} + \theta \begin{bmatrix} 1 \\ 2^2 \\ \vdots \\ T^2 \\ 1 \\ 2^2 \\ \vdots \\ T^2 \\ \vdots \\ T^2 \end{bmatrix} + a \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_T \\ x_1 \\ x_2 \\ \vdots \\ x_T \\ \vdots \\ x_T \end{bmatrix} \quad (8)$$

$$+ \begin{bmatrix} x_1 z_{1,1} & x_1 z_{2,1} & \cdots & x_1 z_{p,1} \\ x_2 z_{1,1} & x_2 z_{2,1} & \cdots & x_2 z_{p,1} \\ \vdots & \vdots & \vdots & \vdots \\ x_T z_{1,1} & x_T z_{2,1} & \cdots & x_T z_{p,1} \\ x_1 z_{1,2} & x_1 z_{2,1} & \cdots & x_1 z_{p,2} \\ x_2 z_{1,2} & x_2 z_{2,1} & \cdots & x_2 z_{p,2} \\ \vdots & \vdots & \vdots & \vdots \\ x_T z_{1,2} & x_T z_{2,1} & \cdots & x_T z_{p,2} \\ \vdots & \vdots & \vdots & \vdots \\ x_T z_{1,N} & x_T z_{2,N} & \cdots & x_T z_{p,N} \end{bmatrix} \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_p \end{bmatrix} + \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_T \\ w_{T+1} \\ w_{T+2} \\ \vdots \\ w_{2T} \\ \vdots \\ w_{NT} \end{bmatrix}.$$

[10] To avoid notational complexity, we ignore the fact that variable x enters the equation with a lag.

[11] As with panel data, one needs to take care that the k lags of independent variable x do not extend into unrelated cross-section units. This requires omitting the first k time series observations for each of the N cross-section units.

All MSAs are assumed to have the same response parameter a for variable x and b_j with $i = 1, \ldots, p$ for the p interaction terms between x and z. Note that variable x varies over time, but not by MSA, whereas variables z_j do not vary over time, but by MSA.

The key point for the interpretation of Eqs. (6) and (8) is that vector b, along with the matrix of interaction terms, allows x to have a differential impact by MSA. Vector b weighs the impact of x by the MSA-specific characteristics z_j. As long as the z_j vary across MSAs, the impact of x will vary. Which of the elements of b is statistically significant is an empirical question. For the estimates of Eq. (8) to be fully consistent with those of Eq. (6), we would expect to see the same elements of z_j to be statistically significant in both Eqs. (6) and (8). To check for robustness of the estimates of Eq. (8), we make alternative assumptions regarding the error term. The assumptions are those appropriate for panel data with large T and small N.[12]

4. Data

We employ monthly seasonally adjusted house price data[13] for the period 1992:06 to 2014:12 for 19 of the 20 MSAs for which Case/Shiller (CS) price indices are available.[14] The CS indices apply a robust value-weighted method based on (repeat) sales transactions. This methodology employed by the CS indices reduces biases stemming from pricing anomalies, physical changes, local neighborhood effects, high turnover frequency, and time between transactions (see Kallberg et al. 2013; Miao et al. 2011).

For the purpose of checking the sensitivity of our results we also employ seasonally adjusted transaction sales price indices from the Federal Housing Finance Agency (FHFA) for the largest 100 MSAs.[15] These indices are available on a quarterly basis. The attraction of the FHFA data lies in the fact that far more MSAs are covered than by the CS data. We select 94 MSAs for which we are able to obtain critical data to construct our interaction terms. The time period covered by our FHFA sample matches that for the CS data, the third quarter of 1992 to the fourth quarter of 2014.

Extending the sample period to 2014 rather than cutting it off after the housing price crash around 2007 has several advantages. First, we cover different phases of the business and real estate cycle, and thus, can account for asymmetries in the transmission channels of local demand and supply variables. Second, a larger sample allows us to include different MSA characteristics in the same specification without causing a simultaneity bias or an omitted variable bias, when they are considered separately.[16] Finally, we increase the number of interest rate regimes, ranging from high interest rates at the beginning to very low interest rate levels at the end of our sample period.

We use the effective, seasonally unadjusted monthly federal funds rate as our monetary policy variable rather than local interest rates or mortgage market related variables because these measures are unlikely to be exogenous. As we make use of monthly or quarterly data, lagged relationships necessarily play a role if one wants to identify policy impacts. It takes a while for the federal funds rate to have an impact on house price inflation. Monetary policy is generally thought to have a lag of at least 6 months on CPI inflation. House price inflation may respond even more sluggishly than CPI inflation because transactions in houses tend to be infrequent relative to those in goods and services. In sum, we need to incorporate lags into the analysis because the federal funds rate at time t will influence house price inflation only at time $t + k$. We proceed by picking alternative lag lengths for the federal funds rate and by estimating a separate model for each chosen lag length.[17] We check the sensitivity of the chosen lag length (k in Eq. (1)) by using lags at 8, 10, 12, 14, and 16 monthly lags and 2, 4, and 6 quarterly lags.[18]

The dependent variable is defined as house price inflation. We construct it by taking the log difference of the monthly (CS data) or quarterly (FHFA data) house price index. The key explanatory variable is the federal funds rate in logarithmic form.[19] It is interacted with variables that capture local demand and supply characteristics, such as population growth or the percentage of undevelopable land. These local conditions do not vary over time but only across MSAs.[20] Their role in our study and their definitions are discussed next.

[12] The STATA input code for the different estimators are available at http://www.sbf.unisg.ch/~/media/internet/content/dateien/instituteundcenters/sbf/publikationen_papers/economic_drivers_fuess_zietz_internet_appendix.pdf

[13] Using seasonally unadjusted data would add a seasonal component to Eqs. (1) and (5) and an additional state equation.

[14] Because the series for Dallas starts in 2000 we exclude this MSA from our sample. The Case/Shiller index is a monthly index for the home prices in 20 MSAs of the U.S.

[15] http://www.fhfa.gov/DataTools/Downloads/Documents/HPI/HPI_PO_metro.txt.

[16] An example for these effects is given by Hilber and Robert-Nicoud (2013) and Gyourko et al. (2013), who show that housing supply becomes more inelastic in locations where demand is high. Similarly, population growth is not entirely exogenous, but can be considered as a function of both housing supply and local demand.

[17] Lag length implies in this context the maximum lag length, without any intermediate lags as in a vector autoregressive model.

[18] We report estimates only for lags 8, 12, and 16 monthly lags.

[19] A common assumption is that a change in the interest rate has a one-time impact on house prices. This is what we would expect from the user cost of capital equation or a discounted cash flow model. However, from the empirical examination of regional house price series, we recognize a long lasting period of continuously increasing (or decreasing) prices, which reflects a change in the slope rather than an immediate shift in the price level. In contrast, the time series of the federal funds rate shows short-term level shifts between a few interest rate regimes. Hence, we specify the dependent variable in log differences, i.e. as growth rates, and the federal funds rate in logarithmic form. In this context, note further that the state-space approach is flexible enough to account for potential non-stationarity in either of the variables. We also considered using first differences (with or without logs) of the federal funds rate. We ran standard vector autoregressions on house price inflation (quarterly 10-city CS data) and the federal funds rate (level and first differences) for alternative lag lengths. The results showed very decisively that house price inflation is Granger caused only by the (log) level of the federal funds rate, not by its first differences (in logs).

[20] The MSA-specific values of these variables for the CS and FHFA data are listed in Tables A.1 and A.2 of the Appendix.

4.1. Local demand factors

Even without a monetary expansion, strong population growth will raise housing demand. Mulder (2006) describes the complex relationship between population and housing. Assuming that the house supply elasticity is not infinite, strong population growth should result in house price inflation.[21] During a period of monetary expansion, MSAs with strong population growth should, therefore, experience above average house price inflation. Leading up to 2006, this was the case, for example, for Las Vegas and Phoenix, both with average annual population growth rates in excess of 3% per year (Appendix Table A.1). We construct for our analysis two population growth rates, one for the time period from 1995 to 2008 (*pop*9508) and another for the period from 2008 to 2013 (*pop*0813). Both are constructed from the Bureau of Economic Analysis Regional Data tables. Separating the time period before the economic downturn in 2008 from the time period afterward allows us to capture the considerable changes in regional and local population growth patterns before and after 2008.[22]

Per capita income growth is another local factor that may increase local housing demand irrespective of any country-wide monetary expansion (Saks, 2008). Income growth may occur locally because of a booming sector, such as IT or mining operations. The per capita income growth may induce residents to upgrade or try to buy second homes, thereby raising housing demand. If a country-wide monetary expansion hits an MSA with these conditions, we expect higher rates of house price appreciation than in areas with declining per capita incomes. To identify such effects, we construct two per capita personal income growth rates in parallel to the two population growth rates, one for the time period from 1995 to 2008 (*inc*9508) and another for the period from 2008 to 2013 (*inc*0813). The data come from the same BEA source as the income growth rates.

