MONETARY POLICY AND HOUSING SECTOR DYNAMICS IN A LARGE-SCALE BAYESIAN VECTOR AUTOREGRESSIVE MODEL

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ABSTRACT. Our paper considers the channel whereby monetary policy, a Federal funds rate shock, affects the dynamics of the US housing sector. The analysis uses impulse response functions obtained from a large-scale Bayesian vector autoregressive model that incorporates 143 monthly macroeconomic variables over the period of 1986:01 to 2003:12, including 21 variables relating to the housing sector at the national and four Census regions. We find at the national level that housing starts, housing permits, and housing sales fall in response to the tightening of monetary policy. Housing sales react more quickly and sharply than starts and permits and exhibit more duration. Housing prices show the weakest response to the monetary policy shock. At the regional level, we conclude that the housing sector in the South drives the national findings in the sense that the response patterns in the South most closely match the response patterns in the nation as a whole. The West's responses differs the most from the other regions, especially for the impulse responses of housing starts and permits.

1. INTRODUCTION

The origins of the business cycle and the designing of appropriate macroeconomic policies to control its fluctuations have occupied economists and policy makers for many decades, nay centuries. The current debate between real-business-cycle and neo-Keynesian theorists hypothesize different causes that lead to different policy recommendations. As one example, the recent observation of the Great Moderation fuelled a debate about whether that moderation came from good policy or good luck.

Recently, Leamer (2007) strongly argues that housing *is* the business cycle, indicating "any attempt to control the business cycle needs to focus especially on residential investment." (p. 150). His main point relates to the dynamics of the construction of homes. To wit, a building boom over one time interval pushes the stock of new homes above trend and that necessitates with some lag another time

interval with a building slump. Thus, monetary policy should focus on preventing booms from occurring to head off eventual slumps. Quoting Leamer (2007), "***The Fed can stimulate now, or later, but not both***." (p. 151, bold, italics in original). Smets (2007) provides commentary on Leamer's paper and argues that interest rates (and monetary policy) crucially determine the linkages between the housing cycle and the business cycle. Leamer (2007) responds that "in the context of my paper, ... the interest rate spread has its impact though housing, though it surely operates through other channels." (p. 249).

Our paper considers this channel whereby monetary policy affects the dynamics of the US housing sector. The analysis uses impulse response functions obtained from a large-scale Bayesian vector autoregressive (LBVAR) model that incorporates 143 monthly macroeconomic variables over the period of 1986:01 to 2003:12. The data set contains 21 variables relating to the housing sector, namely, housing starts, housing permits, housing prices, housing sales, and mobile home shipments at the national level and housing starts, housing permits, housing prices, and housing sales at the four Census regions (Northeast, Midwest, South and West) of the US. As such, the dynamic analysis considers not only how monetary policy affects the housing sector at the national level but also in its four sub-regions.

LBVAR modeling has received much recent attention (see Banbura et al., 2010). When forecasting the national economy, many variables potentially influence the forecast. Traditional time-series modeling approaches such as vector autoregressive (VAR) models face a degrees-of-freedom problem. That is, typical macroeconomic time-series data do not allow the researcher to include too many variables without bumping into problems of degrees of freedom. In sum, LBVAR modeling introduces more relevant information into the forecasting exercise in a tractable way.

We choose the starting point of the sample to consider the uniform monetary policy regime within the Great Moderation. In addition, the starting date comes after the transition of the housing finance system from primarily tightly regulated thrift institutions to the relatively unregulated mortgage securitization controlled largely by mortgage bankers and brokers (McCarthy and Peach, 2002). We end the sample at the end point of the sample in the Stock and Watson (2005) dataset that we use for our estimation. As such, we exclude the dramatic run up in housing prices and their collapse that occurs after our sample ends. Our focus considers the effectiveness of monetary policy during the Great Moderation.

Most central banks today implement monetary policy through control of a short-term interest rate. The central bank actually controls government money, base money, or M_0, which includes currency in circulation plus bank reserves. The central bank can easily control the short-term interest rate (i.e., the Federal funds rate in the US) by injecting or withdrawing government money through open market operations. Central banks may operate with discretion or, more likely, with some monetary policy rule, such as the Taylor rule. For the US, the simple Taylor rule makes changes in the nominal short-term interest rate a function of differences between the actual and target inflation rate and the actual and target output gap. When the inflation rate or the output gap exceed their targets, the central bank raises the nominal short-term interest rate. If the proximate cause of the increase in the nominal interest rate is an increase in the inflation rate, then the nominal interest rate must rise by a larger magnitude so that the real interest rate actually increases as well.

The responsiveness of the housing market to interest rate movements make it an important factor in the national business cycle. Lower (higher) interest rates spur (retard) housing permits and starts, which provide leading indicators of future movements in housing sales and prices. Too easy a monetary policy with low interest rates can lead to an overheating economy. Applying the brakes too strongly and

raising interest rates too smartly can lead to a significant downturn in economic activity and a severe recession. Our analysis not only considers the dynamic effects of changes in the Federal funds rate on the national housing market but also considers the geographic distribution of that dynamic adjustment within the four Census regions in the US. In addition, our dynamic analysis includes 143 monthly macroeconomic variables, including 21 housing market variables, as potential explanatory variables.

Our econometric analysis considers impulse response functions, given a 100-basis point increase in the federal funds rate. As expected, we find at the national level that housing starts, housing permits, and housing sales fall in response to the tightening of monetary policy. Housing sales react more quickly and sharply

than starts and permits and exhibit more duration, still negative, although not significantly so, after 48 months. Housing prices show the weakest response to the federal funds rate shock. At the regional level, we conclude that the housing sector in the South provides the underlying force that drives the national findings. That is, the impulse responses in the South more closely match those of the national housing sector than the other regions. The West's findings differs the most from the other regions and the national level, especially for the impulse responses of housing starts and permits.

The Southern housing market's influence on the national housing market partly reflects that the South, on average, experiences more housing starts, permits, and sales than the other three regions. See Table 1.

Table 1. Summary statistics for the housing variables

Variable	Mean	StDev	Min	Max	Q1	Q3
HStUS	1487.3	232.5	798.0	2088.0	1337.5	1635.8
HStNE	163.5	54.5	76.0	338.0	128.3	174.5
HStMW	306.0	46.3	138.0	428.0	274.3	337.0
HStS	643.2	121.4	345.0	961.0	562.0	723.8
HStW	374.6	68.0	190.0	551.0	333.0	416.8
HPmUS	1452.8	256.4	786.0	1981.0	1307.3	1665.0
HPmNE	166.9	50.4	92.0	317.0	129.3	178.8
HPmMW	297.7	46.9	180.0	462.0	265.3	333.0
HPmS	611.5	132.2	297.0	889.0	519.0	718.5
HPmW	376.7	74.5	217.0	707.0	330.0	416.8
MHSh	252.3	76.0	125.0	390.0	191.0	329.0
HPrUS	1246.2	138.8	1065.3	1641.6	1144.1	1329.1
HPrNE	1608.6	155.6	1329.5	2077.5	1498.9	1725.4
HPrMW	1013.2	136.2	829.0	1340.2	896.9	1133.2
HPrS	1109.4	123.4	952.0	1470.2	1022.3	1167.6
HPrW	1688.3	212.0	1312.6	2373.2	1549.3	1784.0
HSUS	3,861,343	766,447	2,620,000	5,800,000	3,260,000	4,570,000
HSNE	641,620	83,697	430,000	820,000	580,000	710,000
HSMW	1,001,019	152,675	720,000	1,400,000	870,000	1,122,500
HSS	1,363,889	332,672	920,000	2,220,000	1,097,500	1,690,000
HSW	853,843	212,278	510,000	1,380,000	680,000	1,050,000
FFR	5.3	2.1	1.0	9.9	3.8	6.5

Note: The sample includes 216 observations from 1986:1 to 2003:12. The summary statistics include the average (Mean), standard deviation (StDev), the minimum (Min) and maximum (Max) values, and the first (Q1) and third (Q3) quartiles. The other symbols are defined as follows: H = housing, St = starts, Pm = permits, S = sales, Pr = price, MH = mobile home, Sh = shipments, and FFR = Federal funds rate, The geographic indicators are defined as follows: US = national level, NE = Northeast Census region, MW = Midwest Census region, S = South Census region, and W = West Census region.

