University of Pretoria
Department of Economics Working Paper Series

Financial Market Liberalization, Monetary Policy, and Housing Price Dynamics

Rangan Gupta
University of Pretoria
Stephen M. Miller
University of Nevada
Dylan van Wyk
University of Pretoria

Working Paper: 2010-09
March 2010

Department of Economics
University of Pretoria
0002, Pretoria
South Africa
Tel: +27 12 420 2413

Financial Market Liberalization, Monetary Policy, and Housing Price Dynamics*

Rangan Gupta
Department of Economics
University of Pretoria
Pretoria, 0002, SOUTH AFRICA

Stephen M. Miller**
Department of Economics,
University of Nevada, Las Vegas
Las Vegas, Nevada, USA 89154-6005

Dylan van Wyk
Department of Economics
University of Pretoria
Pretoria, 0002, SOUTH AFRICA

Abstract: This paper considers how monetary policy, a Federal funds rate shock, affects the dynamics of the US housing sector and whether the financial market liberalization of the early 1980's influenced those dynamics. The analysis uses impulse response functions obtained from a large-scale Bayesian Vector Autoregression (LBVAR) model over the periods 1968:01 to 1982:12 and 1989:01 to 2003:12, including 21 housing-sector variables at the national and four census regions. Overall, the 100 basis point Federal funds rate shock produces larger effects on the real house prices, both at the regional level and the national level, in the post-liberalization period when compared to the pre-liberalization era. While the precision of the estimates do not imply significant differences, the finding does offer a caution. That is, the housing market appears more sensitive to monetary policy shocks in the post-liberalization period. On the one hand, this suggests that monetary policy possesses increased leverage. On the other hand, the housing market cycle traditionally contributes an important component to the aggregate business cycle. Thus, the monetary authorities may need to exercise more care in implementing Federal funds rate adjustments going forward. In addition, contractionary monetary policy exerts a negative effect on house prices at the national level, indicating the absence of the price puzzle in small structural vector autoregressive models. The puzzle's absence in the housing sector possibly emerges as a result of proper identification of monetary policy shocks within a data-rich environment. Finally, we find that the reaction of housing sector proves heterogeneous across regions, with the housing sector in the South driving the national data after liberalization, while before liberalization, the Middle West appears to drive the housing market. The responses in the West differ the most from the other regions.

Keywords: Monetary policy, Housing sector dynamics, Large-Scale BVAR models

JEL classification: C32, R31

* We would like to thank Marta Banbura for providing us with the codes used in estimating the large-scale BVAR and her assistance with its implementation.
** *Corresponding author*

1. Introduction

A number of papers (e.g., Green 1997, Iacoviello 2005, Case *et al*. 2005, Rapach and Strauss (2006), Leamer 2007, Pariès and Notarpietro (2008), Vargas-Silva 2008a, Bao *et al.* (2009), Christensen *et al.* (2009), Ghent 2009, Ghent and Owyang 2009, Pavlidis *et al.* (2009), Iacoviello and Neri forthcoming) show a strong link between the housing market and economic activity in the US. Stock and Watson (2003) argue that house-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 house price bubbles always lead to significant contractions in the real economy, vouched for by the current economic downturn. Given this, the thorough analysis of the effects of monetary policy on asset prices in general, and real estate prices in particular, will, in turn, lead to better understanding of the effects of monetary policy on the larger economy.

This paper considers how monetary policy, a Federal funds rate (FFR) shock, affects the dynamics of the US housing sector and whether the financial market liberalization of the early 1980's influenced those dynamics. Stock and Watson (2004), Rapach and Strauss (2007, 2008), Vargas-Silva (2008b) and Das *et al*. (forthcoming a,b, 2009) report evidence that numerous economic variables, such as, income, interest rates, construction costs, labor market variables, stock prices, industrial production, and consumer confidence index potentially predict movements in house prices and the housing sector. Thus, we implement our examination using a large scale Bayesian vector autoregressive (LBVAR) model that incorporates 143 monthly macroeconomic variables over the periods 1968:01 to 1982:12 and 1989:01 to 2003:12, including 21 housing-sector variables at the national and four census regions. The analysis uses impulse response functions obtained from the LBVAR model. We examine the model over these two periods to determine the effect of liberalizing the US financial markets on the sensitivity of house prices to interest rate changes.

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 four sub-regions.

We choose 1982 to end the first period in accordance with evidence that financial market liberalization started in the US *circa* 1982 (Iacoviello and Neri forthcoming; Campbell and Hercowitz 2005; and Dynan, lmendorf, and Sichel 2006).[1] We choose to start the second period in 1989. We end the second period at the end point of the sample in the Stock and Watson (2005) dataset that we use for our estimation. In this way, we define two periods of equal length – the period from 1968 to 1982, which measures the US market prior to financial market liberalization,

---

[1] Iacoviello and Neri (forthcoming) argue that financial liberalization started with the Garn-St. Germain Act of 1982, which deregulated the savings and loan industry, while Campbell and Hercowitz (2005) note that "The market innovations that followed the Monetary Control Act of 1980 and the Garn-St. Germain Act of 1982 relaxed collateral constraints on household debt." (p. 1). Dynan, Elmendorf, and Sichel (2006) suggest that from the late 1970's to the early 2000's, businesses experienced far more extensive direct access to the financial markets. Financially weaker firms that in the past could not raise funds could now do so via "the development of an active market for high-risk debt (sometimes known as 'junk bonds')." (p. 127). "New issuance of junk bonds was essentially nil in the mid-1970s but accounted for more than 25% of total non-financial bond issuance by 1984 and 42% in 2004. In addition, the share of capital expenditures undertaken by junk-rated firms climbed from a presumably low value in the mid-1970s to 5% in 1984 and 17% in 2004." (p. 127). These market changes in conjunction with changes in government policies (like the abolition of interest rate ceilings on deposit accounts in the early 1980's) greatly increased the funds available for lending. At the same time that 'easy money' became available, households and businesses increased their propensity to borrow. Dynan, Elmendorf, and Sichel (2006) show that "The ratio of household debt to disposable personal income (DPI) rose from 0.57 in 1960 to 0.64 in 1984 and 1.14 in 2004; personal bankruptcy filings per 100,000 people climbed from 68 in 1960 to 120 in 1984 and 531 in 2004". (p. 128).

and the period from 1989 to 2003, which measures the market after liberalization. The intervening period not in our two samples provides an adjustment period.

Similar to the LBVAR, the FAVAR approach proposed by Bernanke *et al*. (2005) can also handle large amounts of data. The FAVAR approach extracts a few latent common factors from a large matrix of many economic variables, with the latent factors maintaining the same information content of the original data set without confronting degrees of freedom problems. Our preference of the LBVAR over the FAVAR reflects the different requirements that these models exhibit with regard to the use of stationary and non-stationary data. The FAVAR approach requires stationary data so that the required data transformations create first-differences or growth rate versions of the variables under consideration. The LBVAR methodology, based on the appropriate design of the priors, handles non-stationary data without making data transformations, and, in the process, retains the variables in their original form. Moreover, as recently shown by Banbura *et al*. (forthcoming), based on the Stock-Watson data set, the LBVAR model proves better suited to forecast key macroeconomic variables. Hence, the LBVAR becomes the preferred model. Beck *et al*. (2000, 2004) corroborate this view, when they note that forecasting provides the root of inference and prediction in time-series analysis. Further, Clements and Hendry (1998) argue 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.

We use both regional and national housing sector data since the effect of monetary policy on the economy differs according to regions and since economic conditions prevailing during a monetary policy shock do not necessarily correlate perfectly across regions (Carlino and DeFina

1998, 1999, and Vargas-Silva 2008b). This allows us to test for consistency of the results over different regions and to test whether any of the regions drive the US housing market.

Although this paper provides the first analysis of the effects 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), Ndahiriwe and Gupta (forthcoming), Vargas-Silva (2008a, b), Gupta *et al.* (2010, forthcoming) for analyses of the effect of monetary policy shocks on housing in the US, Europe, and South Africa.[2] All these studies, except Vargas-Silva (2008b)[3] and Gupta *et al.* (2010, forthcoming), 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 on the degrees of freedom. As indicated above, a large number of variables potentially affect monetary policy and the housing market. Thus, not including all such varialbes can produce puzzling results due to the omission of important information (Walsh, 2000). Moreover, in these studies, the authors often arbitrarily accept specific variables as the counterparts of the theoretical constructs (e.g., real GDP as a measure of economic activity or the logarithmic first difference of the consumer price index as a measure of inflation), which, in turn, may not perfectly represent the selected variables. In addition, previous studies can only generate impulse response functions

[2] 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 the US house price index. More recently, Iacoviello and Neri (forthcoming) 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. Gupta *et al.* (2009) show that although the DSGE model of Iacoviello and Neri (forthcoming) does not perform well in out-of-sample forecasting, it does achieve the best performance in predicting the turning point in the US house price index in 2006.

[3] Vargas-Silva (2008b) studies the effects of monetary policy on seven housing market variables that include housing starts, housing permits, and mobile home shipments, using a dataset of 120 monthly indicators.

(IRFs) for those few variables included in the model. In the typical VAR, VECM, or SVAR models, the IRFs include only one housing-market variable. The LBVAR model can address all of the above mentioned problems.

Gupta *et al.* (forthcoming) most closely relates to our paper. They assess, using the FAVAR modelling approach, the effects of monetary policy on house 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] Our paper extends this study by ensuring that the variables retain their original structure, given our usage of the Bayesian methodology,[5] and by considering the possible differences in the dynamic adjustment due to monetary policy before and after the financial market liberalizations of the early 1980s.

Our econometric analysis focuses on impulse response functions given a 100-basis point increase in the FFR. We find that across the four regions and the aggregate US economy, monetary policy changes exert a larger effect on real house prices in the post-liberalization period when compared to eh pre-liberalization period. While the precision of the estimates do not imply significant differences, the finding does offer a caution. That is, the housing market appears more sensitive to monetary policy shocks in the post-liberalization period. On the one hand, this suggests that monetary policy possesses increased leverage. On the other hand, the housing market cycle traditionally contributes an important component to the aggregate business cycle. Thus, the monetary authorities may need to exercise more care in implementing FFR adjustments going forward. At the regional level, we conclude that prior to liberalization, the

[4] Gupta *et al.* (2010) analyze the effect of monetary policy on real house 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 *et al.* (forthcoming), since monthly house price data in the nine census regions do not exist prior to 1991, we only use monthly house price information from the four census divisions and the aggregate US economy, which, in turn, becomes available at the beginning of 1968.

housing sector in the Middle West provides the underlying force that drives the national data, while after 1989 the housing sector in the South 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 after 1989. The West appears to differ the most from the other regions in both periods.

We organize the rest of the paper as follows. Section 2 outlines the theory behind the LBVAR model. Section 3 describes the data. Sections 4 and 5 identifies our apriori expectations and reports the results of impulse response functions, respectively. Section 6 concludes.

2. Basics of the LBVAR[6]

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

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

where $c = (c_1, \ldots, c_n)'$ equals an n-dimensional vector of constants, $A_1, \ldots, A_p$ 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 all coefficients of $(A_2, \ldots, A_p)$ toward zero. Further, the Minnesota prior also assumes that the own lags better explain the variability of a given variable

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

than the lags of the other variables and that the more recent lags provide more useful information than more distant lags.

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

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

We assume that $A_1,...,A_p$ are independent and normally distributed coefficients. We also assume that the covariance matrix of the residuals is diagonal, fixed, and known. 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 determines how prior beliefs relate to the information contained in the data. More precisely, λ controls the overall tightness of the prior distribution near δ_i. When $\lambda=\infty$, the prior exerts no influence and, hence, the parameter estimates coincide with the ordinary least squares (OLS) estimates. When $\lambda=0$, the posterior equals the prior and the data exert no influence on the estimation. 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 scales the variability of the data. The coefficient $\vartheta\in(0,1)$ determines how much less important the lags of other variables prove 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 impose a normal prior distribution on the coefficients and an inverted Wishart prior distribution on the covariance matrix of the residuals, alternatively called the inverse-Wishart prior. Imposing these conditions requires that $\vartheta = 1$, which we assume.