Albouy (2012) finds amenities, such as mild seasons, sunshine, hills, coastal proximity, safety, clean air, arts and culture, are key drivers of the quality of life variable (*ql*) he constructs. Many of the MSAs that saw dramatic increases in home prices in the run-up prior to 2007 rank highly on these quality of life criteria. This suggests that a more formal test of the quality of life link between prices in different areas is warranted. We note that Albouy's quality of life ranking cannot be classified as a pure demand-side factor since it also includes geographic constraints, such as coastal proximity and the steepness of land.

[21] See, for example, Saiz (2003, 2007) who demonstrates that prices and rents in housing markets that are characterized by immigrant population shocks undergo price appreciations, which then have an impact on labor mobility of current residents (Ottoviano and Peri, 2007).

[22] For example, a large number of migrant workers from Latin America returned to their home countries as economic growth stalled and GDP started to decline in 2008.

4.2. Local supply factors

Glaeser et al. (2005) emphasize that housing supply constraints arise because of changes in regulatory regimes rather than the lack of developable land. Regulatory barriers to development are related to zoning, which explicitly limits the availability of land, and other land-related regulatory procedures and building restrictions, such as the political process of approval. Current residents often try to restrict zoning via organized community groups because new construction increases the supply of housing and will likely decrease both home values and rents (Glaeser et al., 2005). This is particularly prevalent in high income areas, where households are willing to pay for high-amenity and low-density neighborhoods.

Glaeser et al. (2008) demonstrate the pivotal role of housing supply in shaping the course of house price bubbles. In particular, under the assumption of irrational exuberance, supply inelastic MSAs have larger price increases along with a smaller impact on the housing stock and longer lasting bubbles. In contrast, U.S. cities with more elastic housing supplies have fewer and shorter bubbles, but tend to overbuild in response to bubbles. Hence, in case of inelastic supply an endogenous bubble acts as a short-term demand shock, where rising demand translates into rising prices. Glaeser et al. (2008) find that average estimated real prices appreciated by 81% in MSAs with an inelastic housing supply as compared to 34% in MSAs, where the housing supply was relatively elastic during the boom period 1997–2006.

According to Saiz (2010), housing supply shocks account for most of the differences in the pricing of home values across cities. He emphasizes that the value of the housing supply elasticity is related to both physical and regulatory constraints. Physical constraints arise from the scarcity of developable land, which can be explained by geographic factors, such as the proximity to the ocean, a lake or a river, steep topography, as well as wetlands.

We make use of three different proxies for housing supply conditions. First, we use the measures of supply side conditions developed by Saiz (2010), which are (a) the percentage of undevelopable land and (b) a measure of housing supply elasticity. Saiz (2010) estimated undevelopable land (*ud*) based on adjacency to the ocean or great lakes, area lost to minor water bodies, wetlands, permanent ice caps, bare-rock desert areas, and irreclaimable land with slopes above 15°. This supply measure is exogenous from market conditions since it is based solely on natural land constraints. The supply elasticity proxy (*se*) is based on a function of both physical and regulatory constraints. Because of the severe endogeneity of regulation, Saiz (2010) estimated a simultaneous equation system that provides local supply elasticities by jointly determining housing supply, demand, and regulations. Hence, market clearing prices and quantities in final equilibrium reflect the final regulation level. Our third supply proxy is the Wharton Residential Land Use Regulatory Index (WRLURI) developed by Gyourko et al. (2008). Consistent with the existing literature, we expect that MSAs with tight supply conditions are more likely to react to monetary expansions with above average rates of house price appreciation.

Table 1
Multivariate estimates *without* interaction terms for monthly Case/Shiller data set.

	Lag 8 Coeff	Std err	Lag 12 Coeff	Std err	Lag 16 Coeff	Std err
Atlanta	−0.268***	0.097	−0.135	0.100	−0.193*	0.099
Boston	−0.194**	0.096	−0.034	0.099	−0.069	0.098
Charlotte	−0.248**	0.098	−0.109	0.100	−0.147	0.100
Chicago	−0.225**	0.096	−0.083	0.098	−0.143	0.098
Cleveland	−0.238**	0.097	−0.104	0.099	−0.164*	0.099
Denver	−0.363***	0.099	−0.230**	0.101	−0.290***	0.101
Detroit	−0.206**	0.097	−0.054	0.099	−0.097	0.099
Las Vegas	−0.429***	0.101	−0.321***	0.103	−0.379***	0.103
Los Angeles	−0.382***	0.098	−0.235**	0.100	−0.270***	0.100
Miami	−0.365***	0.098	−0.228**	0.100	−0.285***	0.100
Minneapolis	−0.268***	0.097	−0.107	0.100	−0.155	0.099
New York	−0.186*	0.095	−0.040	0.098	−0.087	0.097
Phoenix	−0.400***	0.100	−0.276***	0.102	−0.331***	0.102
Portland	−0.216**	0.097	−0.086	0.099	−0.149	0.099
San Diego	−0.352***	0.098	−0.188*	0.100	−0.214**	0.100
San Francisco	−0.223**	0.096	−0.093	0.098	−0.156	0.098
Seattle	−0.388***	0.100	−0.230**	0.102	−0.263**	0.102
Tampa	−0.319***	0.097	−0.198**	0.099	−0.256***	0.099
Washington, D.C.	−0.312***	0.096	−0.156	0.098	−0.191*	0.098
LLikelihood	18,957		18,961		18,963	

Notes: Estimations are based on monthly Case/Shiller data for the period 1992:06 to 2014:12. A separate multivariate state-space model (Eqs. (1)–(4)) is run for each lag length (8, 12, and 16). The dependent variable for each of the 19 MSAs is the log difference of the monthly price index. The estimated coefficients and standard errors are multiplied by 100 for the purpose of this table. *** identifies significance at the 1% level, ** at the 5% level, and * at the 10% level.

5. Estimation results

The estimation results for the multivariate model consisting of Eqs. (1)–(4) are presented in Table 1. The logarithm of the federal funds rate serves as our only exogenous variable (x). There are no MSA-specific characteristics on the right-hand side of the equation system. However, the coefficients of the federal funds rate are allowed to vary by MSA (a_i). The multivariate model is estimated for a number of different lag lengths of the federal funds rate.[23] All models are estimated with just one lag of the federal funds rate, which is alternatively placed at 8, 12 and 16 months to account for the well-known fact that a change in monetary policy takes half a year or longer to be visible in output or price statistics. Based on the log-likelihood values, the statistical fit of the multivariate models tends to improve as the lag length increases from 8 to 16 months. However, the MSA-specific coefficients (a_i) tend to be larger in absolute terms and statistically more significant at a lag length of 8 months than at longer lag lengths.[24] We note the large absolute parameter estimates of MSAs with well known price run-ups before the 2007/08 house price crash, such as Las Vegas, Phoenix or Miami.

The economic interpretation of the coefficients presented in Table 1 is as follows. The estimated coefficient for Phoenix at a lag length of 8 months of −0.4 implies that a drop in the log of the federal funds rate by one unit, which is equivalent to 2.7 percentage points for the level of the federal funds rate, raises the monthly house price inflation rate by four tenth of 1%. That translates into a change of 4.8 percentage points at an annual rate, say from a house price inflation rate of 3% to one of 7.8%.[25]

Following Eq. (7) we pool the estimated coefficients of Table 1 across the 19 MSAs and regress them by least squares on the MSA-specific values of the variables in vector z, which play a critical role in Eqs. (5), (6), and (8). Vector z consists of eight variables that vary by MSA, but not across time: the percentage of undevelopable land (ud), the house supply elasticity (se), the Wharton Residential Land Use Regulatory Index (wr), quality of life (ql), and the growth rates of population (pop9508, inc9508) and per capita income (inc9508, inc0813) over the time periods from 1995 to 2008 and from 2008 to 2013. We distinguish between pre- and past-2008 phases to control for the impact of up- and downward movements in the business

[23] Note that several studies highlight the importance of accounting for specific price dynamics in housing markets by including lagged dependent variables (see, e.g., Case and Shiller (1989) and Glaeser et al. (2014)). In our model, however, the persistence in house price changes, i.e. in our left-hand side variable, is captured by the stochastic trend component. Hence, we refrain from modeling house price dynamics by lagged dependent variables separately. In our sensitivity tests based on panel regression we use feasible generalized least squares estimators to correct for autocorrelation. Similarly, one can argue that the federal funds rate is highly persistent even for the long time period considered, which might translate into correlated errors. The potential autocorrelation in this exogenous variable is also captured in the stochastic trend component of our state-space specification.

[24] The loglikelihood values reflect the fact that the models' hyperparameters tend to fit better at longer lags.

[25] For a drop in the log of the federal funds rate larger than 1, say 1.58, which is the standard deviation of the log of the federal funds rate over the sample period from 1992:06 to 2014:12, the predicted change in the house price inflation rate would be 7.6 percentage points. This assumption underlies the summary in Table 6 of this study.

Table 2
Coefficients of Federal Funds Rate as Function of MSA Characteristics.

	Model 1		Model 2	
Variables	Coefficient	*p*-value	Coefficient	*p*-value
Constant	0.214	0.000	0.084	0.003
pop9508	0.074	0.000	0.053	0.000
se	−0.098	0.000		
ud			0.154	0.006
R-squared	0.397		0.350	
Variable addition tests:				
wr		0.362		0.589
ql		0.983		0.432
pop0813, inc9508, inc0813		0.775		0.230

Notes: The 57 coefficients of Table 1 make up the dependent variable. For ease of interpretation, the coefficients of Table 1 are multiplied by (−1) before the OLS regressions are run. A *p*-value less than 0.01 indicates that a parameter (or set of parameters) is (are) statistically significant from zero at better than the 1% level. The variable addition tests suggest that none of the variables or sets of variables adds significant explanatory power.

cycle and for the fact that MSAs with highly pro-cyclical industries tend to be more sensitive to interest rates. As a consequence, in regions with high income and population growth, changes in interest rates can be offset by changes in expected future rent growth, so that the effective impact of monetary policy might be underestimated.

Table 2 presents the results of this exploratory data analysis. Models 1 and 2 contain just two variables, one demand variable and one supply variable. The demand variable is the rate of population growth from 1995 to 2008 (*pop*9508). The two supply variables are *se* and *ud*. Both models can explain a fair amount of the variation in the responsiveness across MSAs of house price inflation to changes in the federal funds rate. The estimated coefficients also have the expected sign. More population growth and a larger share of undevelopable land raise the responsiveness of house price inflation to changes in the federal funds rate, while a higher supply elasticity lowers it. Adding other MSA-specific variables has little impact on the estimates according to a number of variable addition tests. Overall, Table 2 suggests that differences in demand and supply factors across MSAs may indeed play a role in explaining why MSAs respond differently with their house price inflation rates to changes in monetary policy.

The calculations underlying Table 3 involve the multivariate model consisting of Eqs. (2)–(5). In contrast to Table 1 and Eq. (1), the coefficients of the federal funds rate are constrained to be identical across MSAs. Instead, interaction terms between the federal funds rate and MSA-specific demand and supply characteristics are added as separate variables. In line with the results of Table 2, all models in Table 3 contain a number of both demand and supply characteristics. Note that the demand and supply variables only appear as part of the interaction terms, but do not enter as individual explanatory variables because they do not vary over time.

Similar to Table 1, the models containing a lag length of 16 months fit the best based on the log likelihood values. Comparing columns reveals a rather similar pattern across lag lengths. The models shown in Columns (1) and (3) differ only in their choice of *se* or *ud* as supply variables. Based on the exploratory results of Table 2, one would expect the models based on *se* to fit somewhat better than those based on *ud*. However, that is not the case. The models containing *ud* in Columns (3) and (4) clearly dominate those containing *se* in Columns (1) and (2). Another point of interest is the relative significance of variables *wr* and *ql*. As *ql* is added to the model containing *ud* and *wr* in Column (4), the variable *wr* turns insignificant, which is suggestive of collinearity issues. Overall, the model with a lag length of 16 months in Column (4) fits the best based on the log likelihood criterion.[26] This model, together with the other two models in Column (4), suggest that the demand factor population growth, the supply factor undevelopable land, and the factor quality of life influences how the federal funds rate impacts the house price inflation rate for a particular MSA. This largely corroborates the exploratory analysis summarized in Table 2.

To derive from the estimates of Table 3 the response of the house price inflation rate of an individual MSA to a change in the federal funds, we take the partial derivative with respect to the log of the federal funds rate and evaluate the resulting terms at the MSA-specific values of the demand and supply factors, which are specified in Appendix Table A.1. For example, for a lag length of 16 months and the model of Column (4), a unit change in the log of the federal funds rate can be calculated to have the following impact on the inflation rate:

$$\frac{d[d\ln p]}{d\ln ff} = 0.1083 - 0.3948(ud) + 0.0173(wr) - 0.001(ql) - 0.0396(pop9508) - 0.0257(pop0813),$$

where *ff* stands for the federal funds rate and $d\ln p$ is the dependent variable. Employing the demand and supply factors for Phoenix in the above equation and multiplying the result by 12 (to convert to an annual rate) results in

[26] We estimated a number of additional models, including one that eliminated *wr* from the models in Column (4) and added instead the two income terms *inc*9508 and *inc*0813. The income terms turned out to be statistically significant.

Table 3
Multivariate estimates *with* multiple interaction terms for monthly Case/Shiller data set.

	(1) Coeff	Std err	(2) Coeff	Std err	c(3) Coeff	Std err	(4) Coeff	Std err
Lag 8								
ln fedfunds	−0.3179***	0.0963	−0.2871***	0.0965	−0.1718*	0.0963	0.0256	0.1009
ln fedfunds*ud					−0.2006***	0.0322	−0.3889***	0.0433
ln fedfunds*se	0.0837***	0.0182	0.1462***	0.0230				
ln fedfunds*wr	0.0623***	0.0143	0.0578***	0.0143	0.0418***	0.0124	0.0096	0.0133
ln fedfunds*ql			−0.0007***	0.0002			−0.0010***	0.0002
ln fedfunds*pop9508	−0.0366***	0.0103	−0.0414***	0.0103	−0.0265***	0.0097	−0.0186*	0.0097
ln fedfunds*pop0813	−0.0097	0.0156	−0.0424**	0.0169	−0.0057	0.0156	−0.0515***	0.0166
LLikelihood	18,880		18,890		18,889		18,910	
Lag 12								
ln fedfunds	−0.1853*	0.0985	−0.15756	0.0987	−0.0233	0.0986	0.1629	0.1030
ln fedfunds*ud					−0.2178***	0.0325	−0.3960***	0.0436
ln fedfunds*se	0.0936***	0.0183	0.1513***	0.0232				
ln fedfunds*wr	0.0685***	0.0143	0.0644***	0.0143	0.0450***	0.0124	0.0146	0.0133
ln fedfunds*ql			−0.0006***	0.0002			−0.0010***	0.0002
ln fedfunds*pop9508	−0.0508***	0.0103	−0.0550***	0.0103	−0.0393***	0.0097	−0.0315***	0.0097
ln fedfunds*pop0813	0.0028	0.0156	−0.0275	0.0171	0.0077	0.0157	−0.0360**	0.0168
LLikelihood	18,889		18,897		18,898		18,917	
Lag 16								
ln fedfunds	−0.2362**	0.0982	−0.2101**	0.0984	−0.07201	0.0983	0.1083	0.1028
ln fedfunds*ud					−0.2216***	0.0327	−0.3948***	0.0438
ln fedfunds*se	0.0955***	0.0184	0.1512***	0.0235				
ln fedfunds*wr	0.0707***	0.0143	0.0670***	0.0143	0.0468***	0.0124	0.0173	0.0133
ln fedfunds*ql			−0.0006***	0.0002			−0.0010***	0.0002
ln fedfunds*pop9508	−0.0589***	0.0103	−0.0629***	0.0104	−0.0470***	0.0098	−0.0396***	0.0098
ln fedfunds*pop0813	0.0115	0.0157	−0.0177	0.0173	0.0163	0.0157	−0.0257	0.0169
LLikelihood	18,898		18,905		18,907		18,924	

Notes: Estimations are based on monthly Case/Shiller data for the period 1992:06 to 2014:12. A separate multivariate state-space model is estimated for each combination of variables (Columns (1)–(4)) and various lag length (8–16). The dependent variable for each MSA is the log difference of the monthly price index; for readability, the estimated coefficients and associated standard errors are multiplied by 100. All models are run on the sample 1992:06 to 2014:12, which makes the Log Likelihood values (LLikelihood) directly comparable. *** identifies significance at the 1% level, ** at the 5% level, and * at the 10% level.

a value of −1.82. This means that the annualized house price inflation rate in the Phoenix MSA is predicted to increase by 1.82 percentage points (e.g., from 3% to 4.82% per annum) for a unit decrease in the log of the federal funds rate, where the latter is equivalent to a decrease in the level of the federal funds rate by 2.7 percentage points, e.g., from 5% to 2.3%.

Table 4 is based on estimates of Eqs. (2), (4), and (6), plus the assumption that $R_i = R$ in Eq. (3), for all i. With regard to variable selection, the model specifications are similar to those for the multivariate model, except that we add in Column (4) a model with both population and income growth terms. Table 4 only reports the results for the case of a lag length of 8 months, which dominates the cases of 12 and 16 months for this model. The estimation results are similar to those of Table 3. The estimates in Column (4) show signs of collinearity. Based on a likelihood ratio test, the model in Column (3) is preferred by the data. Taking the partial derivative with respect to the log of the federal funds rate for this model, evaluating the MSA-specific factors at the values of Phoenix (Appendix Table A.1) and multiplying by 1 results in a value of −4.73. This implies an increase in the annualized house price inflation rate in the Phoenix MSA of 4.73 percentage points (e.g., from 3% to 7.73% per annum) for a unit decrease in the log of the federal funds rate. This is more than twice the increase predicted by the estimates resulting from Table 3. Although the difference in values for Phoenix is larger between Tables 3 and 4 than for other MSAs, there is a tendency for the univariate model estimates to predict a larger response than the multivariate model. There is a relatively simple reason for this phenomenon. Some of the MSA-specific variation in house price inflation that shows up in the larger absolute values of the estimated coefficients of the univariate model is captured by the MSA-specific error terms R_i in the multivariate model.

We turn next to a sensitivity check that uses a panel estimation framework rather than a state-space approach. Estimation proceeds according to Eq. (8). A key difference to the state-space approach is the way in which pre-existing trends are captured. Instead of a flexible stochastic trend, we now use a far less flexible deterministic quadratic time trend model, with the parameters assumed to be identical for all MSAs. Time-fixed effects turns out to be practically infeasible given the fact that there are 200 time series observation per cross section. Given the large number of time series observations relative to the number of cross-sections (19), we use a feasible generalized least squares estimator and correct for autocorrelation using both a single autocorrelation parameter for the entire sample on the one hand, and 19 MSA-specific parameters on the other. The estimation results are presented in Table 5. Only the estimates for a lag length of 16 months are shown, as these dominate the results for lag lengths

Table 4
Univariate estimates *with* multiple interaction terms for monthly Case/Shiller data set.

	(1) Coeff	Std err	(2) Coeff	Std err	(3) Coeff	Std err	(4) Coeff	Std err
ln fedfunds	−0.0492	0.0947	−0.0350	0.0949	0.3262*	0.1883	0.2786	0.4811
ln fedfunds*ud	−0.3893***	0.1477	−0.3619***	0.1483	−0.6580***	0.1993	−0.4289*	0.2327
ln fedfunds*wr			−0.1478**	0.0742	−0.1872**	0.0762	−0.1188	0.0846
ln fedfunds*ql					−0.0019**	0.0008	−0.0014	0.0010
ln fedfunds*pop9508	−0.0623*	0.0346	−0.1126***	0.0428	−0.0878**	0.0442	0.0094	0.0804
ln fedfunds*pop0813	−0.0504	0.0654	0.0474	0.0818	−0.0697	0.0972	−0.0888	0.1122
ln fedfunds*inc9508							−0.1100	0.1008
ln fedfunds*inc0813							0.1784*	0.1023
LLikelihood	19,989		19,991		19,993		19,995	

Notes: The dependent variable is the log difference of the monthly, seasonally adjusted price index. The panel contains 19 MSAs, each observed for the time period 1992:06 to 2014:12. The estimates for the federal funds rate are based on a lag length of 8 months. The estimated coefficients and standard errors are multiplied by 100 for the purpose of this table. The likelihood values for larger lag lengths are smaller. *** identifies significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table 5
Panel data estimates *with* multiple interaction terms for monthly Case/Shiller data set.

	(1) Coeff	Std err	(2) Coeff	Std err	(3) Coeff	Std err	(4) Coeff	Std err
One AR term								
ln fedfunds	−0.3909***	0.0657	−0.3915***	0.0657	−0.2348*	0.1271	−0.2169	0.3016
ln fedfunds*ud	−0.1530	0.0992	−0.1568	0.1012	−0.2930**	0.1376	−0.3119**	0.1500
ln fedfunds*wr			0.0087	0.0465	−0.0157	0.0493	−0.0228	0.0545
ln fedfunds*ql					−0.0008	0.0005	−0.0008	0.0006
ln fedfunds*pop9508	−0.0530***	0.0212	−0.0500*	0.0268	−0.0427	0.0271	−0.0523	0.0462
ln fedfunds*pop0813	0.0393	0.0416	0.0338	0.0511	−0.0098	0.0592	−0.0078	0.0666
ln fedfunds*inc9508							0.0075	0.0581
ln fedfunds*inc0813							−0.0175	0.0581
Wald statistic χ^2	193		193		198		198	
Panel-specific ARs								
ln fedfunds	−0.3658***	0.0585	−0.3652***	0.0586	−0.0742	0.1344	−0.4147	0.2969
ln fedfunds*ud	0.0086	0.1164	0.0018	0.1192	−0.3228*	0.1800	−0.3269*	0.1961
ln fedfunds*wr			0.0116	0.0429	0.0061	0.0429	−0.0177	0.0531
ln fedfunds*ql					−0.0013**	0.0005	−0.0011**	0.0006
ln fedfunds*pop9508	−0.0343	0.0306	−0.0275	0.0400	−0.0066	0.0408	0.0208	0.0554
ln fedfunds*pop0813	0.0532	0.0436	0.0421	0.0605	−0.0550	0.0724	−0.1029	0.0811
ln fedfunds*inc9508							0.0783	0.0597
ln fedfunds*inc0813							0.0136	0.0523
Wald statistic χ^2	152		152		161		163	

Notes: The dependent variable is the log difference of the monthly, seasonally adjusted price index. The estimated coefficients and standard errors are multiplied by 100 for the purpose of this table. The panel contains 19 MSAs, each observed for the time period 1992:06 to 2014:12. The estimates for the federal funds rate are based on a lag length of 16 months. Estimates refer to panel-based feasible GLS with model-specific AR(1) correction (Stata command: xtgsl, corr(ar1)) or panel-specific AR(1) correction (Stata command: xtgls, corr(psar1)). *** identifies significance at the 1% level, ** at the 5% level, and * at the 10% level.

of 8 and 12. The coefficient estimates of Table 5 follow the pattern of Table 4. Compared to Table 4, however, there are far fewer statistically significant parameter estimates. The model in Column (3) is the one most consistent with the data based on statistical grounds.

Table 6 provides a summary of the estimation results from Tables 1, 3, 4, and 5. All estimates are changes in the house price inflation rate at an annual rate (e.g., −4.0 means that the annual inflation rate drops by 4 percentage points, say from 10% to 6%) in response to a one standard deviation change in the log of the federal funds rate. The latter is 1.58 for the sample period, which translates into a change in the level of the federal funds rate by 4.85 percentage points. A change of this magnitude or larger happened three times during the sample period and each time within a few months: after 2001, after 2004, and around 2008.

The entries in Column (1) of Table 6 are based on a simple average of the coefficient estimates of Table 1, which is then multiplied by 12 and 1.58. The results shown in Columns (2)–(4) make use of the estimates from Tables 3–5 that we consider the most consistent with the data. In contrast to the results of Column (1), the estimates shown in Columns (2)–(4) are evaluated at the MSA-specific demand and supply conditions given in Appendix Table A.1. Column (5) averages the values of the state-space models in Columns (1)–(3). The 19 MSAs are sorted according to the average values in Column (5).