On average, 43.2% of US housing starts occur in the South. The Northeast, Midwest, and West see 11.0, 20.6, and 25.2%, respectively. For housing permits, 42.1% of US housing permits occur in the South. The Northeast, Midwest, and West see 11.5, 20.5, and 25.9%, respectively. For housing sales, 35.3% of US housing sales occur in the South. The Northeast, Midwest, and West see 16.6, 25.9, and 22.1%, respectively. Finally, the average housing price over our sample period in the South comes closest to the average price at the national level, equaling 11.0% lower. Average housing prices in the Northeast, Midwest, and West equal 29.1% higher, 18.7% lower, and 35.5% higher, respectively, than the national average housing price.

Figures 1, 2, 3, and 4 illustrate the time-series relationship between the national and four Census regions for housing starts, housing permits, housing prices, and housing sales.

The grey regions identify the National Bureau of Economic Research (NBER) national recessions. Housing starts, permits, and sales generally fall before a recession begins, providing leading information about the business cycle. The South generally exceeds the other three Census regions in starts, permits, and sales. Even though these housing series are seasonally adjusted, we seem to see seasonal, rather than cyclical, movements in the national housing price. Two Census regions – the Northeast and the West – do show some cyclical activity in price movements.

We organize the rest of the paper as follows. Section 2 reviews of the literature. Section 3 outlines the theory behind the large-scale Bayesian vector autoregressive (LBVAR) model. Section 4 describes the data. Section 5 reports the results of impulse-response functions. Section 6 concludes.
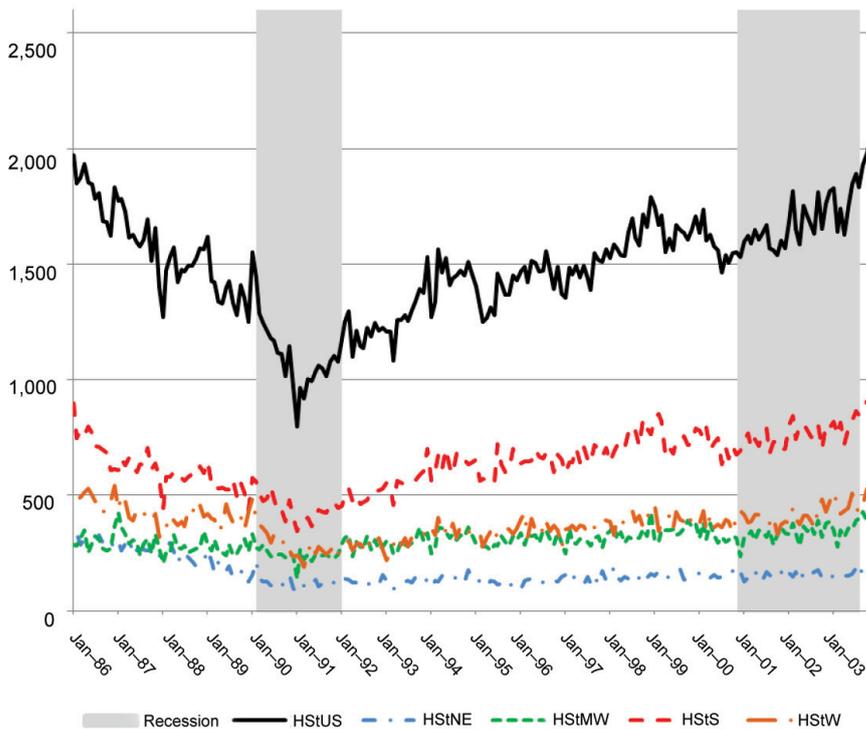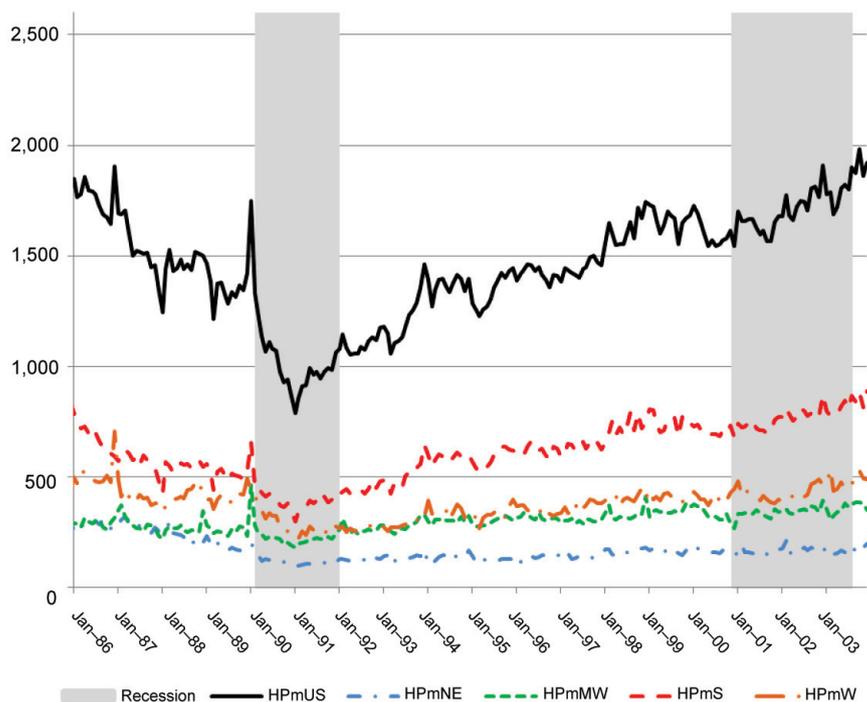

