University of Pretoria
Department of Economics Working Paper Series

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Working Paper: 2008-31
October 2008

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COULD WE HAVE PREDICTED THE RECENT DOWNTURN IN THE SOUTH AFRICAN HOUSING MARKET?

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ABSTRACT

This paper develops large-scale Bayesian Vector Autoregressive (BVAR) models, based on 268 quarterly series, for forecasting annualized real house price growth rates for large-, medium- and small-middle-segment housing for the South African economy. Given the in-sample period of 1980:01 to 2000:04, the large-scale BVARs, estimated under alternative hyperparameter values specifying the priors, are used to forecast real house price growth rates over a 24-quarter out-of-sample horizon of 2001:01 to 2006:04. The forecast performance of the large-scale BVARs are then compared with classical and Bayesian versions of univariate and multivariate Vector Autoregressive (VAR) models, merely comprising of the real growth rates of the large-, medium- and small-middle-segment houses, and a large-scale Dynamic Factor Model (DFM), which comprises of the same 268 variables included in the large-scale BVARs. Based on the one- to four-quarters ahead Root Mean Square Errors (RMSEs) over the out-of-sample horizon, we find the large-scale BVARs to not only outperform all the other alternative models, but to also predict the recent downturn in the real house price growth rates for the three categories of the middle-segment-housing over an *ex ante* period of 2007:01 to 2008:02.

Journal of Economic Literature Classification: C11, C13, C33, C53.
Keywords: Dynamic Factor Model, BVAR, Forecast Accuracy.

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1. INTRODUCTION

This paper develops large-scale Bayesian Vector Autoregressive (BVAR) models, based on 268 quarterly series, for forecasting annualized real house price growth rates, where real house price is the ratio of the nominal house price to the Consumer Price Index (CPI), for large-, medium- and small-middle-segment housing for the South African economy.[1] Given the in-sample period of 1980:01 to 2000:04, the large-scale BVARs, estimated under alternative hyperparameter values specifying the priors, are used to forecast real house price growth rates over a 24-quarter out-of-sample horizon of 2001:01 to 2006:04.[2] The forecast performance of the large-scale BVARs are then compared with classical and Bayesian versions of univariate and multivariate Vector Autoregressive (VAR) models, merely comprising of the real growth rates of the large-, medium- and small-middle-segment houses, and a large-scale Dynamic Factor Model (DFM), which comprises of the same 268 variables included in the large-scale BVARs. Once we determine a model that produces, on average, the minimum one- to four-quarters ahead Root Mean Square Errors (RMSEs) over the out-of-sample horizon, we evaluate, how well the same would have been able to predict the recent downturn, depicted in Figure 1, in the real house price growth rates for the three categories of the middle-segment-housing over an *ex ante* period of 2007:01 to 2008:02.[3]

Now that we know what we are after and the methodologies we will be using to address them, two questions arise immediately. First, why is forecasting real house price growth rates important? And second, why develop large-scale BVARs for this purpose? As far as the answer to the first question is concerned, the importance of predicting house price inflation is motivated by recent studies that conclude that asset prices help forecast both inflation and output (Forni *et al.*, 2003; Stock and Watson, 2003, Gupta and Das, 2008a and Das *et al.*, 2008). Since a large amount of individual wealth is imbedded in houses, similar to other asset prices, house price movements are thus important in signaling inflation.[4] As such, models that forecast real house price inflation can give policy makers an idea about the direction of overall inflation in the future, and hence, can provide a better control for designing of appropriate policies. The rationale for large-scale BVARs to forecast real house price growth rates emanates from the fact that a large number of economic variables help in predicting real housing price growth (Cho, 1996; Abraham and Hendershott, 1996; Johnes and Hyclak, 1999; and Rapach and Strauss, 2007, 2008). For instance, income, interest rates, construction costs, labor market variables, stock prices, industrial production, consumer confidence index, and also variables containing information about the world economy and the major trading partners of South Africa – which are included in the large-scale BVARs, are potential predictors. In addition, given that movements in the housing market are likely to play an important role in the business cycle, not only because housing investment is a very volatile component of demand (Bernanke and Gertler, 1995), but also because changes in house prices tends to have important wealth effects on consumption (International Monetary Fund, 2000) and investment (Topel and Rosen, 1988), the importance of forecasting house price inflation is vital. The housing sector thus plays a significant role in acting as leading indicator of the real sector of the economy, and as such, predicting it correctly cannot be overemphasized, especially in the light of the recent credit crunch in the U.S. that started with the burst of the housing price bubble which, in turn, transmitted to the real sector of the economy driving it towards an imminent recession. Besides this, the fact that BVARs, are quite well-suited in predicting turning points of macroeconomic

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[1] Data on house prices are obtained from the ABSA Housing Price Survey, with ABSA being one of the leading private banks of South Africa. The ABSA Housing Price Survey, distinguishes between three price categories as --- luxury houses (R 2.6 million to R9.5 million), middle-segment houses (R226,000 to R2.6 million) and affordable houses (R226,000 and below with an area in the range of 40 m^2 -79 m^2); and further subdivides the middle segment category based on the square meters of house area into small (80 m^2 -140 m^2), medium (141 m^2 -220 m^2) and large (221 m^2 -400 m^2). Given the easy accessibility of house price data for the middle-segment houses, we restrict our study to this category only. However, given that the market for different house-sizes within this category, behave differently (Burger and van Rensburg, 2008), we consider each of them separately, rather than investigating the overall house price of the middle-segment of the South African housing market.

[2] The choice of the out-of-sample period is exactly the same as used by two recent studies on the South African housing market, namely, Gupta and Das (2008a) and Das *et al.* (2008).

[3] The period 2007:01 to 2008:02 is dubbed *ex ante* simply because our data used in the models end at 2006:04. However, given the availability of data on house prices till 2008:01, we can compare the future forecasts from the models with the original data.

[4] Gupta and Das (2008a) point out that, in South Africa, housing inflation and CPI inflation tend to move together, though the former, understandably, is more volatile.

variables have recently been substantiated by Dua and Ray (1995), Dua and Miller (1996), Del Negro 2001), Gupta and Sichei (2006), Gupta (2006, 2008), and Banerji *et al*. (2008), Zita and Gupta (2008) and Gupta and Das (2008b) amongst others.

To realize the contribution of this study, it is important to place this paper in the context of current research that has been done on forecasting the housing market. In this regard, few studies that are worth mentioning are: Rapach and Strauss (2007, 2008), Gupta and Das (2008a,b), Das *et al.* (2008). Rapach and Strauss (2007) used an autoregressive distributed lag (ARDL) model framework, containing 25 determinants, to forecast real housing price growth for the individual states of the Federal Reserve's Eighth District. Given the difficulty in determining *apriori* the particular variables that are most important for forecasting real housing price growth, the authors also use various methods to combine the individual ARDL model forecasts, which result in better forecast of real housing price growth. Rapach and Strauss (2008) look at doing the same for 20 largest US states based on ARDL models containing large number of potential predictors, including state, regional and national level variables. Once again, the authors reach similar conclusions as far as the importance of combining forecasts are concerned. Given that in practice, forecasters and policymakers often extract information from many series than the ones included in smaller models, like the ones used by Rapach and Strauss (2007, 2008), who also indicate the importance of combining forecast from alternative models, the role of a large-scale models cannot be ignored. In addition, one cannot condone the fact that the main problem of small models, as seen from the studies by Rapach and Strauss (2007, 2008), is in the decision regarding the choice of the correct potential predictors to be included. Due to this reason, Vargas-Silva (2008) uses a Factor Augmented VAR (FAVAR) model containing 120 monthly series to analyze the impact of monetary policy actions on the housing sector of four different regions of the United States. Further, Das *et al*. (2008) show that forecast performances of Spatial BVARs (SBVARs), developed by Gupta and Das (2008a), to predict regional house prices in the middle-segment housing category of South Africa, can be markedly improved using a DFM. Clearly then, the motivation and the need to forecast house prices using large-scale models is quite compelling. However, to the best of our knowledge, this is the first attempt to look into the ability of large-scale BVARs in forecasting and predicting downturns in real house price growth rates.[5,6] The only other study that does look into forecasting the recent downturn in real house price growth rates for the twenty largest states of the US economy, is Gupta and Das (2008b). In this paper, the authors use SBVARs, based merely on real house price growth rates, to predict their downturn over the period of 2007:01 to 2008:01. They find that, though the models are quite well-equipped in predicting the recent downturn, they underestimate the decline in the real house price growth rates by quite a margin. They attribute this underprediction of the models to the lack of any information on fundamentals in the estimation process. In such a backdrop, our paper can thus be viewed as an extension of the abovementioned studies, in the sense that we not only use large-scale BVARs that allow for the role of a widest possible set of domestic, foreign and world fundamentals to affect the housing sector, but also use them to predict the recent downturn in the South African housing market. At this juncture, we must elaborate that given the type of models that we use, the study can easily be carried out for any country(ies). The reason behind using the South African housing market as a case study is simply data driven, especially, as far as data on the 268 macroeconomic variables are concerned, which, in turn, were obtained from the recent study of Gupta and Kabundi (2008a,b,c) and Das *et al.* (2008).[7] The remainder of the paper is organized as follows: Section 2 lays out the basics of the benchmark large-scale BVARs and the alternative models, while, Section 3 discusses the data. Sections 4 and 5 respectively, evaluate the forecasting performances of the models and their ability to predict the recent downturn in the housing market. Finally, Section 6 concludes.

2. THE MODEL

2.1 VARs and BVARs

The Vector Autoregressive (VAR) model, though 'atheoretical', is particularly useful for forecasting purposes. An unrestricted VAR model, as suggested by Sims (1980), can be written as follows:

[5] Note, Dua and Smyth (1995), Dua and Miller (1996) and Dua *et al.* (1999) used coincident and leading indexes in BVAR models to forecast home sales for the Connecticut and the overall US economy, respectively.

[6] Note, even though just like Gupta and Das (2008a) and Das *et al.* (2008), we look at the middle-segment of the South African housing market, unlike them, we do not look into regional data. This is simply because the recent downturn in the housing market has been an economy-wide phenomenon and not been restricted to any specific region (ABSA Quarterly Housing Price Review, 2008Q1, 2008Q2 and 2008Q3).

[7] See Section 3 for further details.

$$y_t = A_0 + A(L)\,y_t + \varepsilon_t \tag{1}$$

where *y* is a $(n \times 1)$ vector of variables being forecasted; *A(L)* is a $(n \times n)$ polynomial matrix in the backshift operator *L* with lag length *p*, *i.e.*, *A(L)* = $A_1 L + A_2 L^2 + \ldots\ldots\ldots\ldots + A_p L^p$; A_0 is a $(n \times 1)$ vector of constant terms, and ε is a $(n \times 1)$ vector of error terms. In our case, we assume that $\varepsilon \sim N(0, \sigma^2 I_n)$, where I_n is a $n \times n$ identity matrix.

Note the VAR model, generally uses equal lag length for all the variables of the model. One drawback of VAR models is that many parameters need to be estimated, some of which may be insignificant. This problem of overparameterization, resulting in multicollinearity and a loss of degrees of freedom, leads to inefficient estimates and possibly large out-of-sample forecasting errors. One solution, often adapted, is simply to exclude the insignificant lags based on statistical tests. Another approach is to use a near VAR, which specifies an unequal number of lags for the different equations.

However, an alternative approach to overcoming this overparameterization, as described in Litterman (1981), Doan *et al.* (1984), Todd (1984), Litterman (1986), and Spencer (1993), is to use a BVAR model. Instead of eliminating longer lags, the Bayesian method imposes restrictions on these coefficients by assuming that they are more likely to be near zero than the coefficients on shorter lags. However, if there are strong effects from less important variables, the data can override this assumption. The restrictions are imposed by specifying normal prior distributions with zero means and small standard deviations for all coefficients with the standard deviation decreasing as the lags increase. The exception to this is that the coefficient on the first own lag of a variable has a mean of unity. Litterman (1981) used a diffuse prior for the constant. This is popularly referred to as the 'Minnesota prior' due to its development at the University of Minnesota and the Federal Reserve Bank at Minneapolis.

Formally, as discussed above, the means and variances of the Minnesota prior take the following form:

$$\beta_i \sim N(1, \sigma^2_{\beta_i}) \text{ and } \beta_j \sim N(0, \sigma^2_{\beta_j}) \tag{2}$$

where β_i denotes the coefficients associated with the lagged dependent variables in each equation of the VAR, while β_j represents any other coefficient. In the belief that lagged dependent variables are important explanatory variables, the prior means corresponding to them are set to unity. However, for all the other coefficients, β_j's, in a particular equation of the VAR, a prior mean of zero is assigned to suggest that these variables are less important to the model.

The prior variances $\sigma^2_{\beta_i}$ and $\sigma^2_{\beta_j}$, specify uncertainty about the prior means $\overline{\beta}_i$ = 1, and $\overline{\beta}_j$ = 0, respectively. Because of the overparameterization of the VAR, Doan *et al.* (1984) suggested a formula to generate standard deviations as a function of small numbers of hyperparameters: *w*, *d*, and a weighting matrix *f(i, j)*. This approach allows the forecaster to specify individual prior variances for a large number of coefficients based on only a few hyperparameters. The specification of the standard deviation of the distribution of the prior imposed on variable *j* in equation *i* at lag *m*, for all *i*, *j* and *m*, defined as $S_1(i, j, m)$, can be specified as follows:

$$S_1(i, j, m) = [w \times g(m) \times f(i, j)] \frac{\hat{\sigma}_j}{\hat{\sigma}_i} \tag{3}$$

with *f(i, j) = 1*, if *i = j* and k_{ij} otherwise, with $(0 \le k_{ij} \le 1)$, *g(m)* = $m^{-d}, d > 0$. Note that $\hat{\sigma}_i$ is the estimated standard error of the univariate autoregression for variable *i*. The ratio $\hat{\sigma}_i / \hat{\sigma}_j$ scales the variables to account for differences in the units of measurement and, hence, causes specification of the prior without consideration of the magnitudes of the variables. The term *w* indicates the overall tightness and is also the standard deviation on the first own lag, with the prior getting tighter as we reduce the value. The parameter *g(m)* measures the tightness on lag *m* with respect to lag 1, and is assumed to have a harmonic shape with a decay factor of *d*, which tightens the prior on increasing lags. The parameter *f(i, j)* represents the tightness of variable *j* in equation *i* relative to variable *i*, and by

increasing the interaction, i.e., the value of k_{ij}, we can loosen the prior.[8] Note, in the standard Minnesota-type prior, the overall tightness (*w*) takes the values of 0.1, 0.2 and 0.3, while, the lag decay (*d*) is generally chosen to be equal to 0.5, 1.0 and 2.0. The interaction parameter (k_{ij}) is traditionally set at = 0.5. The small-scale BVARs would be estimated with this set of parameterization of the priors.

Given that, we have domestic as well as foreign and world variables in the 268 data series used for the large-scale models, and realizing the South Africa is a small open economy, and hence, domestic variables would have minimal, if any, effect on foreign and world variables, while the latter set of variables is sure to have an influence on the South African variables, setting k_{ij} = 0.5 could be a quite far fetched from reality. Hence, borrowing from the BVAR models used for regional forecasting, involving both regional and national variables, and following Kinal and Ratner (1986), Shoesmith (1992) and Gupta and Kabundi (2008b,c), the weight of a foreign or world variable in a foreign or world equation, as well as a domestic equation, is set at 0.6. The weight of a domestic variable in other domestic equation is fixed at 0.1 and that in a foreign or world equation at 0.01. Finally, the weight of the domestic variable in its own equation is 1.0. These weights are in line with Litterman's circle-star structure. Star (foreign or world) variables affect both star and circle (domestic) variables, while circle variables primarily influence only other circle variables.[9] Clearly then, the large-scale BVARs are estimated with asymmetric priors.

Finally, once the priors have been specified, the alternative BVARs, whether based on 1 or 3 or all the 268 variables, are estimated using Theil's (1971) mixed estimation technique. Specifically, suppose we denote a single equation of the VAR model as: $y_1 = X\beta + \varepsilon_1$, with $Var(\varepsilon_1) = \sigma^2 I$, then the stochastic prior restrictions for this single equation can be written as:

$$\begin{bmatrix} M_{111} \\ M_{112} \\ . \\ . \\ . \\ M_{nnm} \end{bmatrix} = \begin{bmatrix} \sigma/\sigma_{111} & 0 & . & . & . & 0 \\ 0 & \sigma/\sigma_{112} & 0 & . & . & 0 \\ . & . & . & . & . & . \\ . & . & . & . & . & . \\ 0 & . & . & . & . & 0 \\ 0 & 0 & . & . & 0 & \sigma/\sigma_{nnm} \end{bmatrix} \begin{bmatrix} a_{111} \\ a_{112} \\ . \\ . \\ . \\ a_{nnm} \end{bmatrix} + \begin{bmatrix} u_{111} \\ u_{112} \\ . \\ . \\ . \\ u_{nnm} \end{bmatrix} \quad (4)$$

Note, $Var(u) = \sigma^2 I$ and the prior means M_{ijm} and σ_{ijm} take the forms shown in (2) and (3). With (4) written as:

$$r = R\beta + u \quad (5)$$

and the estimates for a typical equation are derived as follows:

$$\hat{\beta} = (X'X + R'R)^{-1}(X'y_1 + R'r) \quad (6)$$

Essentially then, the method involves supplementing the data with prior information on the distribution of the coefficients. The number of observations and degrees of freedom are increased by one in an artificial way, for each restriction imposed on the parameter estimates. The loss of degrees of freedom due to over- parameterization associated with a classical VAR model is, therefore, not a concern in the BVARs.

2.2 DFM

This study uses the Dynamic Factor Model (DFM) developed by Forni *et al.* (2005) to extract common components between macroeconomics series, and then these common components are used to forecast real house price growth rates in South Africa. In the VAR models, since all variables are used in forecasting, the number of parameters to be estimated depends on the number of variables *n*. With such a large information set, *n*, the estimation of a large number of parameters leads to a curse of

[8] For an illustration, see Dua and Ray (1995).

[9] We also experimented by assigning higher and lower interaction values, in comparison to those specified above, to the star variables in both the star and circle equations, but, the rank ordering of the alternative forecasts remained the same.

dimensionality, especially in the case of classical VARs. The DFM uses information set accounted by few factors $q << n$, which transforms the curse of dimensionality into a blessing of dimensionality.

The DFM expresses individual times series as the sum of two unobserved components: a common component driven by a small number of common factors and an idiosyncratic component, which are specific to each variable. The relevance of the method is that the DFM is able to extract the few factors that explain the comovement of all South African macroeconomic variables. Forni *et al.* (2005) demonstrated that when the number of factors is small relative to the number of variables and the panel is heterogeneous, the factors can be recovered from the present and past observations.

Consider an $n \times 1$ covariance stationary process $Y_t = (y_1, ..., y_n)'$. Suppose that X_t is the standardized version of Y_t, i.e. X_t has a mean zero and a variance equal to one. Under DFM proposed by Forni *et al.* (2005) X_t is described by a factor model, it can be written as the sum of two orthogonal components:

$$x_{it} = b_i(L) f_t + \xi_{it} = \lambda_i F_t + \xi_{it} \quad (7)$$

or, in vector notation:

$$X_t = B(L) f_t + \xi_{it} = \Lambda F_t + \xi_{it} \quad (8)$$

where f_t is a $q \times 1$ vector of dynamic factors, $B(L) = B_0 + B_1 L + ... + B_s L^s$ is in an $n \times q$ matrix of factor loadings of order s, ξ_t is the $n \times 1$ vector of idiosyncratic components, F_t is $r \times 1$ vector of static factors, with $r \geq q(s+1)$. Let f_t and ξ_t be mutually orthogonal stationary processes and $\chi_t = B(L) f_t$ as the common component. In factor analysis jargon $X_t = B(L) f_t + \xi_{it}$ is referred to as the dynamic factor model, and $X_t = \Lambda F_t + \xi_{it}$ as the static factor model. Similarly, f_t is regarded as vector of the dynamic factors while F_t as the vector of the static factors. Since dynamic common factors are latent, they need to be estimated. Forni *et al.* (2005) estimate dynamic factors through the use of dynamic principal component analysis. It involves the estimating the eigen values and eigen vectors decomposition of spectral density matrix of X_t, which is a generalization of orthogonalization process in case of static principal components. The DFM of Forni *et al.* (2005) is estimated in two steps to solve the end-of-sample problems caused by two-sided filtering encounter with the Dynamic Principle Component Analysis (DPCA) used in Forni *et al.* (2000). Due to end-of-sample problems this method is not suited for forecasting. Firstly, the DPCA is used to compute estimates of covariance matrices of common and idiosyncratic components of X_t at all leads and lags as inverse Fourier transforms of the corresponding estimated spectral density matrices. The spectral density matrix of X_t is given by $\Sigma(\theta) = \Sigma_\chi(\theta) + \Sigma_\xi(\theta)$. Secondly, these estimates are used in the construction of r linear combinations of the observations having smallest idiosyncratic-common variance ratio.

3. DATA

While, the small-scale, univariate and 3-variable multivariate, VARs, both the classical and Bayesian variants, include data on only the three variables of interest, namely, the annualized real house price growth rates of the large-, medium- and small-middle-segment houses, the large-scale BVARs and the DFM is estimated based on includes 268 quarterly series of South Africa, with the data covering the real, nominal, and financial sectors. We also have intangible variables, such as confidence indices, and survey variables. In addition to national variables, the paper uses a set of global variables such as commodity industrial inputs price index and crude oil prices. The data also comprises series of major trading partners such as Germany, the United Kingdom (UK), and the United States (US) of America. The in-sample period contains data from 1980:01 to 2000:04, while the out-of-sample set is 2001:01-2006Q4.[10] All series are seasonally adjusted and were made covariance stationary when estimating the DFM. The more powerful DFGLS test of Elliott, Rothenberg, and Stock (1996), instead of the most

[10]Details about data and the statistical treatment of the variables used to estimate the large-scale BVARs and the DFM are available upon request.

popular ADF test, is used to assess the degree of integration of all series. All non-stationary series are made stationary through differencing. The Schwarz information criterion is used in the selecting the appropriate lag length in such a way that no serial correction is left in the stochastic error term. Where there were doubts about the presence of unit root, the KPSS test proposed by Kwiatowski, Phillips, Schmidt, and Shin (1992), with the null hypothesis of stationarity, was applied. All series are standardized to have a mean of zero and a constant variance. It must however be pointed out that, non-stationarity is not an issue with the BVAR, since Sims *et al.* (1990) indicate that with the Bayesian approach entirely based on the likelihood function, the associated inference does not need to take special account of nonstationarity, since the likelihood function has the same Gaussian shape regardless of the presence of nonstationarity. Hence, for the sake of comparison amongst the VARs, both classical and Bayesian, we make no attempt to make the variables stationary, unlike in the DFM.[11]

There are various statistical approaches in determining the number of factors in the DFM. For example, Bai and Ng (2002) developed some criteria guiding the selection of the number of factors in large dimensional panels. The principal component analysis (PCA) can also be used in establishing the number of factors in the DFM. The PCA suggests that the selection of a number of factors *q* be based on the first eigen values of the spectral density matrix of X_t. Then, the principal components are added until the increase in the explained variance is less than a specific $\alpha = 0.05$. The Bai and Ng (2002) approach proposes five static factors, while Bai and Ng (2007) suggests two primitive or dynamic factors. Similar to the latter method, the principal component technique, as proposed by Forni *et al.* (2000) suggests two dynamic factors. The first two dynamic principal components explain approximately 99 percent of variation, while the eigen value of the third component is $0.005 (< 0.05)$.

4. FORECASTING EVALUATION

Given the specifications of the models, we estimate the four alternative types of models, namely, the univariate and multivariate versions of the classical VAR and the small-scale BVARs, the large-scale BVAR and the DFM over the period of 1980:01 to 2000:04, based on quarterly data. Then we compute the out-of-sample one- through four-quarters-ahead forecasts for the period of 2001:01 to 2006:04, and compare the forecast accuracy of the alternative models. The different types of the VARs are estimated with 8 lags[12] of each variable. Since we use eight lags, the initial eight quarters of the sample, 1980:01 to 1981:04, are used to feed the lags. We generate dynamic forecasts, as would naturally be achieved in actual forecasting practice. The models are re-estimated each quarter over the out-of-sample forecast horizon in order to update the estimate of the coefficients, before producing the 4-quarters-ahead forecasts. This iterative estimation and 4-steps-ahead forecast procedure was carried out for 24 quarters, with the first forecast beginning in 2001:01. This experiment produced a total of 24 one-quarter-ahead forecasts, 24-two-quarters-ahead forecasts, and so on, up to 24 4-step-ahead forecasts. The RMSEs[13] for the 24, quarter 1 through quarter 4 forecasts are then calculated for the annualized real house price growth rates of the large-, medium- and small-middle-segment housing. The values of the RMSE statistic for one- to four-quarters-ahead forecasts for the period 2001:01 to 2006:04 are then examined. The model that produces the lowest average value for the RMSE is selected as the 'optimal' model for a specific category of real house price growth rate.

In Tables 1 through 3, we compare the RMSEs of one- to four-quarters-ahead out-of-sample-forecasts for the period of 2000:01 to 2006:04, generated by the abovementioned alternative models models. At this stage, a few words need to be said regarding the choice of the evaluation criterion for the out-of-sample forecasts generated from Bayesian models. As Zellner (1986: 494) points out the 'optimal' Bayesian forecasts will differ depending upon the loss function employed and the form of predictive

[11] See Dua and Ray (1995) for further details.

[12] The choice of 8 lags is based on the unanimity of the sequential modified LR test statistic, Akaike information criterion (AIC), the final prediction error (FPE) criterion and the Hannan-Quinn (HQ) information criterion applied to a stable VAR estimated with the 3 variables of concern. Note, stability, as usual, implies that no roots were found to lie outside the unit circle.

[13] Note that if A_{t+n} denotes the actual value of a specific variable in period $t + n$ and ${}_tF_{t+n}$ is the forecast made in period t for $t + n$, the RMSE statistic can be defined as: $\sqrt{\frac{1}{N}\Sigma(A_{t+n} - {}_tF_{t+n})^2}$. For $n = 1$, the summation runs from 2001:1 to 2006:4, and for $n = 2$, the same covers the period of 2001:2 to 2006:4, and so on.

probability density function". In other words, Bayesian forecasts are sensitive to the choice of the measure used to evaluate the out-of-sample forecast errors. However, Zellner (1986) points out that the use of the mean of the predictive probability density function for a series, is optimal relative to a squared error loss function and the Mean Squared Error (MSE), and hence, the RMSE is an appropriate measure to evaluate performance of forecasts, when the mean of the predictive probability density function is used. This is exactly what we do below in Tables 1 through 3, when we use the average RMSEs over the one- to four-quarter-ahead forecasting horizon. The conclusions, regarding each of the three categories of real house price growth rate, based on the average one- to four-quarters-ahead RMSEs, from these tables can be summarized as follows:

(i) Irrespective of the hyperparameters specifying the tightness of the prior and the size of the houses within the middle segment category, the large-scale BVARs, outperform all the other models by quite a distance for each of the one- to four-quarters-ahead out-of-sample forecasts. However, within the large-scale BVARs, the model with the most tight priors ($w = 0.1$, $d = 0.2$) is the best performing model on average;

(ii) Based on the average RMSEs, the univariate BVAR models with ($w = 0.1$, $d = 0.2$) are a distant second to the large-scale BVARs in each of the three categories of the middle-segment housing. These models are closely followed in the heels by the small-scale BVAR models with same set of hyperparameters specifying the Minnesota prior.

(iii) In all the three cases, the univariate OLS or the Autoregressive model of order 8, the DFM and the VAR, based on the average RMSEs for the out-of-sample horizon of 2001:10 to 2006:04, are ranked as fourth, fifth and sixth respectively.

[INSERT TABLES 1 THROUGH 3]

Note, unlike Das *et al.* (2008), who found the DFM to be the overwhelming favorite in forecasting regional house price inflation relative to small-scale spatial and non-spatial BVARs and a classical VAR, our results do not indicate so. In fact, the DFM is found to be ranked below the univariate and multivariate small-scale BVARs in our case. However, there is no doubt over the capability of the large-scale BVARs in forecasting the economy-wide annualized real house price growth rates of the large-, medium- and small-middle-segment housing. As an obvious extension of the current study and that of Das *et al.* (2008), one might want to look at the ability of the large-scale BVARs in forecasting regional house price inflation. This would allow for a better comparison of the two large-scale models. As pointed out earlier, given the economy-wide downturn in the real house price growth rates, the need to look into regional real house price growth rates was not really compelling for us.

At this stage, we must, however, point to at least two limitations of the Bayesian approach: First, as is clear from Tables 1 to 3, the forecast accuracy is sensitive to the choice of the priors. So if the prior is not well specified, an alternative model used for forecasting may perform better. Second, for the Bayesian models, one requires to specify an objective function, for example the average RMSEs, to search for the 'optimal' priors, which in turn, needs to be optimized over the period for which we compute the out-of-sample forecasts. However, there is no guarantee that the chosen parameter values specifying the prior will continue to be 'optimal' beyond the period for which it was selected. Nevertheless, the role of BVARs in forecasting macroeconomic variables accurately cannot be underestimated.

In what follows, we look at the ability of the large-scale BVAR model with ($w = 0.1$, $d = 0.2$) in predicting the recent downturn in the real house price growth rate over 2007:01 to 2008:02, in comparison to the AR(8), the VAR, the DFM and those BVARs, univariate and multivariate, that on average produces the minimum average RMSEs for specific values of w and d, specifying the Minnesota prior. As with the large scale BVAR, the univariate and multivariate small-scale BVARs that outperforms the other models within its own category also has a value of $w = 0.1$, $d = 0.2$. Note the objectives of studying the recent downturn is twofold: First, we want to see if with the available information till 2006:04, we could have predicted *ex ante* the recent downturn in the real house price growth rates using the 'optimal' large-scale BVAR model. Second, by recursively estimating the model using *ex ante* forecasted data and then forecasting one-step-ahead based on the 'optimal' Bayesian models, allows us to gauge severity of the possible misspecification of the priors. This is one way of tackling the second of the two problems with Bayesian methods, because recall, the optimality of the priors were decided based on the minimum average RMSEs for one- to four-quarters-ahead forecasts over an out-of-sample horizon of 2001:01 to 2006:04.

5. PREDICTING THE TURNING POINTS

As can be observed from Figures 2 through 4, the 'optimal' large-scale BVAR with (w = 0.1, d = 0.2) is clearly the best suited model in predicting the recent downturn in the real house price growth rates of the large-, medium- and small-middle-segment housing over the *ex ante* period of 2007:01 to 2008:02. Though the model gets the direction of the real house price growth rate right, it however tends to over predict the downturn, especially when the real growth rate becomes negative in case of the large- and small-middle-segment housing. As in Gupta and Das (2008b) the 'optimal' small-scale univariate and multivariate BVARs do a fair job in predicting the downturn, but they are always found to under-predict the size of the decline in the real house price growth rates. The fact that the 'optimal' large-scale BVAR does so well in predicting the recent downturn, while the 'optimal' small-scale univariate and multivariate BVARs under predict the fall in the real house price growth rates, is clearly an indication of the role fundamentals play in affecting real house prices, over and beyond the information contained in the growth rates of the lagged real house prices. Moreover, given that the large-scale BVAR model allows for the domestic variables to have a minimal effect on foreign and world variables, while the latter set of variables to have a strong influence on the South African variables, might be causing it to perform better than the DFM, which also includes the same set of variables, both in terms of forecasting and predicting the recent downturn.

6. CONCLUSIONS

This paper develops large-scale BVAR models, based on 268 quarterly series, for forecasting annualized real house price growth rates for large-, medium- and small-middle-segment housing for the South African economy. Given the in-sample period of 1980:01 to 2000:04, the large-scale BVARs, estimated under alternative hyperparameter values specifying the priors, are used to forecast real house price growth rates over a 24-quarter out-of-sample horizon of 2001:01 to 2006:04. The forecast performance of the large-scale BVARs are then compared with classical and Bayesian versions of univariate and multivariate VAR models, comprising of the real growth rates of the large-, medium- and small-middle-segment houses only, and a large-scale DFM, which comprises of the same 268 variables included in the large-scale BVARs. Once we determine a model that produces, on average, the minimum one- to four-quarters ahead RMSEs over the out-of-sample horizon, we evaluate how well the same would have been able to predict the recent downturn in the real house price growth rates for the three categories of the middle-segment-housing over an *ex ante* period of 2007:01 to 2008:02.

Our results indicate that, irrespective of the hyperparameters specifying the tightness of the prior and the size of the houses within the middle segment category, the large-scale BVARs outperform all the other models by a distance for each of the one- to four-quarters-ahead out-of-sample forecasts. However, within the large-scale BVARs, the model with the most tight priors (w = 0.1, d = 0.2) is the best performing model on average. Moreover, this 'optimal' large-scale BVAR is also capable of tracking closely the recent downturn in the real house price growth rates for the three categories of the middle-segment-housing over an *ex ante* period of 2007:01 to 2008:02. In summary, we find a tight-priored large-scale BVAR model, which not only includes the widest possible set of fundamentals that tends to affect the housing market, but also treats South Africa as a small open economy by allowing for asymmetry in the specification of the prior, is the overwhelming favorite to forecast and predict turning points for the middle-segment category of housing. At this juncture, we must elaborate that given the type of models that we use, the study can easily be carried out for any country(ies).

There are however, as noted earlier, limitations to using the BVAR approach. First, the forecast accuracy depends critically on the specification of the prior, and second, the selection of the prior based on some objective function for the out-of-sample forecasts may not be 'optimal' for the time period beyond the period chosen to produce the out-of-sample forecasts. Besides these, there are two other major concerns, which are however general, to the traditional statistically estimated models used, like the the VARs --- both Classical and Bayesian and the DFM, for forecasting at the business cycle frequencies. First, such procedures perform reasonably well as long there are no structural changes experienced in the economy. Such changes, whether in or out of the sample, would then entail the models inappropriate. Alternatively, these models are not immune to the 'Lucas Critique'[14].

[14] See Lucas (1976) for details.

Furthermore, the estimation procedures used here are linear in nature, and hence, they fail to take into account of the nonlinearities in the data. One and, perhaps, the best response to these objections has been the development of micro-founded Dynamic Stochastic General Equilibrium (DSGE) models, which are capable of handling both the problems arising out of the structural changes and the issues of nonlinearities[16]. As in Iacoviello and Neri (2008), future research should concentrate on using DSGE models to model the housing sector of an economy, and then using the same to forecast house prices.

REFERENCES

Abraham JM, Hendershott PH. (1996), "Bubbles in Metropolitan Housing Markets", *Journal of Housing Research*, **7**: 191–207.

ABSA Housing Price Review. (2008), Quarter 1, Quarter 2 and Quarter 3.

Bai, