Monetary Policy and Housing Sector Dynamics in a Large-Scale Bayesian Vector Autoregressive Model

Rangan Gupta
University of Pretoria

Marius Jurgilas
Bank of England

Alain Kabundi
University of Johannesburg

Stephen M. Miller
University of Connecticut and University of Nevada, Las Vegas

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Abstract

Our paper considers this 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 Autoregression (LBVAR) 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 reacts more quickly and sharply than starts and permits and exhibits 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 data. The responses in the West differ the most from the other regions, especially for the impulse responses of housing starts and permits.

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1. Introduction

The origins of the business cycle and designing 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 origins 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 the eventual slump. 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 Autoregression (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, total new private housing units, mobile home shipments, home sales and home prices at the national level and housing starts, housing permits, home sales, and home prices 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.

We choose the starting point of the sample to consider the uniform monetary policy regime within the Great Moderation. We end the sample at the end point of the sample in the Stock and Watson (2005) dataset that we use for our estimation.

Our econometric analysis focuses on impulse response functions, given a 100-basis point increase in the federal funds rate. 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 reacts more quickly and sharply than starts and permits and exhibits 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 data. That is, the impulse responses in the South more closely match those of the national housing sector than the other regions. The West appears to differ the most from the other regions, especially for the impulse responses of housing starts and permits.

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.

2. Literature Review

A number of papers (Green 1997, Iacoviello 2005, Case *et al*. 2005, Leamer 2007, Iacoviello and Neri 2008, Vargas-Silva 2008a, Ghent 2009, Ghent and Owyang 2009, amongst others) 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. The Conference Board includes building permits in its leading economic index.

Stock and Watson (2003) pointed out that housing price movements lead real activity, inflation, 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 prices bubble always leads significant contractions in the real economy, vouched for by the current economic downturn. Given this, it is crucial that one analyzes thoroughly the effects of monetary policy on asset prices in general, and real estate in particular, which, in turn, would lead to the understanding of the effects of policy on the economy at large;

Stock and Watson (2004), Rapach and Strauss (2007, 2008), Vargas-Silva (2008b) and Das *et al*. (2008a,b, 2009) report evidence that numerous economic variables, such as, income, interest rates, construction costs, labor market variables, stock prices, industrial production, consumer confidence index, and so on potentially predict movements in house prices and the housing sector.

Similar to the LBVAR, the FAVAR approach proposed by Bernanke *et al*. (2005) can also 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. However, our preference of the LBVAR over the FAVAR is due to the fact that the latter requires one to ensure stationarity, which entails data transformations, and hence, creating first-differenced or growth rate versions of the variables under considerations. The LBVAR methodology, based on the appropriate design of the priors, allows us to handle non-stationarity of the data without making data transformations, and, in the process, allows us to retain the variables in their original forms.

Moreover, as recently shown by Banbura *et al*. (2008), based on this data set, the LBVAR is better suited in forecasting key macroeconomic variables, and, hence, should be the preferred model. Such a thought process is also corroborated by Beck *et al*. (2000, 2004), who points out that, forecasting is at the root of inference and prediction in time series analysis. Further, Clements and Hendry (1998) argues that in time series models, estimation and inference essentially means minimizing of the one-step (or multi-step) forecast errors, Therefore establishing a model's superiority boils down to showing that it produces smaller forecast errors than its competitors.

Finally, the need to use both regional and national housing sector data emanates from the fact that the impact of monetary policy on the economy differs according to regions, since economic conditions prevailing during a monetary policy shock are not necessarily the same across the regions (Carlino and DeFina 1998, 1999, and Vargas-Silva 2008b).

Although this study provides the first analysis of 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 (2008), Vargas-Silva (2008a, b), Gupta and Kabundi (2009a, b) for analyses of the effect of monetary policy shocks on housing in the US, Europe, and South Africa.[1] All these studies, except Vargas-Silva (2008b) and Gupta and Kabundi (2009a, b), who use a FAVAR approach, rely on either a reduced-form Vector Autoregression (VAR) model, a Vector Error Correction Model (VECM) or a Structural VAR (SVAR) model, which, in turn, limits them to at the most 8 to 12 variables to conserve

[1] Note that 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 (2008) 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.

the degrees of freedom. Arguably, and as indicated above, a large number of variables potentially affect monetary policy and the housing market, and not including them 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 (for example the gross domestic product as a measure of economic activity or the first difference of the logarithm transformed consumer price index as a measure of inflation), which, in turn, may not be perfectly represented by the selected variables. In addition, previous studies can only obtain the impulse response functions (IRFs) from those few variables included in the model, implying that in each VAR, VECM 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 solves all these problems.

Vargas-Silva (2008b) and Gupta and Kabundi (2009a, b) employ FAVAR models in their analysis. 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 (2009a) 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.[2] Against this backdrop, our current paper extends these two 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.[3].

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[2] Gupta and Kabundi (2009b) 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.

[3] Unlike Gupta and Kabundi (2009a), 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[4]:

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

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

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

Litterman (1986) proposes the Minnesota prior, where the researcher assumes that all equations approximate the random walk with drift. Formally,

$$Y_t = c + Y_{t-1} + u_t \qquad (2)$$

This essentially implies shrinking the diagonal and off-diagonal coefficients of A_1 toward one and zero, respectively, as well as the diagonal and off-diagonal coefficients ($A_2, \dots, A_p$) all toward zero. Further, the Minnesota prior also assumes that the more recent lags carry more useful information than more distant lags, and that the own lags explain more of the variability of a given variable than the lags of the other variables in each equations of the VAR model.

The prior imposes the following moments for the prior distribution of the coefficients:

$$E[(A_k)_{ij}] = \begin{cases} \delta_i, & j=i, k=1 \\ 0, & otherwise \end{cases}, \quad V[(A_k)_{ij}] = \begin{cases} \frac{\lambda^2}{k^2}, & j=i \\ \vartheta \frac{\lambda^2 \sigma_i^2}{k^2 \sigma_j^2}, & otherwise \end{cases}. \qquad (3)$$

We assume that the coefficients $A_1, \dots, A_p$ are independent and normally distributed. We also assume that the covariance matrix of the residuals is diagonal, fixed, and known.

[4] This section relies heavily on the discussion available in Banbura *et al*. (2008) and Bloor and Matheson (2008). We retain their symbolic representations of the equations.

Formally, $\Psi = \Sigma$, where $\Sigma = diag(\sigma_1^2,...,\sigma_n^2)$. Litterman's (1986) original specification assumes a diffuse prior on the intercept term and sets $\delta_i = 1$ for all i, implying that all variables exhibit high persistent. If the researcher believes that some of the variables experience substantial mean reversion, 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 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 monetary 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:

$$\Delta Y_t = c - \left(I_n - A_1 - ... - A_p\right) Y_{t-1} + B_1 \Delta Y_{t-1} + ... + B_{p-1} \Delta Y_{t-p+1} + u_t . \qquad (4)$$

The sums-of-coefficients prior impose the restrictions that $\left(I_n - A_1 - ... - A_p\right)$ equal a matrix entirely of zeros. The hyperparameter τ controls the degree of shrinkage of the sums-of-coefficients prior. 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.

Rewrite the VAR in equation (1) in matrix notation as follows:

$$Y = X\mathrm{B} + U, \tag{5}$$

where $Y = (Y_1, ..., Y_\mathrm{T})'$, $X = (X_1, ..., X_\mathrm{T})'$, $U = (u_1, ..., u_\mathrm{T})'$, and $B = \left(A_1, ..., A_p, c\right)'$. Further, $X_t = (Y'_{t-1}, ..., Y'_{t-p}, 1)'$ and $B = \left(A_1, ..., A_p, c\right)'$ equals the $k \times n$ matrix of all coefficients with $k = np + 1$. Then, we can write the Normal inverted Wishart prior as follows:

$$vec\left(B\right) / \Psi \sim \mathrm{N}\left(vec(B_o), \Psi \otimes \Omega_0\right) \text{ and } \Psi \sim iW(S_0, \alpha_0), \tag{6}$$

where we choose the prior parameters B_0, Ω_0, S_0, and α_0 to ensure that the prior expectations and variances of B identified in equation (3) and the expectation of Ψ equals the Minnesota prior of the residual covariance matrix. Implementing the modified Litterman (1986) prior, which includes both the Minnesota prior and the sums-of-coefficients prior, we add dummy observations. Adding T_d dummy observations Y_d and X_d amounts to imposing the Normal inverted Wishart prior with $B_0 = \left(X'_d X_d\right)^{-1} X'_d Y_d$, $\Omega_0 = \left(X'_d X_d\right)^{-1}$, $S_0 = \left(Y_d - X_d B_0\right)' \left(Y_d - X_d B_0\right)$, and $\alpha_0 = \mathrm{T}_d - k - n - 1$.