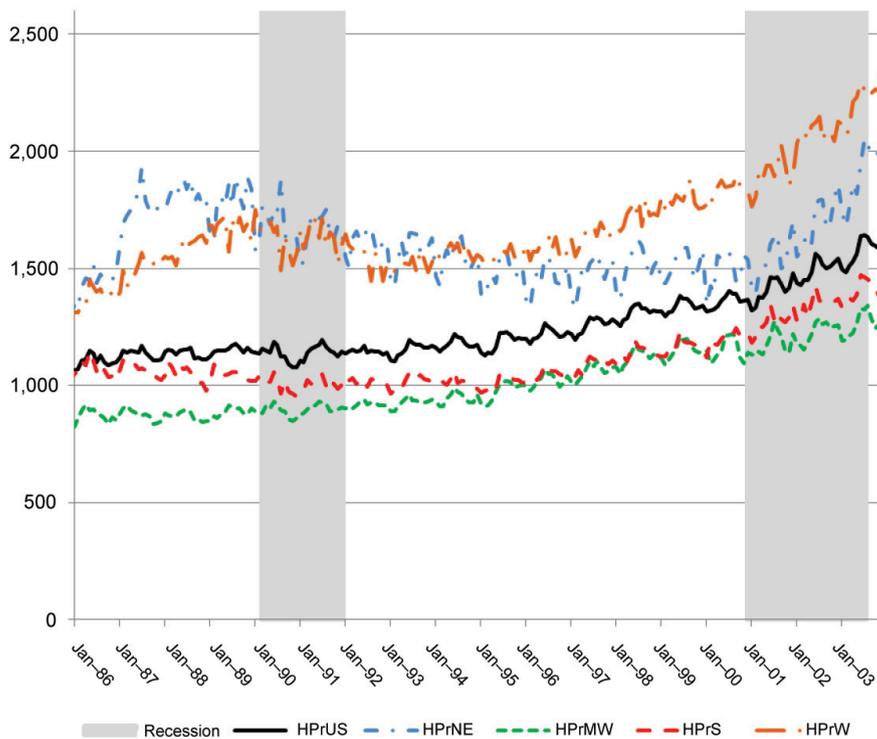**Figure 1.** Monthly housing starts

Figure 2. Monthly housing permits
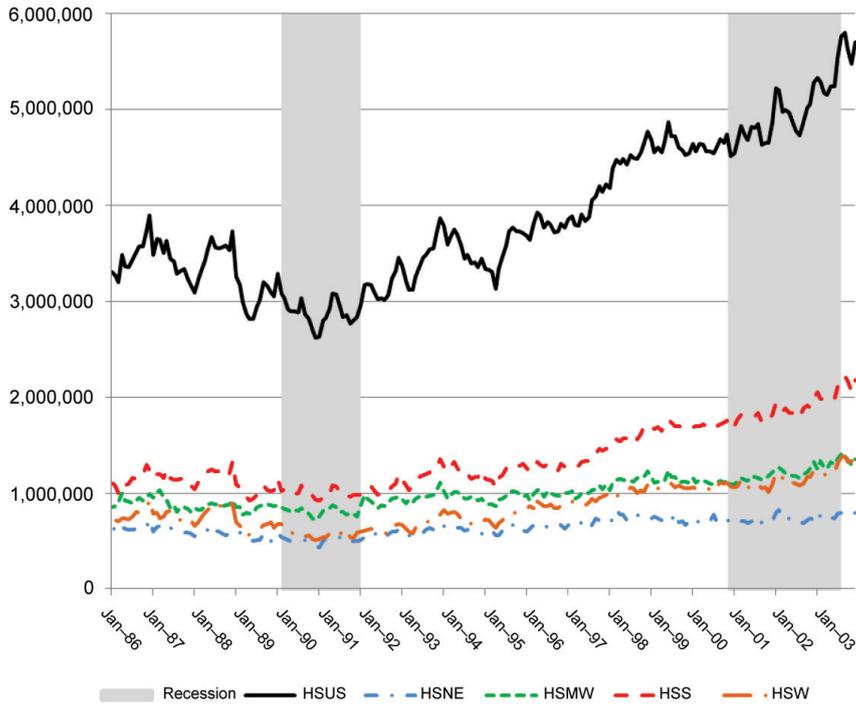
Figure 3. Monthly housing prices

Figure 4. Monthly housing sales

2. LITERATURE REVIEW

Many papers (e.g., Green, 1997; Iacoviello, 2005; Case et al., 2005; Leamer, 2007; Jarociński and Smets, 2008; Vargas-Silva, 2008a; Ghent, 2009; Ghent and Owyang, 2009; Iacoviello and Neri, 2010) show a strong link between the housing market and economic activity in the US. Also as indicated by Vargas-Silva (2008a), a large drop in housing starts tend to precede a recession. In this regard, the Conference Board includes building permits in its leading economic index.[1]

Stock and Watson (2003) pointed out that housing price movements lead real activity, in-flation, or both, and, hence, can indicate where the economy will head. Moreover, the recent emergence of boom-bust cycles in house prices cause much concern and interest amongst policy markers (Borio et al. 1994; Bernanke and Gertler, 1995, 1999), since the bust of housing price bubbles frequently lead to significant contractions in the real economy, vouched for by the current economic downturn. Given the importance of housing market events on the business cycle, researchers need to analyze thoroughly the effects of monetary policy (i.e., changes in the Federal funds rate) on asset markets, in general, and real estate markets, in particular, which, in turn, leads to the understanding of the effects of policy on the economy at large.

Stock and Watson (2004), Rapach and Strauss (2007, 2009), Vargas-Silva (2008b) and Das et al. (2009, 2010, forthcoming) report evidence that numerous economic variables, such as, income, interest rates, construction costs, labor market variables, stock prices, industrial

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[1] In 1995, the Bureau of Economic Analysis of the Department of Commerce sold the rights to produce and disseminate its monthly economic indicators to the Conference Board, including the leading, coincident, and lagging indicators of the US economy. The Conference Board, founded in 1916, maintains a web site of economic information at http://www.conferenceboard.org/

production, consumer confidence index, and so on can predict movements in house prices and the housing sector.

Similar to the LBVAR, Bernanke et al. (2005) propose the factor-augmented vector autoregressive (FAVAR) model to handle large amounts of data. Intuitively, the FAVAR approach boils down to extracting a few latent common factors from a large matrix of many economic variables, with the former maintaining the same information contained in the original data set without running into the risk of the degrees of freedom problem. We, however, prefer the LBVAR, over the FAVAR, model, since the latter requires data transformations to ensure stationarity series and, hence, creates first-differenced or growth-rate versions of the variables under consideration. The LBVAR methodology, based on the appropriate design of the priors, can handle non-stationarity data without making data transformations and, in the process, retains the variables in their original forms. Moreover, as recently shown by Banbura et al. (2010), based on this data set, the LBVAR produces better forecasts of key macroeconomic variables and, hence, is the preferred model. Beck et al. (2000, 2004) also corroborate this process, when they argue that forecasting is at the root of inference and prediction in time series analysis. Further, Clements and Hendry (1998a, b) argue that in time-series models, estimation and inference essentially mean minimizing the one-step (or multi-step) forecast error(s), Therefore establishing a model's superiority boils down to showing that it produces smaller forecast errors than its competitors.

Finally, we use both regional and national housing sector data, since the effect of monetary policy on the economy differs across regions and since regional economic conditions that prevail during a monetary policy shock do not necessarily match (Carlino and DeFina, 1998, 1999; and Vargas-Silva, 2008b).