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:

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

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

Now, rewrite the VAR in equation (1) in matrix notation as follows:

$$Y = X\mathrm{B} + U, \qquad (5)$$

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, in *X*, $X_t = (Y'_{t-1},...,Y'_{t-p},1)'$. Thus, $B = \left(A_1,...,A_p,c \right)'$ equals the $k \times n$ matrix of all coefficients with $k = np + 1$. Then, we can write the Normal inverted Wishart prior as follows:

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

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 equal 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 T_d dummy observations Y_d and X_d which 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:

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

where $K = 1, ..., p$, $K_d = diag(K)$, and ε is very small. 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.* (forthcoming) in choosing λ and τ.

Since the LBVAR model 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,[7] we use the former for our structural analysis discussed below.[8] 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.* (forthcoming) 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, where in our case, as in Banbura *et al.* (forthcoming), we chose three variables -- employment, the consumer price index, and the FFR; (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.* (forthcoming); 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:

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

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 $t = 1, ..,. T_0 -1$, 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,

---

[7] See Banbura *et al.* (forthcoming).

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

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

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 $\Psi \propto |\Psi|^{-(n+3)/2}$. Once done, the posterior exhibits the following form:

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

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

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 equation (10).

3. 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 goods and services, 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 their 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 house prices to real values by deflating with the personal consumption expenditure deflator.[9] 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 date corresponds to the data set in Stock and Watson (2005). As in Banbura *et al.* (forthcoming), 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.[10]

4. A Priori Expectations

The deregulation of the US savings and loan industry, the development of higher-risk debt, and certain government policies enabled financially weaker firms and individuals to raise funds that they could not raise prior to these changes. Financially weaker individuals could now purchase homes and financially weaker firms could purchase physical capital – as witnessed by the large increase in the share of capital expenditures undertaken by junk-rated firms from the mid 1970's to 2004. These financially weaker agents could 'operate at the margin' in the sense that any slight increase in the FFR could prevent them from meeting repayment schedules, cause

[9] 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.

[10] Appendix A in Banbura *et al.* (forthcoming) 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 take natural logarithms. We impose $\delta_i = 0$ for mobile home shipments and $\delta_i = 1$ for home sales and prices, given their time-series behavior.

bankruptcy, and lead to repossession of property (shown by a more than four-fold increase in the personal bankruptcy filings between 1984 and 2004), resulting in an increase in the relative supply of houses and a decrease in the price. Further, the rising ratio of debt to personal disposable income severely constrains the ability of individuals to meet repayment schedules in the face of rising interest rates.

We, therefore, expect to see an increase in the sensitivity of house prices to a given shock in the FFR during the post-liberalization period. Furthermore, we expect the housing markets in the West and the South to drive the national housing data. These Sun-Belt states experienced relatively rapid migration and population growth over our sample period. In addition, the West's popularity and favorable climate led to high house prices in comparison with prices in other parts of the country, suggesting that changes in house prices in the West should disproportionally influence the index of US house prices. We do not expect massive building in large parts of the Snow-Belt states in the Mid-West and the East to drive the index of US house prices. In addition, the South also experiences significant building activity. To see if the Sun-Belt states in the West and South drive the US housing market and if house prices respond more quickly after financial liberalization, we turn to our impulse response function analysis.

5. Impulse Response Function Analysis

In this section, we analyze the effects of a monetary policy (FFR) shock on the 21 housing-market 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 FFR 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 $D = \mathrm{diag}(\Psi)$. 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:

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

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

In our impulse response analysis, we increase contemporaneously the FFR 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.

Table 1 reports the impulse responses and Figures 1 and 2 provide the plots for the 4 regional real house prices and the aggregate real US house price based on the periods 1968:01 to 1982:12 and 1989:01 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. In Figures 1 and 2, we plot the behaviour of the functions over 48 months following a monetary policy shock. Figure 1 shows the effect of 100-basis-point monetary policy shock on house price indexes with confidence bands to determine regions of significance during the period 1968 to 1982 and Figure 2 does the same for the period 1989 to 2003. In Figures 1 and 2, the shaded regions indicate the posterior coverage intervals corresponding to both 90 (lighter shaded region) and 68 (darker shaded region) percent levels of confidence.