We add the following dummy observations to match the Minnesota moments:

$$Y_d = \begin{pmatrix} \frac{diag(\delta_1\sigma_1,...,\delta_n\sigma_n)}{\lambda} \\ 0_{n(p-1)\times n} \\ \cdots\cdots\cdots\cdots \\ \frac{diag(\delta_1\mu_1,...,\delta_n\mu_n)}{\tau} \\ \cdots\cdots\cdots\cdots \\ diag(\sigma_1,...,\sigma_n) \\ \cdots\cdots\cdots\cdots \\ 0_{1\times n} \end{pmatrix}; \text{and } X_d = \begin{pmatrix} \frac{K_d \otimes diag(\sigma_1,...,\sigma_n)}{\lambda} & 0_{np\times 1} \\ \cdots\cdots\cdots\cdots & \cdots \\ \frac{K \otimes diag(\delta_1\mu_1,...,\delta_n\mu_n)}{\tau} & 0_{n\times 1} \\ \cdots\cdots\cdots\cdots & \cdots \\ 0_{n\times np} & 0_{n\times 1} \\ \cdots\cdots\cdots\cdots & \cdots \\ 0_{1\times n} & \varepsilon \end{pmatrix} \quad (7)$$

where $K = 1, ..., p$, $K_d = diag(K)$, and ε is a very small value. Generally, the first block of dummies imposes prior beliefs on the autoregressive coefficients, the second block of dummies enforces the sums of coefficients priors, and the third and fourth blocks apply the priors for the covariance matrix and the uninformative prior for the intercept, respectively. 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*. (2008) 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,[5] we use the former for our structural analysis discussed below.[6] 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) argues that the overall tightness governed by λ should reflect the size of the

[5] Banbura *et al*. (2008) find the same results.

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

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*. (2008), 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*. (2008); 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:

$$\lambda(Fit) = \arg\min_{\lambda} \left| Fit - \frac{1}{3}\sum_{i=1}^{3} \frac{MSE_i^{w}}{MSE_i^{0}} \right|, \tag{8}$$

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 sample, which, in our case, equals 1970:01 to 1979:12, and $t = 1, \ldots, T_0 - 1$, 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., λ =0), while the baseline *Fit* equals the average relative MSE from an OLS-estimated VAR containing the three variables. That is,

$$Fit = \frac{1}{3}\sum_{i=1}^{3} \left(MSE_i^{\infty} \Big/ MSE_i^{0} \right). \tag{9}$$

After augmenting the regression model (5) with the dummies in (7), we obtain the following:

$$Y_* = X_* \mathrm{B} + U_*, \tag{10}$$

where $Y_* = \left(Y', Y_d'\right)'$, $X_* = \left(X', X_d'\right)$, and $U_* = \left(U', U_d'\right)'$. To insure the existence of the prior expectation of Ψ, we add the diffuse prior $\Psi \propto \left|\Psi\right|^{-(n+3)/2}$. Once done, the posterior exhibits the following form:

$$vec(B)|\Psi, Y \sim N\left(vec\left(\hat{B}\right), \Psi \otimes \left(X_*' X_*\right)\right)^{-1} \text{ and}$$

$$\Psi / Y \sim iW(\tilde{\Sigma}, \mathrm{T}_d + 2 + T - k), \quad (11)$$

where $\tilde{B} = \left(X_*' X_*\right)^{-1} X_*' Y_*$ and $\tilde{\Sigma} = \left(Y_* - X_* \tilde{B}\right)' \left(Y_* - X_* \tilde{B}\right)$.

Given the dummy observations in (7), the posterior parameter estimates will tend toward the OLS estimates from the system defined in (5), since the Minnesota and sums-of-coefficients dummies tend to zero as λ and τ tend toward infinity. In other words, the posterior expectation of the parameters coincides with the OLS estimates of the system defined in (10).

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 home 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, 2008), we convert housing prices to real values by deflating with the personal consumption expenditure deflator.[7] The data spans the period of 1968:01 through 2003:12. The start date coincides with data availability of home sales and prices,

[7] 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.

while the end data corresponds to the data set in Stock and Watson (2005). As in Banbura *et al*. (2008), 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.[8]

5. Impulse Responses:

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

Let $B = CD^{1/2}$ equal the $n \times n$ lower diagonal Cholesky matrix of the covariance of the residuals of the VAR in its reduced form. Specifically, $CDC' = E[u_t u_t'] = \Psi$ and $D = \text{diag}(\Psi)$. Let $e_t = C^{-1}u_t$, where the monetary policy shock appears in the row of e_t that corresponds to the position of r_t. Given this, we can write the structural VAR as follows:

$$\Pi_0 Y_t = \nu + \Pi_1 Y_{t-1} + ... + \Pi_p Y_{t-p} + e_t, \qquad (12)$$

[8] Appendix A in Banbura *et al*. (2008) 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.

where $v = C^{-1}c$, $\Pi_0 = C^{-1}$, and $\Pi_j = C^{-1}A_i$, $i = 1, \ldots, p$.

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 $(A_1, \ldots\ldots A_p, \Psi)$. We can compute B and C and then A_i, $i = 1, \ldots, p$ for each draw Ψ.

Figures 1, 2, 3, and 4 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 behaviour 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) percent levels of confidence.

The Federal funds rate (FFR) increases by one percent and remains significant for about 20 months. From Figure 1, contractionary monetary policy exerts a negative and significant effect on US housing starts (HStUS). This matches the findings by Banbura *et al*. (2008) and Vargas-Silva (2008a). A contractionary monetary policy increases the cost of financing and consequently 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 two percent after two years. 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 reaction at national level. The magnitudes and durations of the effects, however, differ across regions. For example, housing starts in New England (HStNE) and Middle West (HStMW) follow more or less the same pattern, a significant decrease immediately after the shock reaching two percent 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 Vagars-Silva (2008b) and Gupta and Kabundi (2009), 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 (2008a) also observes this puzzling effect but for a shorter time period.

Figure 2 depicts impulse response functions of housing permits following a one percent rise in the Federal funds rate. The shape of the impulse responses in Figure 2 prove somewhat similar to those plotted in Figure 1. 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 increase the cost of financing, which, in turn, affects housing permits negatively. Just like housing starts, housing permits reach their minimum of two percent after two years, then recover, 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 New England (HPmNE) drop, reaching a minimum of approximately one percent 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 Middle West (HPmMW) and the West (HPmW) portray a shape almost identical to that obtained in housing starts. Finally, mobile home shipments (MHS) respond negatively and significantly to a monetary policy shock, lasting for approximately three years. This result supports economic theory, where a negative reaction of mobile shipments occurs as a result of higher financing costs. Figure 2 shows that mobile-home shipments do not exhibit any puzzling effects, which Vagars-Silva (2008b) uncovers.

Figure 3 shows how a contractionary monetary policy drops US housing prices at national level (HPrUS) (Figure 3). In contrast to housing starts and housing permits, housing prices recover rapidly, reaching a minimum of approximately one percent after six months. No evidence emerges of a *home price* puzzle observed by McCarthy and Peach (2002). Gupta and Kabundi (2009) 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 (2009), the effect persists for more than ten quarters. The difference observed probably reflects data treatment. Gupta and Kabundi (2009) use housing price growth rather than the housing price. Furthermore, the magnitude and the duration of monetary policy shocks differ. Once more, Figure 3 displays the heterogeneous responses across region in the US. While the housing price in the South (HPrS) appears to drive the national response, the West (HPrW) shows a relatively weak, short-lived response. Housing prices in New England (HPrNE) and Middle West (HPrMW) exhibit identical responses, relatively weak, short-lived responses, but larger than the West (HPrW).

Finally, Figure 4 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 New England (HSNE) and in Middle West (HSMW), although only significantly in the short-term of about ten months. Finally, the sales decline in the sales in the West (HSW) lasts relatively longer than those of sales in New England (HSNE) and in the Mid West (HSMW), but relatively shorter when compared to the South (HSS).

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, total new private housing units, mobile home shipments, home sales and home prices at the national level and housing starts, housing permits, home sales and home prices 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 New England 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 differ the most from the national responses and from the other three regions.

References

Ahearne, A. G., Ammer, J., Doyle, B. M., Kole, L. S., and Martin, R. F., 2005. Monetary Policy and House Prices: A Cross-Country Study. Central Bank of Chile, *Working Paper 344*.

Banbura, M, Gianonne, D., and Reichlin, L., 2008. Bayesian VARs with Large Panels. *Journal of Applied Econometrics*, forthcoming.

Beck, N., King, G., and Zeng, L., (2000). Improving Quantitative Studies of International Conflict: A Conjecture. *American Political Science Review* 94, 21–36.

Beck, N., King, G., and Zeng, L., (2004). Theory and Evidence in International Conflict: A Response to de Marchi, Gelpi, and Grynaviski. *American Political Science Review* 98, 379–389.

Bernanke, B. S., and Gertler, M., 1995. Inside the Black Box: The Credit Channel of Monetary Policy Transmission. *The Journal of Economic Perspectives* 9, 27–48.

Bernanke, B. S., and Gertler, M., 1999. Monetary Policy and Asset Volatility. Federal Reserve Bank of Kansas City, *Economic Review* 84, 17-52.

Bernanke, B. S., Boivin, J., and Eliazs, P., 2005. Measuring the Effects of Monetary Policy: A Factor Augmented Vector Autoregressive (FAVAR) Approach. *The Quarterly Journal of Economics* 120, 387–422.

Bloor, C., and Matheson, T., 2008. Analysing Shock Transmission in a Data-Rich Environment: A Large BVAR for New Zealand. Reserve Bank of New Zealand, Discussion Paper Series DP2008/09.

Borio, C. E. V., Kennedy, N., and Prowse, S. D., 1994. Exploring Aggregate Asset Price Fluctuations Across Countries: Measurement, Determinants, and Monetary Policy Implications. BIS Economics Paper No. 40.

Clements, M, and Hendry, D. 1998. *Forecasting Economic Time Series*. New York: Cambridge University Press.

Canova, F., 1991. The Sources of Financial Crisis: Pre- and Post-Fed Evidence. *International Economic Review* 32, 689–713.

Carlino, G. A., and DeFina, R. H., 1998. The Differential Regional Effects of Monetary Policy. *The Review of Economics and Statistics* 80, 572–587.

Carlino, G. A., and DeFina, R. H., 1999. Do States Respond Differently to Changes in Monetary Policy? Federal Reserve Bank of Philadelphia, *Business Review,* (July/August), 17–27.

Case, K., Shiller, R., and Quigley, J., 2005. Comparing Wealth Effects: The Stock Market Versus the Housing Market. *Advances in Macroeconomics* 5, 1-32.

Chowdhury, A., and Wheeler, M., 1993. The Housing Market, Macroeconomic Activity and Financial Innovation: An Empirical Analysis of US Data. *Applied Economics* 25, 1385–1392.

Christiano, L., Eichenbaum, M., Evans, C., 2005. Nominal Rigidities and the Dynamic Effects of a Shock to Monetary Policy. *Journal of Political Economy* 113, 1–45.

Clements, M. P., and Hendry, D. F., 1998. Forecasting Economic Processes. *International Journal of Forecasting* 14, 111-131.

Das, S., Gupta, R., and Kabundi, A., 2008a. Is a DFM Well-Suited for Forecasting Regional House Price Inflation? Economic Research Southern Africa, Working Paper No. 85.

Das, S., Gupta, R., and Kabundi, A., 2008b. Could We Have Forecasted the Recent Downturn in the South African Housing Market? *Journal of Housing Economics*, forthcoming.

Das, S., Gupta, R., and Kabundi, A., 2009. Forecasting Real House Price Growth in the Nine Census Divisions of the US. Department of Economics, Working Paper No. 200902, University of Pretoria.

De Mol, C., Gianonne, D., and Reichlin, L., 2008. Forecasting Using a Large Number of Predictors: Is Bayesian Regression a Valid Alternative to Principal Components? *Journal of Econometrics*, forthcoming.

Doan, T., Litterman, R., and Sims, C., 1984. Forecasting and Conditional Projections Using Realistic Prior Distributions. *Econometric Reviews* 3, 1–100.

Ewing, B. T., and Wang, Y., 2005. Single Housing Starts and Macroeconomic Activity: An Application of Generalized Impulse Response Analysis. *Applied Economic Letters* 12, 187–190.

Falk, B., 1986. Unanticipated Money-Supply Growth and Single-Family Housing Starts in the US: 1964–1983. *Housing Finance Review* 5, 15–23.

Ghent, A., 2009. Sticky Housing and the Real Effects of Monetary Policy. Revise and Resubmit for *Journal of Money, Credit and Banking*.

Ghent, A., and Owyang, M., 2009. Is Housing the Business Cycle? Evidence from US Cities, Mimeo, Department of Real Estate, Zicklin School of Business, Baruch College, CUNY.

Gordon, D. B., and Leeper, E. M., 1994. The Dynamic Impacts of Monetary Policy: An Exercise in Tentative Identification. *Journal of Political Economy* 102, 1228–1247.

Green, R., 1997. Follow the Leader: How Changes in Residential and Non-Residential Investment Predict Changes in GDP. *Real Estate Economics* 25, 253–270.

Gupta, R., and Kabundi, A., 2009a. The Effect of Monetary Policy on House Price Inflation: A Factor Augmented Vector Autoregression (FAVAR) Approach, Department of Economics, Working Paper 200903, University of Pretoria.

Gupta, R., and Kabundi, A., 2009b. The Effect of Monetary Policy on Real House Price Growth Rate in South Africa: A Factor Augmented Vector Autoregression (FAVAR) Approach. Department of Economics, Working Paper 200905, University of Pretoria.

Iacoviello, M., 2002. House Prices and Business Cycles in Europe: A VAR Analysis. Department of Economics, Working Paper No. WP540, Boston College.

Iacoviello, M., 2005. House Prices, Borrowing Constraints, and Monetary Policy in the Business Cycle. *American Economic Review* 95, 739–764.

Iacoviello, M., and Minetti R., 2003. Financial Liberalisation and the Sensitivity of House Prices to Monetary Policy: Theory and Evidence. *The Manchester School* 71, 20-34.

Iacoviello, M., and Minetti R., 2008. The Credit Channel of Monetary Policy: Evidence from the Housing Market. *Journal of Macroeconomics* 30, 69-96.

Iacoviello, M., and Neri S., 2008. Housing Market Spillovers: Evidence from an Estimated DSGE Model. Department of Economics, Working Paper No. 659, Boston College.

Kasai N., and Gupta R., 2008. Financial Liberalization and the Effectiveness of Monetary Policy on House Prices in South Africa. Department of Economics; Working Paper No. 11 200803, University of Pretoria.

Kadiyala, K. R., and Karlsson, S., 1997. Numerical Methods for Estimation and Inference in Bayesian VAR Models. *Journal of Applied Econometrics* 12, 99-132.

Litterman, R., 1986. Forecasting with Bayesian Vector Autoregressions - Five Years of Experience. *Journal of Business and Economic Statistics* 4, 25–38.

McCarthy, J., and Peach, R., 2002. Monetary Policy Transmission to Residential Investment. *Economic Policy Review*, 139–158.

Rapach, D. E., and Strauss, J. K., 2007. Forecasting Real Housing Price Growth in the Eighth District States. Federal Reserve Bank of St. Louis, *Regional Economic Development* 3, 33–42.

Rapach, D. E., and Jack K. S., 2008. Differences in Housing Price Forecast Ability Across U.S. States. *Journal of Economic Studies,* Forthcoming.

Sims, C., 1992. Interpreting the Macroeconomic Time Series Facts: The Effects of Monetary Policy. *European Economic Review* 36, 975-1000.

Sims, C. A., and Zha, T., 1998. Bayesian Methods for Dynamic Multivariate Analysis. *International Economic Review* 39, 949–968.

Stock, J. H., and Watson, M. W., 2002. Macroeconomics Forecasting Using Diffusion Indexes. *Journal of Business and Economic Statistics* 20, 147–62.

Stock, J. H., and Watson, M. W., 2003. Forecasting Output and Inflation: The Role of Asset Prices. *Journal of Economic Literature* 41, 788-829.

Stock, J. H., and Watson, M. W., 2004. Combination Forecasts of Output Growth in a Seven-Country Data Set. *Journal of Forecasting* 23, 405-430.

Stock, J. H., and Watson, M, W., 2005. Implications of Dynamic Factor Models for VAR Analysis. National Bureau of Economic Research, Working Paper, 11467.

Vargas-Silva, C., 2008a. Monetary Policy and the US Housing Market: A VAR Analysis Imposing Sign Restrictions. *Journal of Macroeconomics* 30, 977–990

Vargas-Silva, C., 2008b. The Effect of Monetary Policy on Housing: A Factor-Augmented Vector Autoregression (FAVAR) Approach. *Applied Economics Letters* 15, 749 - 752.

Walsh, C.E., 2000. *Monetary Theory and Policy*. The MIT Press, Cambridge: Massachusetts.

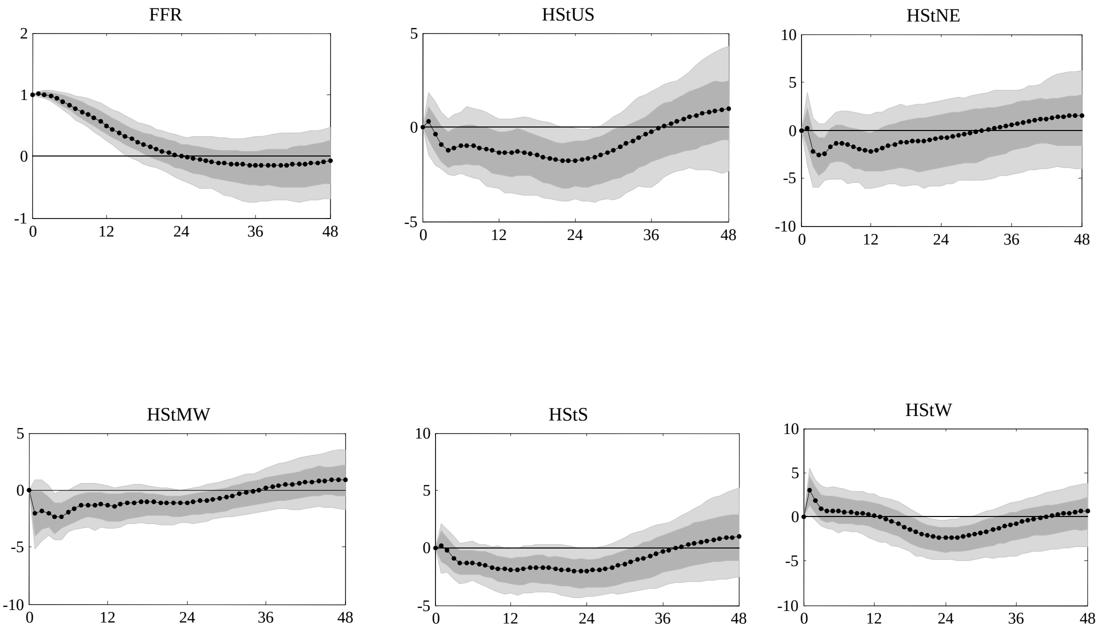

Figure 1. Impact of 100 Basis Points Monetary Policy Shock on Housing Starts

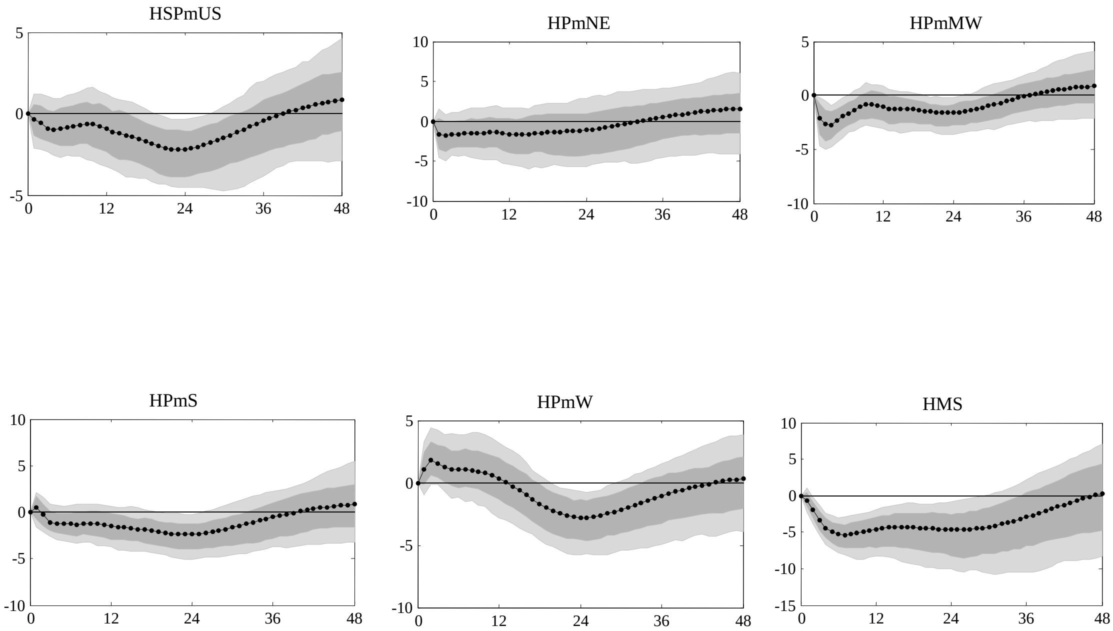

Figure 2. Impact of 100 Basis Points Monetary Policy Shock on Housing Permits

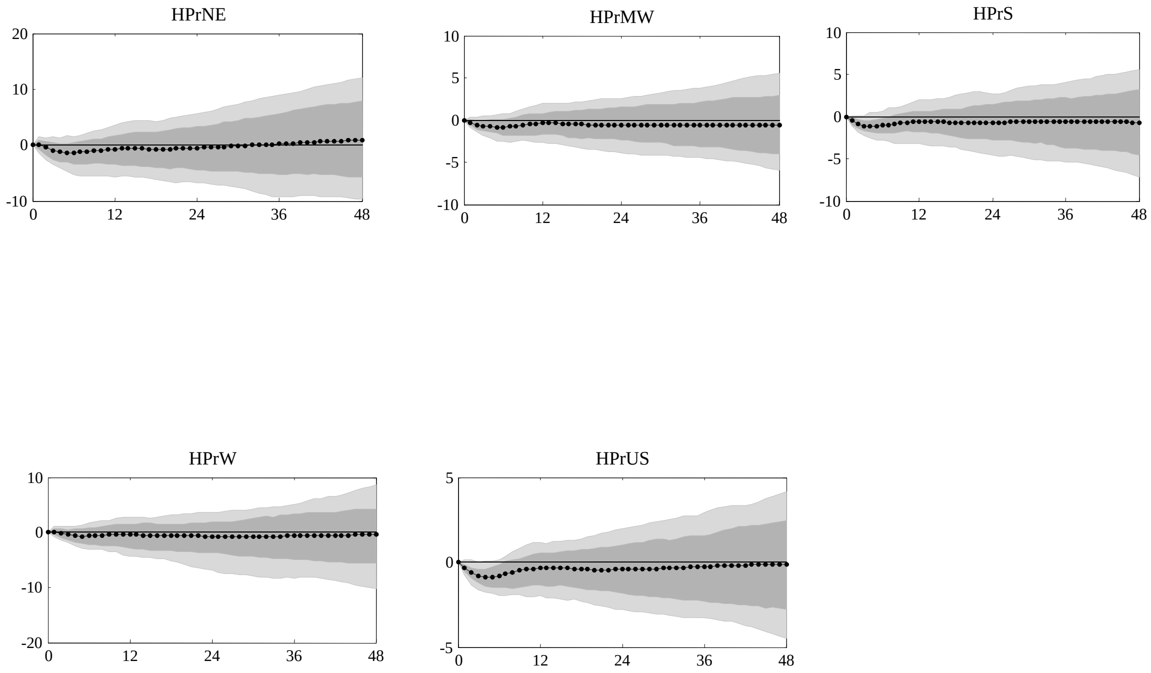

Figure 3. Impact of 100 Basis Points Monetary Policy Shock on Housing Price

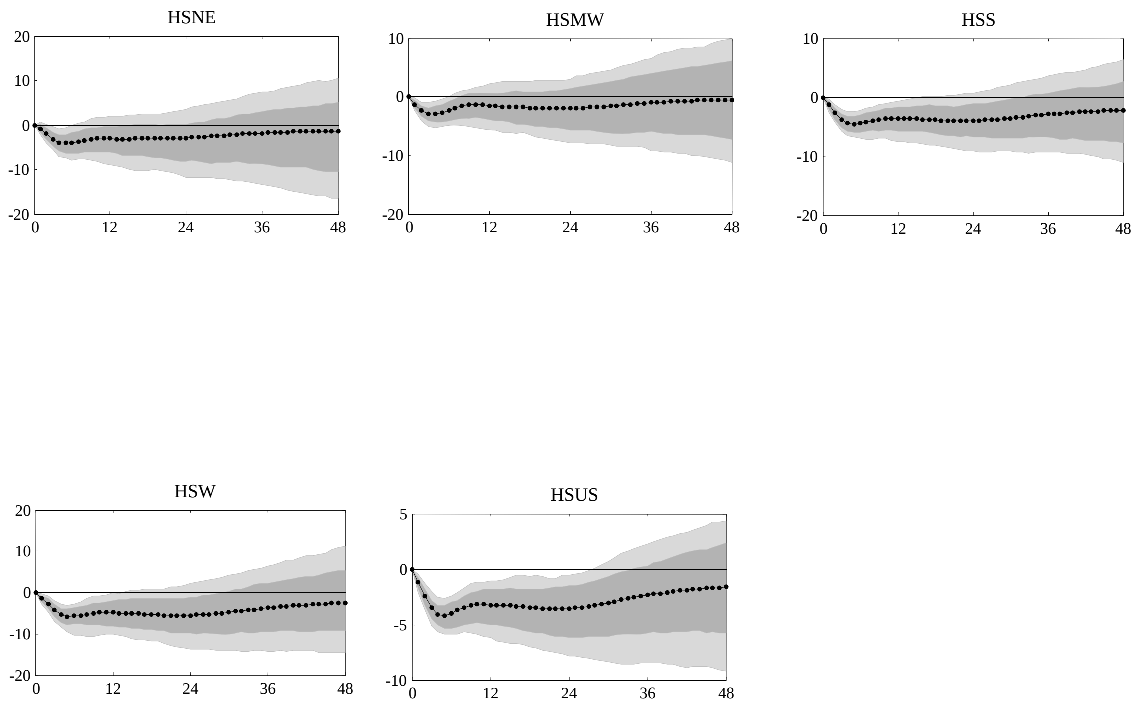

Figure 4. Impact of 100 Basis Points Monetary Policy Shock on Housing Sales