Although this study provides the first analysis of the effect of monetary policy on the US housing sector using a LBVAR model, many other studies examine the effect of monetary policy on housing. See, for example, Falk (1986), Chowdhury and Wheeler (1993), Iacoviello (2002), McCarthy and Peach (2002), Iacoviello and Minetti (2003, 2008), Ahearne et al. (2005), Ewing and Wang (2005), Kasai and Gupta (2010), Vargas-Silva (2008a, b), Gupta et al. (2010), Gupta and Kabundi (2010) and Musso et al. (2011) for analyses of the effect of monetary policy shocks on housing in the US, Europe, and South Africa.[2] All these studies, except Del Negro and Otrok (2007), Vargas-Silva (2008b), Gupta et al. (2010), and Gupta and Kabundi (2010), who use a FAVAR approach, rely on either a reduced-form vector autoregressive (VAR) model, a vector error-correction (VEC) model, or a structural VAR (SVAR) model, which, in turn, limits them to at the most 8 to 12 variables to conserve the degrees of freedom. Arguably, and as indicated above, a large number of variables potentially affect monetary policy and the housing market. Not including a more complete set of variables often leads to puzzling results that do not conform with economic theory due to the small number of variables in the information set (Walsh, 2000). Moreover, in these studies, the authors often arbitrarily accept specific variables as the counterparts of the theoretical constructs (e.g., gross domestic product measures economic activity or the logarithmic first difference of the consumer price index measures inflation), which, in turn, may not be perfectly represented by the one selected variable. In addition, previous studies can only obtain the impulse-response functions (IRFs) from those few variables included in the model, implying

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[2] Besides their empirical evidence, Iacoviello and Minetti (2003) use a calibrated Dynamic Stochastic General Equilibrium (DSGE) model to analyze the effect of monetary policy on housing prices. More recently, Iacoviello and Neri (2010) employ a more elaborate, estimated DSGE model for this purpose. The authors restrict the model, however, in the sense that they use only 10 macroeconomic variables, including only four housing-market variables.

that in each VAR, VEC, or SVAR, the IRFs are typically obtained with respect to only one variable related to the housing market. Given its econometric construct, the LBVAR model addresses all these problems.

Most of these models, given the issues with degrees of freedom, use the real house price and occasionally housing starts as the main housing related variable, in addition to other standard macroeconomic variables such as measures of output or real activity, the price level, the interest rate, and monetary aggregates. Except for Vargas-Silva (2008a), existing research does not generally consider regional-level housing variables and the importance of regional heterogeneity. Even when the research does consider regional effects, the authors typically estimate the regional level models separately and generally include one regional housing variable and other national macroeconomic variables. Estimating regions separately probably leads to an overestimate of the effect of monetary policy on regional variables.

Theory implies that contractionary monetary policy negatively affects housing starts and real housing prices. These studies frequently generate theoretically inconsistent results. The biggest problem: small-scale modeling with small information sets leads to impulse-response functions following a monetary policy shock that prove inconsistent with theory. For instance, many studies (e.g., McCarthy and Peach, 2002; Vargas-Silva, 2008a; Kasai and Gupta, 2010; Musso et al., 2011) observe the "*price puzzle*", where a positive interest rate shock leads to a significant rise in the real house price for some initial months or quarters. To ensure theoretically consistent results in the housing market, Vargas-Silva (2008a) suggests imposing the sign-restrictions approach proposed by Uhlig (2005). Alternatively, as suggested earlier, one can expand the information set by employing large-scale

models based on factors or a Bayesian model to avoid the "curse of dimensionality."[3]

Del Negro and Otrok (2007), Vargas-Silva (2008b), and Gupta and Kabundi (2010) employ FAVAR models in their analyses. Del Negro and Otrok (2007) find that movements in house prices respond mainly to state- or region-specific variables, using a dynamic factor model estimated via Bayesian methods. The authors then use a standard monetary VAR, also employed in Vargas-Silva (2008a), that includes the common component of the house price derived from the dynamic factor model to investigate the extent to which monetary policy affects this common component. They find that the effect of monetary policy shocks on house prices is small. Vargas-Silva (2008b) studies the effect of monetary policy on seven housing market variables that relate to housing starts, housing permits, and mobile home shipments, using a dataset of 120 monthly indicators. Gupta and Kabundi (2010) assess the effects of monetary policy on housing price inflation for the nine Census divisions of the US economy, using a data set including 126 quarterly series over the period 1976:01 to 2005:02.[4] Against this backdrop, our current paper extends these three studies by not only allowing for a wider set of housing market variables, but also ensuring that the variables retain their original structure, given our usage of the Bayesian methodology.[5]

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[3] The "curse of dimensionality" means that increasing the number of variables considered in an econometric specification increases the number of observations needed to estimate the increasing number of parameters of that system.

[4] Gupta et al. (2010) analyze the effect of monetary policy on real housing price growth in South Africa, using a large data set including 246 quarterly series over the period 1980:01 to 2006:04.

[5] Unlike Gupta and Kabundi (2010), since monthly data prior to 1991 on housing prices in Census regions do not exist, we only use monthly housing price information from the four Census divisions and the aggregate US economy, which, in turn, becomes available at the beginning of 1968.

3. BASICS OF THE LBVAR [6]

Let $Y_t = (y_{1,t} \; y_{2,t} ... y_{n,t})'$ equal a vector of random variables. We represent a VAR(p) model of these time series as follows:

$$Y_t = c + A_1 Y_{t-1} + ... + A_p Y_{t-p} + u_t, \qquad (1)$$

where: $c = (c_1, ..., c_n)'$ equals an *n*-dimensional vector of constants; $A_1, ..., A_p$ equal $n \times n$ autoregressive matrices, and u_t equals an *n*-dimensional white noise process with covariance matrix $E u_t u_t' = \Psi$.

The VAR model generally uses equal lag lengths for all the variables of the model. Thus, the researcher must estimate many parameters, many of which may prove insignificant. This problem of overparameterization, resulting in multicollinearity and a loss of degrees of freedom, leads to inefficient estimates. One solution, often adapted, simply excludes the insignificant lags based on statistical tests. Another approach uses a near VAR, which specifies an unequal number of lags for the different equations. As an alternative, Litterman (1986) proposes a Bayesian vector autoregressive (BVAR) model. Instead of eliminating longer lags, the Bayesian method imposes restrictions on these coefficients by assuming that they more likely equal zero than the coefficients on shorter lags. If, however, strong effects from less important variables exist, then the data can override this assumption. The restrictions are imposed by specifying normal prior distributions with zero means and small standard deviations for all coefficients with the standard deviation decreasing as the lag length increase. The exception, the coefficient on the first own lag of a variable has a mean of unity. Litterman (1986) uses a diffuse prior

for the constant. This specification is popularly referred to as the 'Minnesota prior' due to its development at the University of Minnesota and the Federal Reserve Bank at Minneapolis. The prior imposes the following moments for the prior distribution of the coefficients:

$$E\left[(A_k)_{ij}\right] = \begin{cases} \delta_i, \; j = i, \, k = 1 \\ 0, \; otherwise \end{cases},$$

$$V\left[(A_k)_{ij}\right] = \begin{cases} \lambda^2/k^2, \; j = i \\ \vartheta \lambda^2 \sigma_i^2 / k^2 \sigma_j^2, \; otherwise \end{cases}. \qquad (2)$$

We assume that the coefficients $A_1, ..., A_p$ are independent and normally distributed. We also assume that the covariance matrix of the residuals is diagonal, fixed, and known. Formally, $\Psi = \sum$, where $\sum = diag(\sigma_1^2, ..., \sigma_n^2)$. As discussed above, Litterman's (1986) original specification sets $\delta_i = 1$ for all i, implying that all variables exhibit high persistence. If the researcher believes that some of the variables experience substantial mean reversion, however, the researcher can impose $\delta_i = 0$, wherever necessary.

The hyperparameter λ controls the overall tightness of the prior distribution near δ_i. Alternatively, λ determines the importance of the prior beliefs in relation to the information contained in the data. When $\lambda = 0$, the posterior equals the prior and the data exert no influence on the estimation. When $\lambda = \infty$, no influence of the prior exists and, hence, the parameter estimates coincide with the Ordinary Least Squares (OLS) estimates. The factor $1/k^2$ equals the rate by which the prior variance decreases as the lag length of the VAR increases, and σ_i^2/σ_j^2 accounts for the scale difference and data variability. The coefficient $\vartheta \in (0,1)$ governs the extent to which the lags of other variables are "less important" relative to the own lags.

To analyze the impulse responses of the housing market variables following a mon-

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[6] This section relies heavily on the discussion available in Banbura et al. (2010), Bloor and Matheson (2010), and Koop and Korobilis (2010). We retain their symbolic representations of the equations.

etary policy shock, one must incorporate possible correlation among the residual of the different variables. Hence, we must address Litterman's (1986) assumption of fixed and diagonal covariance matrix. Following Kadiyala and Karlsson (1997) and Sims and Zha (1998), we handle the problem by imposing a normal prior distribution for the coefficients and an inverted Wishart prior distribution for the covariance matrix of the residuals, alternatively called the inverse-Wishart prior. This is possible under the condition: $\vartheta = 1$.

Due to the common practice of specifying a VAR in first differences, Doan et al. (1984) propose another modification of the Minnesota prior by incorporating the sums of coefficients prior. Consider the VAR in equation (1) in its error-correction form as follows:

$$\Delta Y_t = c - (I_n - A_1 - ... - A_p)Y_{t-1} + \Delta Y_{t-1} + ... + B_{p-1}\Delta Y_{t-p+1} + u_t. \tag{3}$$

The sums-of-coefficients prior impose the restrictions that $(I_n - A_1 - ... - A_p)$ equal a matrix entirely of zeros. We use a hyperparameter τ to control the degree of shrinkage of the sums-of-coefficients prior.[7] As τ goes to zero, the VAR model increasingly satisfies the prior, while as τ goes to ∞, the prior exerts no influence on the VAR estimates. Following Litterman (1986) and Sims and Zha (1998), we set the prior for the scale parameter σ_i^2 equal to the residual variance from a univariate autoregression of order p for y_{it}. Similarly, we determine the prior for the average of y_{it} (i.e., governed by the parameter μ_i) as the sample average of the variable y_{it}. Further, we follow Banbura et al. (2010) in choosing λ and τ.

Since the LBVAR with the sums-of-coefficients and Minnesota priors produce better forecasts for key macroeconomic variables relative to the LBVAR model based on only the

Minnesota prior,[8] we use the former for our structural analysis discussed below.[9] Further, for the LBVAR with only the Minnesota prior, the posterior coverage intervals of the impulse response functions become wider two years after the shock, and eventually explode. De Mol et al. (2008) argue that the overall tightness governed by λ should reflect the size of the system -- as the number of variables increases, the parameters should shrink to avoid overfitting. To select the values for λ and τ, we use the following algorithm: (i) Select n^* $(n^* < n)$ variables as benchmarks to evaluate the in-sample fit. In our case, as in Banbura et al. (2010), we chose three variables -- employment, the consumer price index, and the Federal funds rate. (ii) Evaluate the in-sample fit with these n^* variables of the OLS-estimated VAR model. (iii) Set τ proportional to λ as $\tau = 10\lambda$, matching Banbura et al. (2010). And, (iv) choose λ and τ to execute the same in-sample fit as the benchmark VAR based on the n^* variables. Specifically, for a desired *Fit,* we choose λ as follows:

$$\lambda(Fit) = \arg\min_{\lambda} \left| Fit - \frac{1}{3}\sum_{i=1}^{3} \frac{MSE_i^w}{MSE_i^0} \right|, \tag{4}$$

where:

$$MSE_i^{\lambda} = \sum_{t=p}^{T_0-2} (y_{i,t+1|t}^{\lambda} - y_{i,t+1})^2 \Big/ (T_0 - p - 1).$$

That is, MSE_i^{λ} equals the one-step-ahead mean squared error evaluated using the training (benchmark) sample, which, in our case, equals 1970:01 to 1979:12, and $t = 1, ..., T_0 - 1$, where T_0 equals the beginning of the sample period and p is the order of the VAR. Thus, MSE_i^0 equals the *MSE* of variable i with the prior restriction imposed exactly (i.e., $\lambda = 0$),

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[7] See equation (7) in Bloor and Matheson (2010) for further details.

[8] Banbura et al. (2010) find the same results.

[9] The forecast performance of the alternative BVARs for the key macroeconomic variables are available upon request from the authors.

while the baseline *Fit* equals the average relative MSE from an OLS-estimated VAR containing the three variables. That is,

$$Fit = \frac{1}{3}\sum_{i=1}^{3}(MSE_i^{\infty}/MSE_i^{0}). \qquad (5)$$

Finally, once the priors are specified, we estimate the BVAR model using Theil's (1971) mixed estimation technique. Essentially, the method involves supplementing the data with prior information on the distribution of the coefficients. The number of observations and degrees of freedom increase by one in an artificial way, for each restriction imposed on the parameter estimates. The loss of degrees of freedom due to over-parameterization associated with a classical VAR model, therefore, does not arise in the BVAR estimation.

4. DATA

We use the data set of Stock and Watson (2005), which includes 132 monthly macroeconomic indicators covering income, industrial production, measure of capacity, employment and unemployment, prices relating to both consumer and producer, wages, inventories and orders, stock prices, interest rates for different maturities, exchange rates, money aggregates, consumer confidence, and so on. In the housing sector, this data set includes ten variables, housing starts for the US and the four Census divisions, total new private housing units for the US, and residential building permits for the four Census regions. To this data set, we add economy-wide mobile home shipments (US Census Bureau) and single-family existing housing sales and median prices for the four Census regions and the US economy (National Association of Realtors). In total, we use 143 monthly series. Following Rapach and Strauss (2007, 2009), we convert housing prices

to real values by deflating with the personal consumption expenditure deflator.[10] The data spans the period of 1968:01 through 2003:12. The start date coincides with data availability of home sales and prices, while the end data corresponds to the data set in Stock and Watson (2005). As in Banbura et al. (2010), we take logarithms for most of the series, except for those already in rates. In addition, for non-stationary variables, we set $\delta_i = 1$, while for stationary variables, we use $\delta_i = 0$, implying random walk and white noise priors, respectively.[11] Given the widespread evidence that monetary policy takes more than a year to affect the economy,[12] we use thirteen lags in the LBVAR model, which implies that the observations available to us for the analysis starts at 1969:02. The training (benchmark) sample for determining the values for λ and τ runs from 1970:01 to 1979:12. Finally, we estimate the impulse responses for the LBVAR model for a sample period entirely within the period of the Great Moderation in the US (i.e., 1986:1 to 2003:12).

5. IMPULSE RESPONSES

In this section, we analyze the effects of a monetary policy (Federal funds rate) shock

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[10] While the personal consumption (PCE) deflator comes from the calculation of real GDP, the Bureau of Economic Analysis also computes the PCE on a monthly basis. See Table 2.8.4. Price Indexes for Personal Consumption Expenditures at http://www.bea.gov/national/nipaweb/SelectTable.asp?Selected=N.

[11] Appendix A in Banbura et al. (2010) reports the description of the data set and the transformations and the specification of δ_i for each series, except, of course, for the 11 additional housing-related variables that we added. For mobile home shipments, home sales, and prices, we took logarithms. We impose $\delta_i = 0$ for mobile home shipments and $\delta_i = 1$ for home sales and prices, given their behavior.

[12] See Bernanke et al. (2005) and Banbura et al. (2010) for further details.

on the 21 housing related variables. For this purpose, following Christiano et al. (2005) and Bernanke et al. (2005), we identify the monetary shock based on a recursive identification scheme, categorizing the 143 variables as either slow (S_t) or fast-moving (F_t) variables. Generally speaking, the former set includes real variables and prices, while the latter consists of financial variables. All housing market variables appear in the slow-moving segment. Defining the monetary shock variable as r_t, we order the variables as follows: $Y_t = (S_t, r_t, F_t)$. The ordering embodies two key assumptions about identification: the variables in F_t respond contemporaneously with the monetary shock, while the variables in S_t do not. Moreover, we also assume the Federal funds rate shock lies orthogonal to all other shocks driving the economy.

In our impulse response analysis, we increase contemporaneously the Federal funds rate by one hundred basis points. Following Canova (1991) and Gordon and Leeper (1994), we can easily compute the impulse response functions, given just identification, by generating draws from the posterior of $(A_1, ... A_p, \Psi)$.

Figures 5, 6, 7, and 8 report the impulse responses of the 21 housing variables based on the sample 1986:01 to 2003:12 obtained from a LBVAR with the modified Minnesota prior, estimated with p=13 and λ =0.0465 based on the desired fit. We plot the behavior of the functions over 48 months following a monetary policy shock. The shaded regions indicate the posterior coverage intervals corresponding to both 90 (lighter shaded region) and 68 (darker shaded region) % levels of confidence.

The Federal funds rate (FFR) increases by 1% and remains significant for about 20 months. From Figure 5, contractionary monetary policy exerts a negative and significant effect on US housing starts (HStUS). This matches the findings by Banbura et al. (2010) and Vargas-Silva (2008a). A contractionary monetary policy increases the cost of financing and consequently
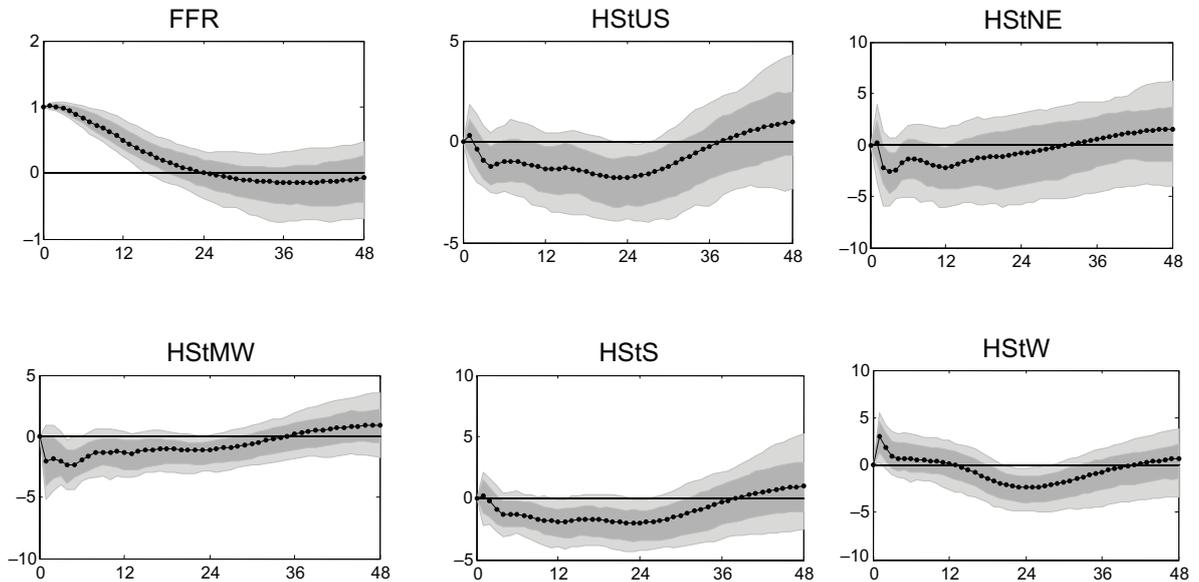

Figure 5. Effect of 100-basis-point monetary policy shock on housing starts
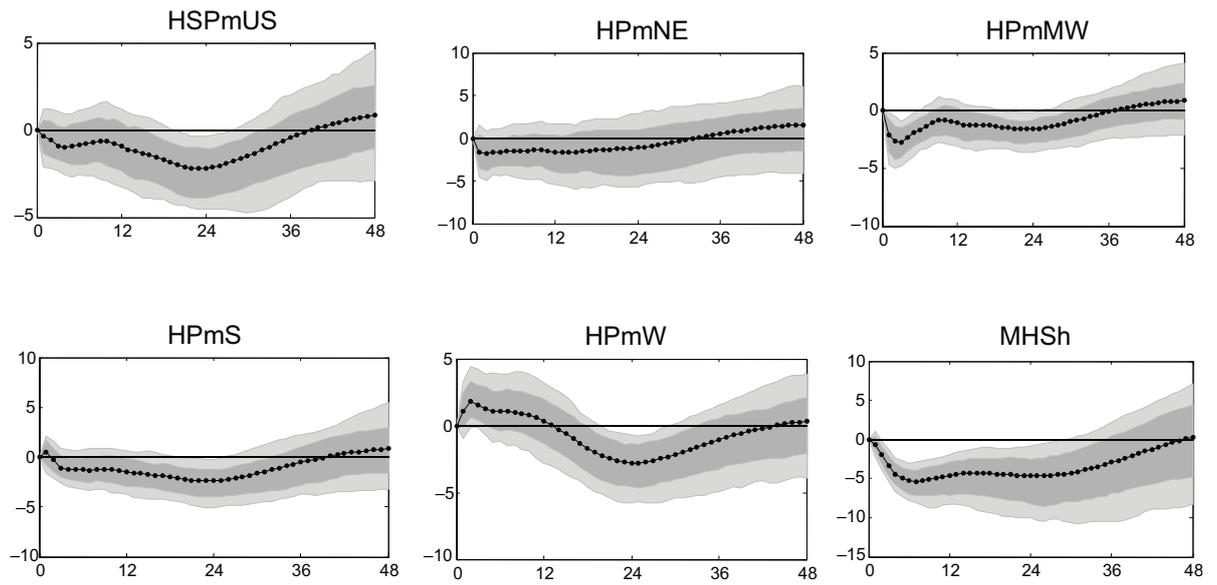
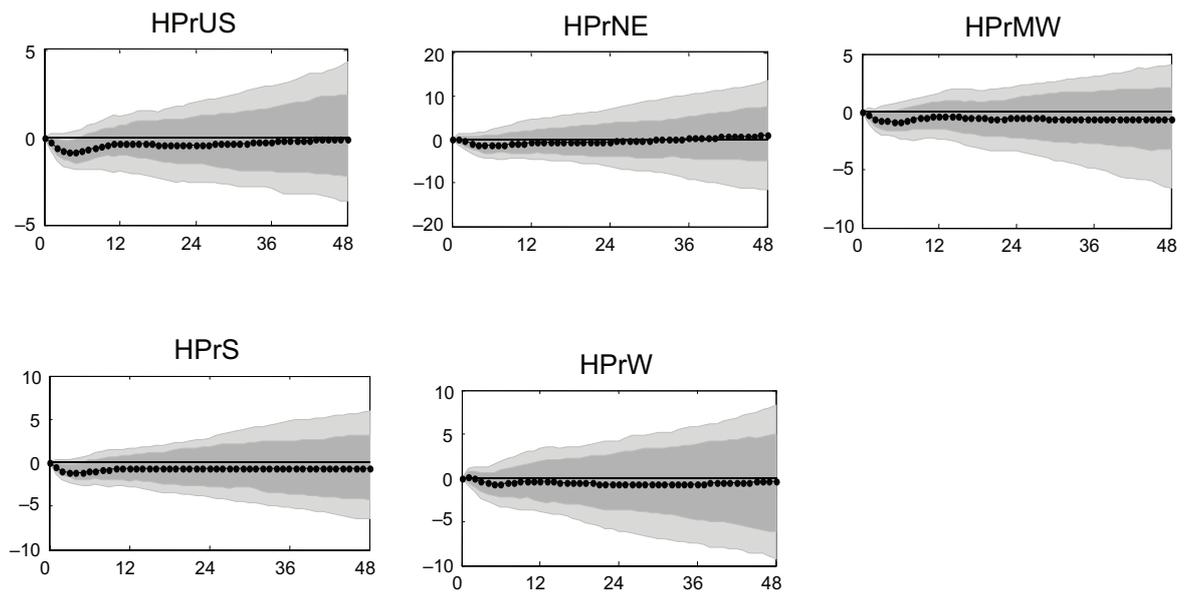**Figure 6.** Effect of 100-basis-point monetary policy shock on housing permits