The rank order of MSAs affected the most by changes in the federal funds rate is consistent with our premise

Table 6
Impact of federal funds rate on annual house price inflation rate for monthly Case/Shiller data set.

	(1) No interaction term	(2) Models with interaction terms	(3)	(4)	(5) Average of (1)–(3)
	multivariate	multivariate	univariate	panel	
Las Vegas	−7.14	−6.91	−11.30	−9.19	−8.45
Miami	−5.54	−5.50	−12.29	−8.47	−7.78
Phoenix	−6.37	−2.82	−7.61	−5.84	−5.60
San Francisco	−2.98	−4.88	−8.66	−7.29	−5.51
Seattle	−5.57	−3.03	−7.63	−6.19	−5.41
San Diego	−4.77	−4.41	−7.05	−6.83	−5.41
Atlanta	−3.77	−3.81	−7.33	−7.54	−4.97
Tampa	−4.89	−4.55	−5.39	−7.23	−4.95
Minneapolis	−3.35	−4.12	−7.37	−7.79	−4.95
Los Angeles	−5.60	−3.38	−4.76	−5.78	−4.58
Washington	−4.17	−2.80	−5.89	−7.25	−4.29
Denver	−5.59	−1.68	−5.47	−5.08	−4.24
Detroit	−2.26	−4.42	−4.93	−7.87	−3.87
Boston	−1.88	−2.04	−7.56	−5.36	−3.83
Portland	−2.85	−3.27	−5.25	−6.06	−3.79
Charlotte	−3.18	−3.63	−4.18	−6.85	−3.66
Cleveland	−3.19	−4.00	−2.49	−6.73	−3.23
Chicago	−2.85	−3.47	−3.35	−6.19	−3.22
New York	−1.98	−2.79	−4.81	−5.72	−3.19
Mean	−4.10	−3.76	−6.49	−6.80	−4.79
Std. dev.	1.56	1.22	2.48	1.09	1.42
Max	−7.14	−6.91	−12.29	−9.19	−8.45
Min	−1.88	−1.68	−2.49	−5.08	−3.19

Notes: The panel contains 19 MSAs, each observed for the time period 1992:06 to 2014:12. Column (1) presents averages of the three coefficient estimates of Table 1, multiplied by 12 (to annualize the inflation rate) and by 1.58 (the standard deviation of the log of the fed funds rate over the sample period). Column (2) is based on Column (4) of Table 3, third panel, evaluated at the MSA-specific values of the interaction terms and multiplied by 12 and 1.58. Column (3) relates to Column (3) of Table 4; adjusted as Column (2). Column (4) is based on Column (3) of Table 5, second panel; adjusted as Column (3). The estimates are marginal effects giving the change in the inflation rate from a one standard deviation increase in the log of the federal funds rate. For example, if the log of the federal funds rate decreases by a standard deviation (1.58), which translates to 4.86 percentage points for the federal funds rate, then the home price inflation rate in the Phoenix MSA is predicted to go up by 5.6 (e.g., from 5% to 10.6%) based on the average estimate in Column (5).

that local demand and supply factors are key drivers of an MSA's response to changes in monetary policy. This is apparent if one considers, for example, the first ten MSAs listed in Table 6 and the characteristics associated with these MSAs (Appendix Table A.1). Both Las Vegas and Phoenix experienced an extraordinary increase in population from 1995 to 2008, with Atlanta following closely and with Minneapolis not far behind. For the coastal cities of Miami, San Francisco and Los Angeles, by contrast, the percentage of undevelopable land plays the key role. Seattle and Tampa are subject to both high population growth and limited developable land.

Table 6 reveals that the multivariate state-space estimates tend to predict a lower average response of house price inflation to a change in the federal funds rate than the univariate model or the panel data estimate. Across all state-space models, the predicted variation of the response of inflation across MSAs is larger than that for the panel data models. At a value of 2.48, the standard deviation of the univariate state-space model is more than twice the size of the variation observed for the panel data model. We note in this context that the relatively low variation across MSAs for the panel data model changes little regardless of the particular type of panel data estimator that is used. But one can observe the following trend: the fewer parameters one uses to capture differences in error variation across MSAs, the larger is the absolute predicted response to changes in the federal funds rate and the larger is also the variation of this response across MSAs. This result also holds, although in somewhat muted form, for the estimates of the state-space models. This brings up a key point regarding the essence of the interaction type model suggested in Eqs. (5), (6) and (8). If one accounts for differences in the policy response of MSAs by estimating generic MSA-specific parameters, such as MSA-specific autocorrelation coefficients, variances, or intercept terms (as in fixed effects models), one can reduce the importance of the interaction terms. But in doing that, one is moving away from an economic explanation of why MSAs react so differently to monetary policy to an explanation that is based purely on statistical grounds. That would be contrary to the purpose of this study, which show a way to reveal the *economic* reasons for the differences.

Tables 7–9 provide a sensitivity check of the results for a set of 94 MSAs and quarterly FHFA house price data over the time period from 1992:3 to 2014:4. Given that there are only 96 observations over time, it is not feasible to estimate a multivariate state-space model with

Table 7
Univariate estimates *with* multiple interaction terms for quarterly FHFA data set.

	(1) Coeff	Std err	(2) Coeff	Std err	(3) Coeff	Std err	(4) Coeff	Std err
ln fedfunds	−0.0616	0.0826	−0.0639	0.0824	−0.0182	0.1564	−0.4019	0.3558
ln fedfunds*ud	−1.5489***	0.1664	−1.3936***	0.1725	−1.4367***	0.2131	−1.4806***	0.2154
ln fedfunds*wr			−0.1658***	0.0499	−0.1732***	0.0542	−0.1838***	0.0563
ln fedfunds*ql					−0.0002	0.0007	−0.0002	0.0007
ln fedfunds*pop9508	−0.2463***	0.0494	−0.2399***	0.0493	−0.2413***	0.0495	−0.2020***	0.0628
ln fedfunds*pop0813	0.1281	0.0743	0.1075	0.0744	0.1032	0.0755	0.0321	0.0947
ln fedfunds*inc9508							0.1044	0.0764
ln fedfunds*inc0813							−0.0182	0.0506
LLikelihood	21,825		21,830		21,830		21,831	

Notes: The dependent variable is the log difference of the quarterly, seasonally adjusted price index. The panel contains 94 MSAs, each observed for the time period 1992:3 to 2014:4. The estimates for the federal funds rate are based on a lag length of 2 quarters. The estimated coefficients and standard errors are multiplied by 100 for the purpose of this table. The likelihood values for larger lag lengths are smaller. *** identifies significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table 8
Panel data estimates *with* multiple interaction terms for quarterly FHFA data set.

	(1) Coeff	Std err	(2) Coeff	Std err	(3) Coeff	Std err	(4) Coeff	Std err
One AR term								
ln fedfunds	−0.8376***	0.0603	−0.8373***	0.0603	−0.6042***	0.1027	−0.0104***	0.2239
ln fedfunds*ud	−0.3279***	0.0996	−0.3498***	0.1034	−0.5686***	0.1292	−0.6079***	0.1304
ln fedfunds*wr			0.0236	0.0300	−0.0160	0.0331	−0.0318	0.0344
ln fedfunds*ql					−0.0012***	0.0004	−0.0012***	0.0004
ln fedfunds*pop9508	−0.1608***	0.0297	−0.1623***	0.0297	−0.1708***	0.0298	−0.1246***	0.0385
ln fedfunds*pop0813	0.1382***	0.0449	0.1419***	0.0452	0.1171**	0.0459	0.0368	0.0581
ln fedfunds*inc9508							0.1137**	0.0472
ln fedfunds*inc0813							−0.0108	0.0309
Wald statistic χ^2	632		633		645		653	
Panel-specific ARs								
ln fedfunds	−0.5736***	0.0497	−0.5720***	0.0498	−0.3800***	0.0869	−0.6981***	0.1746
ln fedfunds*ud	−0.1209	0.0909	−0.1321	0.0935	−0.3363***	0.1200	−0.3917***	0.1230
ln fedfunds*wr			0.0126	0.0251	−0.0030	0.0257	−0.0121	0.0269
ln fedfunds*ql					−0.0010***	0.0004	−0.0010***	0.0004
ln fedfunds*pop9508	−0.0549**	0.0280	−0.0565***	0.0281	−0.0783***	0.0292	−0.0385	0.0348
ln fedfunds*pop0813	0.0440	0.0378	0.0472	0.0383	0.0477	0.0382	−0.0161	0.0479
ln fedfunds*inc9508							0.0858**	0.0382
ln fedfunds*inc0813							−0.0075	0.0273
Wald statistic χ^2	411		411		422		429	

Notes: The dependent variable is the log difference of the quarterly, seasonally adjusted price index. The panel contains 94 MSAs, each observed for the time period 1992:3 to 2014:4. The estimates for the federal funds rate are based on a lag length of 6 quarters. The estimated coefficients and standard errors are multiplied by 100 for the purpose of this table. All model variants contain a quadratic time trend common to all MSAs. The models are estimated with panel-based feasible GLS, with sample AR(1) correction or panel-specific AR(1) correction; panel-corrected standard errors are reported. *** identifies significance at the 1% level, ** at the 5% level, and * at the 10% level.

94 separate MSA equations. We are therefore limited to a univariate state-space model and a panel data estimator. The univariate results are contained in Table 7. The panel data estimates are shown in Table 8. Table 9 provides a summary of the results similar in spirit to that of Table 6.

Table 7 reveals a very strong response to the supply side variable *ud*. Also consistently strong is the response to the variable capturing land use restrictions (*wr*). This is a variable that is far less convincing as a predictor of differences in the response across MSAs in the smaller Case/Shiller sample. By contrast, the strong showing of population growth before the house price crash of 2007/8 is very similar to that found for the Case/Shiller data. Table 8 is consistent with Table 7 and with the Case/Shiller results in that the degree of undevelopable land (*ud*) and population growth (*pop*9508) are important predictors. But unlike the results of Table 7, quality of life (*ql*) is statistically far more important than the index of land use restrictions (*wr*). In addition, there is evidence that income growth over the time period from 1995 to 2008 is important to understanding the differences in the response of MSAs to changes in monetary policy.

Table 9 contains a summary of the results from both Tables 7 and 8. The MSAs are ordered from large to low response by the impact estimated for the univariate state-space model. The mean responses of the univariate state-space model and the panel data estimator are both quite

Table 9
Impact of federal funds rate on annual house price inflation rate for quarterly FHFA data set.

	(1) Univariate	(2) Panel		(1) Univariate	(2) Panel		(1) Univariate	(2) Panel
Oxnard	−9.78	−4.66	New Haven	−5.03	−3.77	Washington	−3.01	−3.57
North Port	−9.35	−4.66	New York	−4.92	−3.54	Nashville	−2.95	−3.78
Las Vegas	−9.27	−5.74	Colorado Springs	−4.88	−3.59	Houston	−2.91	−4.12
Fort Lauderdale	−9.00	−5.00	Milwaukee	−4.72	−4.09	Silver Spring	−2.89	−3.44
Miami	−8.96	−4.74	Bridgeport	−4.70	−3.51	Columbia	−2.67	−3.78
West Palm Beach	−8.36	−5.04	Knoxville	−4.52	−4.29	New Orleans	−2.63	−3.52
Riverside	−7.41	−4.26	Baltimore	−4.49	−3.39	Albany	−2.62	−4.04
San Francisco	−7.33	−3.67	Denver	−4.48	−3.33	Pittsburgh	−2.55	−3.99
Orlando	−7.29	−4.65	Stockton	−4.39	−4.00	Birmingham	−2.37	−4.03
Elgin	−7.29	−5.08	Chicago	−4.33	−3.84	Richmond	−2.29	−3.98
San Diego	−7.26	−3.71	Newark	−4.28	−3.34	San Antonio	−2.28	−4.03
Salt Lake City	−7.25	−4.27	Providence	−4.25	−3.10	Grand Rapids	−2.18	−4.59
Jacksonville	−6.81	−4.66	Fresno	−4.10	−3.76	Greenville	−2.12	−4.19
Oakland	−6.78	−3.75	Albuquerque	−4.07	−3.61	Columbus	−2.10	−3.93
Tacoma	−6.59	−3.39	Atlanta	−3.99	−4.49	Winston-Salem	−2.10	−3.96
Tucson	−6.46	−3.42	Austin	−3.96	−3.66	Greensboro	−1.96	−3.96
San Jose	−6.42	−3.75	Memphis	−3.85	−4.67	Detroit	−1.94	−4.37
Anaheim	−6.42	−3.67	Baton Rouge	−3.75	−4.18	Louisville	−1.90	−3.80
Virginia Beach	−6.34	−3.93	Minneapolis	−3.68	−4.11	Little Rock	−1.82	−3.49
Phoenix	−6.07	−4.03	Cleveland	−3.59	−4.20	Philadelphia	−1.79	−3.53
Bakersfield	−5.94	−5.20	Allentown	−3.55	−4.02	Cincinnati	−1.32	−3.82
Los Angeles	−5.94	−3.62	Hartford	−3.50	−3.83	Kansas City	−1.21	−3.78
Seattle	−5.92	−3.52	Dallas	−3.40	−4.34	Akron	−1.20	−3.38
Charleston	−5.92	−4.03	Charlotte	−3.36	−4.13	Buffalo	−1.19	−4.10
Worcester	−5.90	−3.52	Wilmington	−3.33	−3.11	Indianapolis	−1.12	−4.08
Raleigh	−5.88	−4.32	Warren	−3.25	−4.95	Omaha	−1.12	−3.35
Tampa	−5.64	−4.45	El Paso	−3.20	−4.03	St. Louis	−1.09	−3.73
Portland	−5.53	−4.11	Rochester	−3.19	−4.47	Tulsa	−1.01	−3.06
Cambridge	−5.11	−3.24	Camden	−3.18	−3.78	Syracuse	−0.95	−4.24
Boston	−5.04	−3.19	Gary	−3.05	−3.67	Oklahoma City	−0.95	−2.87
Nassau County	−5.04	−3.46	Fort Worth	−3.01	−4.11	Wichita	−0.25	−3.71
						Dayton	0.24	−3.64
Mean	−4.18	−3.95						
Std. dev.	2.28	0.52						
Max	−9.78	−5.74						
Min	0.24	−2.87						

Notes: The panel contains 94 MSAs, each observed for the time period 1992:3 to 2014:4. Column (1) uses the estimates of Column (2) of Table 7, multiplied by 4 (to annualize the inflation rate) and by 1.57 (the standard deviation of the log of the fed funds rate over the sample period). Column (2) is based on the estimates of Column (4), lower panel, of Table 8, adjusted as Column (1). The estimates are marginal effects. They give the change in the inflation rate from a one standard deviation increase in the log of federal funds rate. For example, if the log of the federal funds rate drops by 1.57, which translates to 4.8 percentage points of the federal funds rate, then the annual home price inflation rate in the Phoenix MSA is predicted to go up by 6.1 percentage points, e.g., from 5% to 11.2%, based on the results in Column (1). The basic statistics at the end of the table refer to all 94 MSAs.

similar at around −4. This is somewhat below the corresponding values of Columns (3) and (4) of Table 6. But that is not surprising given that the FHFA data contain many MSAs with relatively low house price inflation rates before 2007 and correspondingly low to moderate values for the MSA-specific demand and supply factors (Appendix Table A.2). The standard deviation of the response across MSAs to a change in monetary policy is unusually low (0.52) for the panel estimator, not only compared to the univariate state-space model in Table 9, but also compared to the values shown for the panel estimator in Table 6. By contrast, the variation estimated for the univariate state-space model (2.28) is fully consistent with that reported in Table 6. A comparison of the rank order of MSAs in Table 9 to the MSA-specific factors (Appendix Table A.2) reveals that MSAs with little developable land and high population growth can be found toward to the top of the list. What also appears to be important, however, are large values for land use restrictions (*wr*) and high income growth during the period before the house price crash in 2007/08. Both of these factors appeared generally less important for the much smaller Case/Shiller sample of MSAs.

6. Conclusion

We identify the role that local demand and supply conditions play for the impact that changes in the federal funds rate have had on house price inflation rates at the level of the Metropolitan Statistical Area (MSA) during the period from 1992 to 2014. The paper is motivated by the fact that the period of house price inflation prior to the economic downturn in 2008/9 was characterized by significant differences in inflation rates across

MSAs. At the same time, advances in information technology and changes in regulations made financial markets far more integrated than at any time before. This suggests that local conditions played a key role in the observed differences in inflation rates. The importance of local conditions was identified earlier by Glaeser et al. (2008) and Saiz (2010).

In this paper, we suggest a novel way to directly link house price inflation at the local level to national monetary policy. For that purpose we employ a set of interaction terms between the monetary policy stance, which we identify with the federal funds rate, and the MSA-specific demand/supply conditions. These interaction terms allow for a weighted impact of national changes in monetary policy on MSA-specific home price inflation rates. Thus, we offer a flexible, data driven way to capture the impact of unobserved and unknown variables which may significantly impact the estimates and policy conclusions.

We incorporate the interaction terms into a state-space framework. This choice allows us not only to identify the impact of local demand/supply indicators and monetary policy on house price inflation with a minimal number of parameters, but also to employ a flexible way to account for pre-existing trend conditions and, equally important, unobserved variables. We employ both multivariate and univariate models. As a robustness check we also estimate standard panel data models.

Our focus is on the monthly Case/Shiller price index series for 19 MSAs over the time period from 1992:06 to 2014:12. These data allow us to estimate all models. As a robustness check we also estimate univariate state-space and panel data models on quarterly FHFA data from 1992:3 to 2014:4. Given constraints on data availability for MSA characteristics, we limit the FHFA data to 94 MSAs. We find the results to be largely consistent across methodology and data sets.

The estimates suggest that local population growth is a key demand side factor and the percentage of undevelopable land a primary supply side factor that determine how national monetary policy impacts house price inflation rates at the MSA level. We find that MSAs with a high share of undevelopable land or strong population growth are far more prone to experience house price inflation from a reduction in the federal funds rate than MSAs without those characteristics. A higher quality of life, by contrast, appears to moderate the impact of a change in the federal funds rate on house price inflation. For the larger set of MSAs contained in the FHFA data set, there is evidence that large values for land use restrictions (*wr*) and high income growth during the period before the house price crash in 2007/8 are also important to explain a strong response of MSAs to changes in monetary policy.

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Appendix

Table A1
MSA characteristics for Case/Shiller monthly data set.

MSA	*ud*	*wr*	*cse*	*ql*	*pop*9508	*inc*9508	*pop*0813	*inc*0813
Atlanta	0.0430	0.03	1.94	175	2.7	3.6	1.3	0.7
Boston	0.3406	1.67	0.65	45	0.4	4.9	0.9	2.0
Charlotte	0.0519	−0.53	2.59	123	2.8	3.7	1.7	1.6
Chicago	0.4028	0.01	0.73	81	0.6	4.0	0.3	1.2
Cleveland	0.4054	−0.18	0.90	128	−0.2	4.4	−0.2	1.6
Denver	0.1656	0.81	1.18	26	2.0	4.4	1.8	1.6
Detroit	0.2458	0.07	1.04	217	−0.1	3.2	−0.2	1.6
Las Vegas	0.3627	−0.68	1.82	152	4.8	3.5	1.2	−0.7
Los Angeles	0.5343	0.50	0.57	15	0.6	4.6	0.7	1.8
Miami	0.7691	0.94	0.57	39	1.4	4.0	1.3	0.7
Minneapolis	0.1932	0.38	1.18	174	1.2	4.3	0.9	1.6
New York	0.4051	0.67	0.64	51	0.5	4.6	0.6	1.5
Phoenix	0.1523	0.60	1.29	72	3.1	4.1	1.4	0.6
Portland	0.3646	0.26	1.01	37	1.7	3.7	1.3	1.5
San Diego	0.6363	0.44	0.68	8	1.1	5.2	1.2	1.8
San Francisco	0.7239	0.78	0.59	4	0.7	5.0	1.3	2.4
Seattle	0.4288	0.93	0.78	22	1.4	4.9	1.5	1.5
Tampa	0.4219	−0.24	1.03	87	1.6	3.8	0.9	1.2
Washington, D.C.	0.1450	0.21	1.28	122	1.5	4.7	1.8	1.0

Notes: The listed MSA-specific demand and supply characteristics are taken to construct the interaction terms with the federal funds rate. *ud and se* tand for the share of undevelopable land and the housing supply elasticity developed by Saiz (2010). Variable *wr* is the Wharton Residential Land Use Regulatory Index. Variable *ql* is the (adjusted) quality of life ranking from Albouy (2012). Variables *pop*9508 and *pop*0813 are the compound annual growth rates of population between 1995 and 2008 and between 2008 and 2013, respectively, as taken from the Bureau of Economic Analysis Regional Data tables. Variables *inc*9508 and *inc*0813 are the corresponding growth rates for per capita personal income, also taken from the BEA.

Table A2
MSA characteristics for FHFA quarterly data set.

MSA (MSAD)	*ud*	*wr*	*se*	*ql*	*pop*9508	*inc*9508	*pop*0813	*inc*0813
Akron OH	0.0653	0.00	1.90	128	0.2	3.9	0.1	2.2
Albany-Schenectady-Troy NY	0.2262	−0.01	1.45	196	0.3	4.3	0.3	2.7
Albuquerque NM	0.1363	0.36	1.58	34	1.8	3.6	0.9	0.7
Allentown-Bethlehem-Easton PA-NJ	0.2092	0.02	1.54	143	1.0	4.0	0.3	2.0
Anaheim-Santa Ana-Irvine CA (MSAD)	0.5343	0.50	0.57	15	1.0	4.8	1.0	1.1
Atlanta-Sandy Springs-Roswell GA	0.0430	0.03	1.94	175	2.7	3.6	1.3	0.7
Austin-Round Rock TX	0.0442	−0.27	2.41	67	3.6	4.4	2.9	2.2
Bakersfield CA	0.2938	0.39	1.34	231	2.2	3.9	1.1	3.8
Baltimore-Columbia-Towson MD	0.2225	1.65	0.86	122	0.6	5.1	0.7	2.1
Baton Rouge LA	0.3373	−0.83	1.86	166	1.2	4.6	0.8	2.5
Birmingham-Hoover AL	0.1476	−0.24	1.79	213	0.8	4.4	0.4	1.4
Boston MA (MSAD)	0.3406	1.67	0.65	45	0.4	5.0	1.0	2.1
Bridgeport-Stamford-Norwalk CT	0.4456	0.19	0.86	51	0.5	4.8	0.8	1.2
Buffalo-Cheektowaga-Niagara Falls NY	0.1925	−0.28	1.49	230	−0.4	4.0	0.0	3.1
Cambridge-Newton-Framingham MA (MSAD)	0.3406	1.67	0.65	45	0.4	4.9	0.9	1.8
Camden NJ (MSAD)	0.1050	1.13	1.10	195	0.5	4.5	0.1	1.7
Charleston-North Charleston SC	0.6072	−0.81	1.38	56	1.6	5.1	2.0	2.0
Charlotte-Concord-Gastonia NC-SC	0.0519	−0.53	2.59	123	2.8	3.7	1.7	1.6
Chicago-Naperville-Arlington Heights IL (MSAD)	0.4028	0.01	0.73	81	0.4	4.2	0.3	1.1
Cincinnati OH-KY-IN	0.1023	−0.58	2.15	187	0.6	4.1	0.4	1.9
Cleveland-Elyria OH	0.4054	−0.18	0.90	128	−0.2	3.7	−0.2	2.3
Colorado Springs CO	0.2240	0.85	1.31	25	1.9	4.1	1.8	1.4
Columbia SC	0.1580	−0.76	2.57	102	1.7	4.0	1.3	1.1
Columbus OH	0.0263	0.25	1.88	161	1.3	3.7	1.1	2.8
Dallas-Plano-Irving TX (MSAD)	0.0923	−0.27	1.88	206	2.5	4.4	1.9	1.3
Dayton OH	0.0108	−0.50	2.91	163	−0.1	3.3	0.1	2.1
Denver-Aurora-Lakewood CO	0.1656	0.81	1.18	26	2.0	4.4	1.8	1.6
Detroit-Dearborn-Livonia MI (MSAD)	0.2458	0.07	1.04	217	−0.9	3.3	−1.0	1.6
Elgin IL (MSAD)	0.4028	0.01	0.73	81	2.5	2.9	0.6	1.6
El Paso TX	0.1285	0.71	1.42	193	1.3	4.5	1.5	2.7
Fort Lauderdale-Pompano Beach-Deerfield Beach FL (MSAD)	0.7605	0.70	0.71	39	1.4	3.8	1.3	0.3
Fort Worth-Arlington TX (MSAD)	0.0504	−0.28	2.27	206	2.4	4.6	1.7	1.8
Fresno CA	0.1356	0.90	1.31	97	1.5	4.0	1.0	2.5
Gary IN (MSAD)	0.3163	−0.69	1.59	81	0.4	4.0	0.0	2.1
Grand Rapids-Wyoming MI	0.0948	−0.14	1.93	204	1.0	3.0	0.6	2.2
Greensboro-High Point NC	0.0341	−0.29	2.39	126	1.4	3.2	0.8	1.3
Greenville-Anderson-Mauldin SC	0.1281	−0.94	2.70	167	1.5	3.7	1.0	1.4
Hartford-West Hartford-East Hartford CT	0.2228	0.51	1.19	156	0.5	4.4	0.2	1.7
Houston-The Woodlands-Sugar Land TX	0.0893	−0.30	2.01	268	2.3	5.5	2.1	1.4
Indianapolis-Carmel-Anderson IN	0.0150	−0.74	3.36	189	1.4	3.6	1.1	1.7
Jacksonville FL	0.4775	−0.03	1.06	110	2.0	4.2	1.1	1.2
Kansas City MO-KS	0.0608	−0.80	2.82	184	1.1	4.2	0.8	1.3
Knoxville TN	0.3740	−0.38	1.42	114	1.1	3.9	0.6	2.3
Las Vegas-Henderson-Paradise NV	0.3627	−0.68	1.82	152	4.8	3.5	1.2	−0.7
Little Rock-North Little Rock-Conway AR	0.1364	−0.88	2.73	116	1.3	4.4	1.2	1.9
Los Angeles-Long Beach-Glendale CA (MSAD)	0.5343	0.50	0.57	15	0.5	4.6	0.6	2.0
Louisville/Jefferson County KY-IN	0.1256	−0.46	2.02	144	0.9	3.9	0.7	1.7
Memphis TN-MS-AR	0.1233	1.16	1.17	244	1.0	3.7	0.5	1.9
Miami-Miami Beach-Kendall FL (MSAD)	0.7691	0.94	0.57	39	1.2	4.3	1.4	1.5
Milwaukee-Waukesha-West Allis WI	0.4198	0.45	0.86	106	0.3	4.1	0.4	1.8
Minneapolis-St. Paul-Bloomington MN-WI	0.1932	0.38	1.18	174	1.2	4.3	0.9	1.6
Nashville-Davidson –Murfreesboro–Franklin TN	0.1261	−0.46	2.03	90	2.0	3.9	1.6	2.6
Nassau County-Suffolk County NY (MSAD)	0.4051	0.67	0.64	51	0.4	4.7	0.3	1.4
Newark NJ-PA (MSAD)	0.3021	0.73	0.92	51	0.5	4.5	0.4	1.2
New Haven-Milford CT	0.4456	0.19	0.86	51	0.4	4.2	0.1	1.9
New Orleans-Metairie LA	0.7501	−1.25	0.83	82	−1.2	5.5	1.8	0.2
New York-Jersey City-White Plains NY-NJ (MSAD)	0.4051	0.67	0.64	51	0.5	4.6	0.7	1.6
North Port-Sarasota-Bradenton FL	0.6681	0.89	0.99	19	1.9	4.1	1.0	0.4
Oakland-Hayward-Berkeley CA (MSAD)	0.6010	0.63	0.66	4	0.9	4.8	1.3	2.0
Oklahoma City OK	0.0257	−0.38	2.58	137	1.2	5.4	1.6	1.6
Omaha-Council Bluffs NE-IA	0.0351	−0.56	2.83	134	1.2	4.4	1.2	1.6
Orlando-Kissimmee-Sanford FL	0.3666	0.31	1.15	78	3.0	3.9	1.7	0.7
Oxnard-Thousand Oaks-Ventura CA	0.8010	1.22	0.73	15	1.1	4.3	0.8	1.7
Philadelphia PA (MSAD)	0.1050	1.13	1.10	195	−0.2	4.6	0.6	2.4
Phoenix-Mesa-Scottsdale AZ	0.1523	0.60	1.29	72	3.1	4.1	1.4	0.6
Pittsburgh PA	0.3052	0.08	0.99	218	−0.4	4.7	0.0	2.6
Portland-Vancouver-Hillsboro OR-WA	0.3646	0.26	1.01	37	1.7	3.7	1.3	1.5

(*continued on next page*)

Table A2 (*continued*)

MSA (MSAD)	*ud*	*wr*	*se*	*ql*	*pop*9508	*inc*9508	*pop*0813	*inc*0813
Providence-Warwick RI-MA	0.1423	2.07	0.97	70	0.3	4.5	0.0	2.3
Raleigh NC	0.0845	0.62	1.50	74	3.8	3.6	2.4	1.4
Richmond VA	0.0906	−0.38	2.19	178	1.4	4.1	0.9	1.5
Riverside-San Bernardino-Ontario CA	0.3873	0.57	0.92	15	2.6	3.8	1.3	1.4
Rochester NY	0.3055	0.04	1.20	194	0.1	3.7	0.1	2.8
St. Louis MO-IL	0.1122	−0.73	2.10	179	0.4	4.1	0.2	1.5
Salt Lake City UT	0.6536	−0.03	0.86	55	1.5	4.9	1.6	1.2
San Antonio-New Braunfels TX	0.0394	−0.26	2.26	188	2.1	4.3	2.0	2.3
San Diego-Carlsbad CA	0.6363	0.44	0.68	8	1.1	5.2	1.2	1.8
San Francisco-Redwood City-South San Francisco CA (MSAD)	0.7239	0.78	0.59	4	0.4	5.3	1.2	3.1
San Jose-Sunnyvale-Santa Clara CA	0.6271	0.21	0.75	4	0.8	4.8	1.3	3.7
Seattle-Bellevue-Everett WA (MSAD)	0.4288	0.93	0.78	22	1.3	4.9	1.7	1.6
Silver Spring-Frederick-Rockville MD (MSAD)	0.1450	0.21	1.28	122	1.3	4.8	1.4	0.5
Stockton-Lodi CA	0.1193	0.59	1.53	91	2.0	3.6	1.0	2.0
Syracuse NY	0.1717	−0.70	1.97	260	−0.1	4.1	0.1	2.5
Tacoma-Lakewood WA (MSAD)	0.3601	1.34	0.96	22	1.5	5.0	0.9	1.1
Tampa-St. Petersburg-Clearwater FL	0.4219	−0.24	1.03	87	1.6	3.8	0.9	1.2
Tucson AZ	0.2452	1.55	1.03	32	1.8	4.7	0.6	0.3
Tulsa OK	0.0641	−0.75	3.02	173	1.0	5.5	1.0	1.8
Virginia Beach- Norfolk-Newport News VA-NC	0.6004	0.12	0.78	54	0.6	4.8	0.5	1.9
Warren-Troy-Farmington Hills MI (MSAD)	0.2458	0.07	1.04	217	0.6	3.0	0.4	1.5
Washington-Arlington-Alexandria DC-VA-MD-WV (MSAD)	0.1450	0.21	1.28	122	1.6	4.7	1.9	1.2
West Palm Beach-Boca Raton-Delray Beach FL (MSAD)	0.6411	0.30	0.99	66	1.9	3.7	1.2	0.2
Wichita KS	0.0173	−1.20	5.16	220	0.9	4.4	0.6	0.8
Wilmington DE-MD-NJ (MSAD)	0.1469	0.46	1.48	18	1.0	4.0	0.5	1.8
Winston-Salem NC	0.0341	−0.29	2.39	126	1.4	3.2	0.6	1.3
Worcester MA-CT	0.3406	1.67	0.65	45	0.7	4.5	0.4	2.2

Notes: The listed MSA-specific demand and supply characteristics are taken to construct the interaction terms with the federal funds rate. *ud and se* stand for the share of undevelopable land and the housing supply elasticity developed by Saiz (2010). Variable *wr* is the Wharton Residential Land Use Regulatory Index. Variable *ql* is the (adjusted) quality of life ranking from Albouy (2012). Variables *pop*9508 and *pop*0813 are the compound annual growth rates of population between 1995 and 2008 and between 2008 and 2013, respectively, as taken from the Bureau of Economic Analysis Regional Data tables. Variables *inc*9508 and *inc*0813 are the corresponding growth rates for per capita personal income, also taken from the BEA.

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