Note from Table 1 and Figures 1 and 2, no evidence emerges of a *home price* puzzle observed by McCarthy and Peach (2002), in either the pre- or post-liberalization periods. Gupta *et al.* (forthcoming) use the FAVAR approach, which also accommodates large number of economic variables, and find similar results.[11] Figure 1 illustrates how a contractionary monetary policy drops the US house price index at national level pre-1982. The Federal funds rate (FFR) increases by one percent and remains significant for about 15 months.[12] House prices persist and remain significant for more than two years. Comparing regions, we can see that house prices in North East (HPNE) and the Middle West (HPMW) show a strong, persistent response – particularly in the Middle West where the responses remain significant for about 23 months, though the size of the effect in North East is bigger in magnitude. The response of house prices in the West (HPW) and the South (HPS) seem weak and short lived and it appears that the Middle West drives the US house market.

Table 1 and Figure 2 show the effect of contractionary monetary policy on US house prices from 1989 to 2003. Table 1 shows that the effect of the monetary shock on the real house prices, both at the regional level and the national level, during the post-liberalization period exceed the effect in the pre-liberalization era. As in the pre-liberalization period, Figure 2 also displays the heterogeneous responses across regions in the US. While house prices in the South (HPS) appear to drive the national response, the West (HPW) shows a relatively weak, short-lived response. House prices in North East (HPNE) and Middle West (HPMW) exhibit identical

---

[11] Gupta *et al.* (forthcoming) conduct their quarterly dynamic analysis from 1976:01 through 2005:02 and do not indicate how the financial market liberalization in the early 1980s may affect those dynamics.

[12] We report all results based on the 68 percent level of significance.

responses, relatively weak, short-lived responses, with the effect in the North East (HPNE) exceeding that in the West (HPW) and the Middle West (HPMW).

6. Conclusions

This paper assesses the effects of monetary policy on US house price indexes, national and regional, using impulse response functions obtained from a LBVAR model that incorporates 143 monthly macroeconomic variables over the periods 1968:01 to 1982:12 and 1989:01 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 in 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 FFR. We compare the responses over two sub-samples to investigate the effect that financial market liberalization exerted on the sensitivity of house prices to changes in the interest rate. Overall, the 100 basis point FFR shock produces larger effects on the real house prices, both at the regional level and the national level, in the post-liberalization period when compared to the pre-liberalization era. While the precision of the estimates do not imply significant differences, the finding does offer a caution. That is, the housing market appears more sensitive to monetary policy shocks in the post-liberalization period. On the one hand, this suggests that monetary policy possesses increased leverage. On the other hand, the housing market cycle traditionally contributes an important component to the aggregate business cycle. Thus, the monetary authorities may need to exercise more care in implementing Federal funds rate adjustments going forward. In addition, contractionary monetary policy exerts a negative effect on house prices at the national level, indicating the absence of the price puzzle in small structural vector autoregressive models. The puzzle's absence in the housing sector possibly emerges as a result of proper identification of monetary policy shocks within a data-rich environment.

At the national level, the negative effect of the monetary policy shock on house prices persists and remains significant for more than two years before liberalization, while after liberalization, prices recover rapidly in about one year. The reaction of the national housing sector proves heterogeneous across regions. Over time, certain dynamics change – the Middle West appears to drive house prices before 1982, the South emerges as the driving force behind the dynamics observed in national housing sector after 1989. That is, after 1989, the impulse responses in the South more closely match those of the national housing sector than the other regions. While the North East and the Mid West display similar responses in duration over the pre- and post-liberalization phases, the North East responds more strongly to the monetary policy shock During both periods, the West shows a relatively weak, short-lived response.

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.

Bao, Y. C., Guay, C.L., and Li, S.M., 2009. A small Open Economy DSGE Model with a Housing Sector. *Preliminaly Draft paper prepared for the Conference of Economists*, Department of Economics, the University of Melbourne.

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.

Campbell, J., and Hercowitz, Z., 2005. The Role of Collateralized Household Debt in Macroeconomic Stabilization. NBER Working Paper 11330.

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.

Christensen, I., Corrigan, P., Mendicino, C. and Nishiyama, S-I., 2009. Consumption, Housing collateral, and the Canadian Business Cycle. Bank of Canada *Working paper 2009-26*, Bank of Canada.

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., Is a DFM Well-Suited for Forecasting Regional House Price Inflation? *Journal of Forecasting*, forthcoming a. .

Das, S., Gupta, R., and Kabundi, A., 2009. Could We Have Forecasted the Recent Downturn in the South African Housing Market? *Journal of Housing Economics* 18: 325-335.

Das, S., Gupta, R., and Kabundi, A. Forecasting Real House Price Growth in the Nine Census Divisions of the US. *Journal of Housing Research*, forthcoming b.

De Mol, C., Gianonne, D., and Reichlin, L. 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.

Dynan, K. E., Elmendorf, D. W., and Sichel, D., 2006. Can Financial Innovation Help to Explain the Reduced Volatility of Economic Activity? *Journal of Monetary Economics* 53, 123-150.

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. Mimeo, Department of Real Estate**,** Zicklin School of Business, Baruch College, CUNY.

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., Jurgilas, M., and Kabundi, A. The Effect of Monetary Policy on House Price Inflation: A Factor Augmented Vector Autoregression (FAVAR) Approach. *Journal of Economic Studies*, forthcoming..

Gupta, R., Jurgilas, M., and Kabundi, A., 2010. The Effect of Monetary Policy on Real House Price Growth Rate in South Africa: A Factor Augmented Vector Autoregression (FAVAR) Approach. *Economic Modelling*, 27: 315-323.

Gupta, R., Kabundi, A., and Miller, S. M. 2009. Forecasting the US Real House Price Index: Structural and Non-Structural Models with and without Fundamentals. *Working Paper No. 2009-42, Department of Economics, University of Connecticut*.

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.,. Housing Market Spillovers: Evidence from an Estimated DSGE Model. *American Economic Journal: Macroeconomics*, forthcoming.

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.

Ndahiriwe**.** K., and Gupta R. Financial Liberalization and the Effectiveness of Monetary Policy on House Prices in South Africa. *ICFAI Journal of Monetary Economics*, forthcoming.

Pariès, M.D., and Notarpietro, A., 2008.Monetary Policy and Housing prices in an estimated DSGE Model for the US and Euro area. *Working paper series no 972,* European Central Bank.

Pavlidis, E., Paya, I., Peel, D., and Spiru, A., 2009. Bubbles in House Prices and their impact on consumption: Evidence for the US. Department of Economics *Working paper 2009/025*. Lancaster University Management School.

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 Strauss, J.K., 2008. Differences in Housing Price Forecast Ability Across U.S. States. *Journal of Economic Studies,* Forthcoming.

Rapach, D. E., and Strauss, J. K., 2006. The Long-Run Relationship Between Consumption and Housing Wealth in the Eighth District States. Federal Reserve Bank of St. Louis Regional Economic Development 2(2), 140-147.

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.

Table 1: Impulse Response Results: Pre- and Post-Liberalization

	Pre-Liberalization Impulses					Post-Liberalization Impulses				
Periods	**HPNE**	**HPMW**	**HPS**	**HPW**	**HPUS**	**HPNE**	**HPMW**	**HPS**	**HPW**	**HPUS**
0	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
1	-0.207	-0.088	-0.025	-0.121	-0.080	-0.005	-0.336	-0.673	-0.105	-0.450
2	-0.336	-0.220	-0.084	-0.214	-0.164	-0.819	-0.730	-1.203	-0.668	-0.937
3	-0.411	-0.323	-0.180	-0.240	-0.249	-1.372	-1.008	-1.337	-1.069	-1.184
4	-0.430	-0.348	-0.233	-0.220	-0.287	-1.638	-1.135	-1.428	-1.232	-1.269
5	-0.383	-0.339	-0.243	-0.221	-0.292	-1.748	-1.200	-1.494	-1.312	-1.312
6	-0.354	-0.319	-0.218	-0.224	-0.282	-1.842	-1.225	-1.440	-1.146	-1.277
7	-0.348	-0.286	-0.171	-0.222	-0.261	-1.857	-1.208	-1.376	-0.988	-1.212
8	-0.346	-0.255	-0.127	-0.222	-0.237	-1.762	-1.149	-1.304	-0.894	-1.122
9	-0.347	-0.231	-0.104	-0.227	-0.222	-1.587	-1.037	-1.210	-0.798	-1.002
10	-0.363	-0.224	-0.098	-0.245	-0.222	-1.442	-0.926	-1.135	-0.707	-0.898
11	-0.384	-0.236	-0.109	-0.271	-0.236	-1.310	-0.844	-1.076	-0.691	-0.828
12	-0.413	-0.258	-0.137	-0.297	-0.262	-1.161	-0.788	-1.024	-0.702	-0.770
13	-0.441	-0.280	-0.172	-0.317	-0.290	-1.067	-0.756	-1.011	-0.721	-0.738
14	-0.461	-0.300	-0.204	-0.334	-0.314	-1.037	-0.759	-1.020	-0.746	-0.732
15	-0.474	-0.315	-0.226	-0.345	-0.332	-1.053	-0.794	-1.047	-0.774	-0.749
16	-0.482	-0.323	-0.238	-0.348	-0.342	-1.096	-0.848	-1.089	-0.803	-0.782
17	-0.485	-0.325	-0.240	-0.347	-0.345	-1.151	-0.904	-1.136	-0.833	-0.824
18	-0.483	-0.324	-0.237	-0.346	-0.344	-1.203	-0.949	-1.178	-0.860	-0.862
19	-0.479	-0.320	-0.231	-0.345	-0.341	-1.241	-0.975	-1.208	-0.884	-0.891
20	-0.475	-0.316	-0.225	-0.347	-0.338	-1.257	-0.982	-1.227	-0.907	-0.907
21	-0.474	-0.312	-0.220	-0.349	-0.336	-1.257	-0.975	-1.235	-0.929	-0.913
22	-0.475	-0.308	-0.217	-0.351	-0.334	-1.248	-0.961	-1.237	-0.951	-0.913
23	-0.477	-0.305	-0.215	-0.353	-0.333	-1.236	-0.945	-1.238	-0.975	-0.911
24	-0.481	-0.303	-0.214	-0.355	-0.332	-1.225	-0.933	-1.241	-1.001	-0.911
25	-0.484	-0.301	-0.212	-0.355	-0.331	-1.218	-0.926	-1.248	-1.030	-0.912
26	-0.487	-0.298	-0.209	-0.353	-0.330	-1.215	-0.923	-1.257	-1.058	-0.917
27	-0.489	-0.294	-0.204	-0.351	-0.326	-1.215	-0.924	-1.270	-1.087	-0.922
28	-0.490	-0.289	-0.199	-0.347	-0.322	-1.216	-0.927	-1.283	-1.113	-0.928
29	-0.490	-0.284	-0.192	-0.343	-0.317	-1.215	-0.930	-1.296	-1.138	-0.933
30	-0.490	-0.278	-0.184	-0.338	-0.311	-1.212	-0.933	-1.309	-1.159	-0.937
31	-0.489	-0.272	-0.176	-0.333	-0.304	-1.205	-0.936	-1.322	-1.177	-0.939
32	-0.487	-0.267	-0.167	-0.328	-0.297	-1.195	-0.938	-1.335	-1.192	-0.940
33	-0.486	-0.262	-0.158	-0.323	-0.291	-1.183	-0.940	-1.349	-1.205	-0.940
34	-0.484	-0.257	-0.150	-0.319	-0.284	-1.169	-0.942	-1.364	-1.217	-0.940
35	-0.482	-0.252	-0.141	-0.315	-0.277	-1.155	-0.946	-1.381	-1.227	-0.940
36	-0.481	-0.248	-0.132	-0.311	-0.270	-1.140	-0.950	-1.400	-1.237	-0.942
37	-0.479	-0.244	-0.123	-0.307	-0.263	-1.127	-0.956	-1.421	-1.246	-0.944
38	-0.477	-0.240	-0.114	-0.304	-0.257	-1.115	-0.963	-1.445	-1.255	-0.948
39	-0.475	-0.236	-0.105	-0.302	-0.250	-1.105	-0.971	-1.471	-1.263	-0.953
40	-0.473	-0.233	-0.096	-0.299	-0.244	-1.097	-0.980	-1.498	-1.272	-0.960
41	-0.470	-0.230	-0.088	-0.297	-0.238	-1.091	-0.991	-1.528	-1.280	-0.967
42	-0.468	-0.228	-0.079	-0.296	-0.232	-1.087	-1.003	-1.559	-1.288	-0.977
43	-0.466	-0.226	-0.071	-0.295	-0.226	-1.086	-1.015	-1.592	-1.296	-0.987
44	-0.464	-0.224	-0.063	-0.294	-0.221	-1.087	-1.027	-1.625	-1.305	-0.998
45	-0.463	-0.223	-0.055	-0.293	-0.215	-1.090	-1.039	-1.659	-1.313	-1.009
46	-0.461	-0.221	-0.048	-0.293	-0.211	-1.095	-1.051	-1.694	-1.321	-1.022
47	-0.459	-0.220	-0.041	-0.293	-0.206	-1.102	-1.063	-1.728	-1.329	-1.034
48	-0.458	-0.220	-0.034	-0.293	-0.202	-1.111	-1.075	-1.763	-1.338	-1.047

Note: The 0- to 48-month ahead impulse responses.

Figure 1: Effect of 100-Basis-Point Monetary Policy Shock on House Price Indexes with Confidence Bands: 1968 – 1982

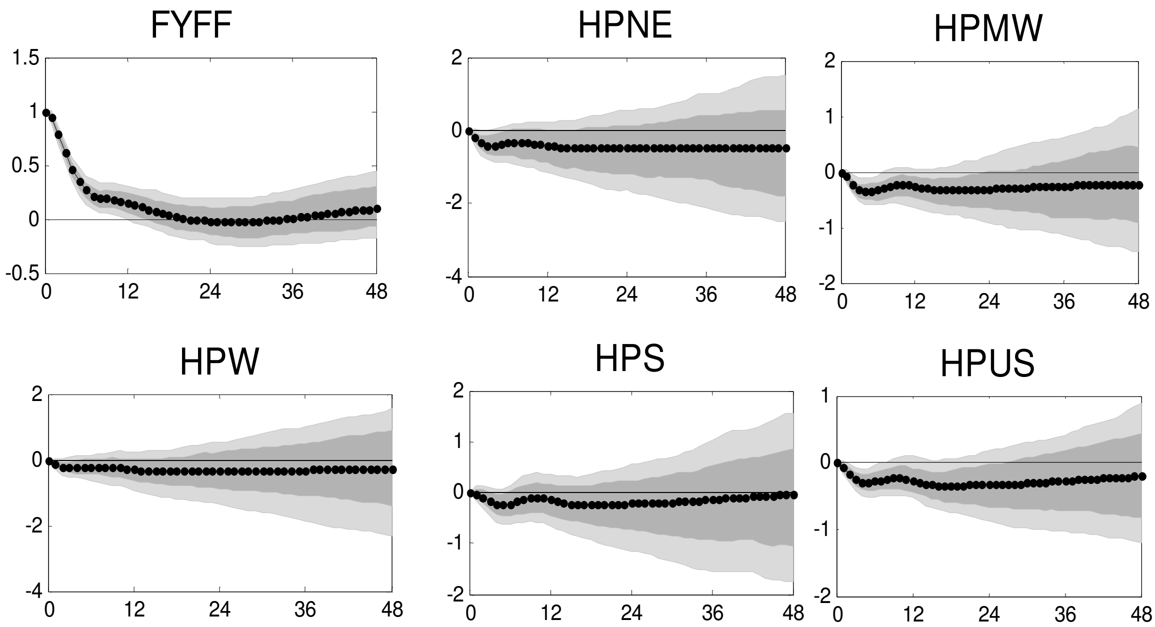

Figure 2: Effect of 100-Basis-Point Monetary Policy Shock on House Price Indexes with Confidence Bands: 1989 – 2003