Figure 7. Effect of 100-basis-point monetary policy shock on housing price
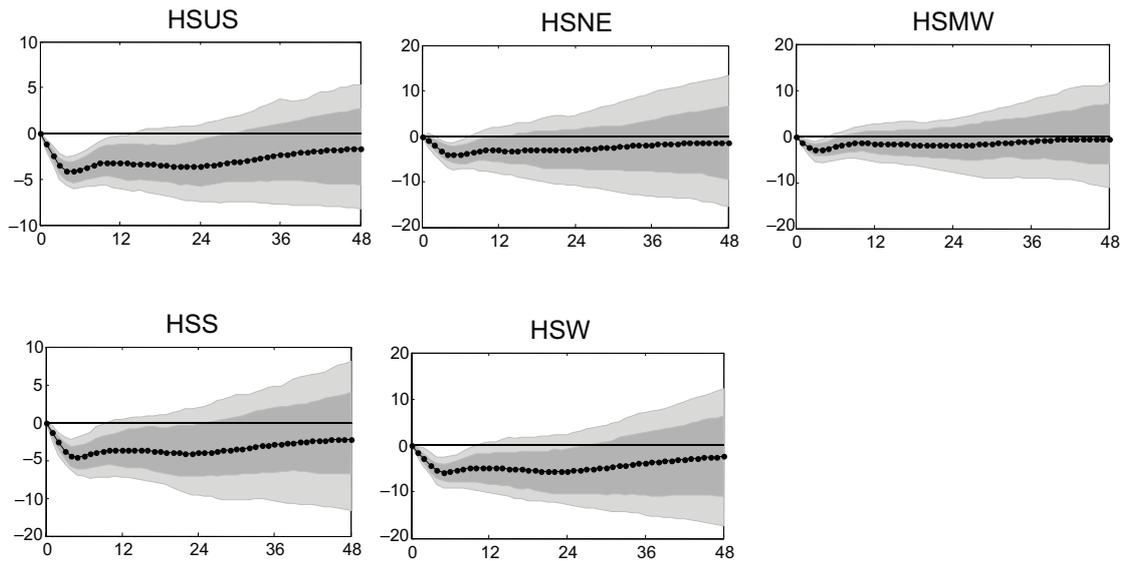
Figure 8. Effect of 100-basis-point monetary policy shock on housing sales

puts downward pressure on housing starts. A closer look indicates that a short-term increase in US housing starts occurs after the shock. This short-run rise in US housing starts is short-lived and, subsequently, US housing starts decrease and reach the minimum of -12.24% after 23 months (see Table 2).[13] Then, the effect dies out progressively, becoming insignificant in month 30.

Across the four Census regions, the housing starts show negative and significant effects, similar to the reaction at the national level. The magnitudes and durations of the effects, however, differ across regions. For example, housing starts in Northeast (HStNE) and Midwest (HStMW) follow more or less the

same pattern, a significant decrease immediately after the shock reaching 12% after approximately four months followed by a gradual recovery.

The impulse responses of housing starts in the South (HStS) resemble, in large part, the impulse responses of US housing starts (HStUS). The similarity of the impulse responses of housing starts in the South to the responses of housing starts at the national level support the findings of Vargas-Silva (2008b) and Gupta and Kabundi (2010), finding that housing-market dynamics housing in the US largely reflect the dynamics in the South. That is, most housing activity in the US takes place in the South.

Housing starts in the West (HStW) display a much different pattern, a prolonged positive effect of more than a year. Hence, a rise in the Federal fund rate affects housing starts negatively in the West only after 12 months and becomes insignificant later on, similar to other regions, after month 30. Vargas-Silva

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[13] Figures 5, 6, 7 and 8 plot the impulse responses based on the natural logarithm of the housing variables. We transform the impulse responses so that they reflect percentage changes from the mean level of the housing variables. The percentages reported in the rest of the paper as well as in Table 2 reflect similar percentage changes. Table 2 provides summary statistics on the impulse response series calculated in this fashion.

Table 2. Summary statistics on impulse response findings

	HStUS	HStNE	HStMW	HStS	HStW	
Mean	−5.15	−2.34	−3.66	−5.89	−2.89	
Median	−7.48	−3.45	−5.79	−8.52	−1.98	
Standard Deviation	6.19	6.29	5.24	6.23	7.25	
Range	19.67	20.54	18.12	18.77	32.86	
Minimum	−12.24	−12.42	−12.78	−12.12	−13.23	
Maximum	7.44	8.11	5.33	6.65	19.63	
	HPmUS	HPmNE	HPmMW	HPmS	HPmW	MHSh
Mean	−5.97	−2.52	−4.63	−6.44	−3.82	−17.11
Median	−6.32	−5.31	−6.12	−7.88	−3.55	−21.12
Standard Deviation	6.18	5.85	5.23	6.13	7.85	7.88
Range	21.17	17.54	19.54	19.97	26.85	27.61
Minimum	−14.78	−9.10	−14.58	−14.23	−15.26	−25.76
Maximum	6.39	8.44	4.96	5.74	11.60	1.85
	HPrUS	HPrNE	HPrMW	HPrS	HPrW	
Mean	−2.68	−2.01	−3.96	−4.91	−4.19	
Median	−2.57	−3.23	−3.98	−4.61	−4.36	
Standard Deviation	1.32	4.65	0.71	0.96	1.22	
Range	5.25	16.33	3.41	4.35	6.47	
Minimum	−6.03	−9.56	−5.64	−7.79	−5.43	
Maximum	−0.77	6.77	−2.24	−3.44	1.04	
	HSUS	HSNE	HSMW	HSS	HSW	
Mean	−35.27	−28.01	−18.48	−37.72	−44.34	
Median	−38.71	−30.38	−19.57	−40.82	−48.58	
Standard Deviation	7.69	7.87	6.92	6.68	9.13	
Range	30.04	31.85	26.47	30.57	37.14	
Minimum	−46.87	−42.40	−33.48	−47.60	−54.60	
Maximum	−16.83	−10.55	−7.02	−17.04	−17.46	

Note: See Table 1. Figures 5, 6, 7 and 8 plot the impulse responses based on the natural logarithm of the housing variables. The statistics reported in this Table transform the impulse responses so that they reflect percentage changes from the mean level of the housing variables. The impulse responses over 48 months.

(2008a) also observes this puzzling effect, but for a shorter time period.

Figure 6 depicts impulse responses of housing permits following a one-percent rise in the Federal funds rate. The shape of the impulse responses in Figure 6 prove somewhat similar to those plotted in Figure 5. The housing permits at national level (HPmUS) display a negative, significant, and gradual response to a monetary policy shock. A rise in short-term interest rates increases the cost of financing, which, in turn, affects housing permits negatively. Just like housing starts, housing permits reach their minimum of -14.78% after 23 months, then re-

cover, and ultimately become insignificant after three years following the shock.

Again, the housing permits in the South (HPmS) seem to drive the dynamics in housing permits in the US, exhibiting similar responses. That is, housing permits of the South respond with a small, short-lived, positive effect of one month. Moreover, housing permits in Northeast (HPmNE) drop, reaching a minimum of -9.1% after one month following the shock, and then the effect dies out gradually. In this case, the reactions appear insignificant. The impulse responses of housing permits in the Midwest (HPmMW) and the West (HPmW)

portray a shape almost identical to that obtained in housing starts.

Comparing the impulse response findings for housing starts and permits, permits fall, on average, by -5.97% while starts fall, on average, by -5.15%. Moreover, average permits uniformly decrease by more than starts across the four Census regions. The West exhibits the most volatility in its impulse responses over time for both permits and starts while the Midwest exhibits the least volatility.

Mobile home shipments (MHSh) respond negatively and significantly to a monetary policy shock, lasting for approximately three years. They trough with a loss of -25%. This result supports economic theory, where a negative reaction of mobile shipments occurs as a result of higher financing costs. Figure 6 shows that mobile-home shipments do not exhibit any puzzling effects, which Vargas-Silva (2008b) uncovers.

Figure 7 shows how a contractionary monetary policy drops US housing prices at national level (HPrUS). In contrast to housing starts and housing permits, housing prices recover rapidly, corroborating the findings of Del Negro and Otrok (2007), reaching a minimum of -6.03% after six months. Housing prices in the US fall, on average, by -2.68%. No evidence emerges of a *housing price* puzzle observed by McCarthy and Peach (2002). Gupta and Kabundi (2010) use the FAVAR approach, which also accommodates large number of economic variables, and find similar results. The difference resides on the duration of the effect. In the present study, the transmission of monetary policy to US housing prices (HPrUS) lasts for about a year, whereas in Gupta and Kabundi (2010), the effect persists for more than ten quarters. The difference observed probably reflects data treatment. Gupta and Kabundi (2010) use the housing price growth rate rather than the housing price level. Furthermore,

the magnitude and the duration of monetary policy shocks differ.

Housing prices in the South, on average, show the largest decrease of -4.91% while the Northeast posts the lowest average decrease of -2.01%, The pattern of housing price impulse responses in the Northeast, however, tells a much different story than the other three Census regions. The other three regions exhibit consistently negative impulse responses, except for the positive first month in the West. The Northeast, however, exhibits positive impulse responses after 33 months until the end in the 48th month as well as an insignificant positive impulse response in the first month. As such, the Northeast experiences the highest volatility of housing price impulse responses relative to the other regions. Once again, the Midwest experiences the lowest volatility.

Finally, Figure 8 illustrates the transmission of the monetary shock on housing sales nationally and across different regions in the US. Housing sales respond negatively to monetary policy at the national as well as regional levels. The reaction of sales occurs quickly and remains prolonged both nationally (HSUS) and in the South (HSS). Housing sales respond negatively with some persistence in Northeast (HSNE) and in Midwest (HSMW), although only significantly in the short-term for about ten months. Finally, the sales decline in the West (HSW) lasts relatively longer than those of sales in Northeast (HSNE) and the Mid West (HSMW), but relatively shorter when compared to the South (HSS).

The impulse responses, on average, show decreased sales of -35.27% in the US. Differing average decreases occur in the four Census regions with the West experiencing the largest decrease (i.e., -44.34%) and the Midwest experiencing the smallest (i.e., -18.48%). So, once again, the West exhibits the highest volatility of sales impulse responses and the Midwest the lowest.

6. CONCLUSIONS

This paper assesses the effects of monetary policy on the US housing sector, national and regional, using impulse-response functions obtained from a LBVAR model that incorporates 143 monthly macroeconomic variables over the period of 1986:01 to 2003:12. The housing variables include 21 series relating to housing starts, housing permits, housing prices, housing sales, and mobile home shipments at the national level and housing starts, housing permits, housing prices, and housing sales at the level of the four Census regions (Northeast, Midwest, South, and West) of the US.

Our econometric analysis focuses on impulse response functions, given a 100-basis point increase in the federal funds rate. Overall, the results show that contractionary monetary policy exerts a negative effect on the housing sector at the national level, indicating the absence of puzzling effects common in small structural vector autoregressive models. The nonexistence of puzzles relating to the housing sector possibly emerges as a result of proper identification of monetary policy shocks within a data-rich environment.

The reaction of national housing sector proves heterogeneous across regions. Housing permits, housing starts, and housing sales react strongly to a contractionary monetary policy, compared to housing prices. The South remains the driving force behind the dynamics observed in national housing sector. That is, the impulse responses in the South more closely match those of the national housing sector than the other regions. While Northeast and the Mid West display similar responses in size and duration, they generally do not achieve the same magnitude of response as does the responses in the South. Further, the responses of housing starts and housing permits to the monetary policy shock in the West differs the most from the national responses and from the other three regions.

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SANTRAUKA

PINIGŲ POLITIKA IR BŪSTO SEKTORIAUS DINAMIKA TAIKANT PLATAUS MASTO BAJESO VEKTORINĮ AUTOREGRESINĮ MODELĮ

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Straipsnyje nagrinėjama, kokiais kanalais pinigų politika (sukrėtimai dėl federalinių fondų palūkanų normos) veikia JAV būsto sektoriaus dinamiką. Analizei naudojamos reakcijos į impulsus funkcijos, gautos iš plataus masto Bajeso vektorinio autoregresinio modelio, kuris apima laikotarpį nuo 1986 m. sausio mėn. iki 2003 m. gruodžio mėn. ir 143 mėnesinius makroekonominius kintamuosius, įskaitant 21 su būsto sektoriumi susijusį kintamąjį nacionaliniu mastu pagal keturis statistinius regionus (angl. *Census regions*). Nustatyta, kad, nacionaliniu lygmeniu griežtėjat pinigų politikai, statoma mažiau naujų būstų, išduodama mažiau leidimų gyvenamajai statybai ir parduodama mažiau būstų. Prekybos būstais sektorius reaguoja sparčiau ir aštriau nei naujų statybų ir leidimų sektorius, o reakcija trunka ilgiau. Nustatyta, kad būstų kainos į pinigų politikos sukrėtimus reaguoja menkiausiai. Daroma išvada, kad regioniniu lygmeniu Pietų regiono būstų sektorius labiausiai prisideda prie nacionalinių išvadų tuo požiūriu, jog reakcijos pobūdis Pietuose panašiausias į bendrą nacionalinį reakcijos pobūdį. Vakarų reakcija nuo kitų regionų skiriasi labiausiai, ypač kalbant apie reakcijas į impulsus, susijusias su statomais būstais ir statybų leidimais.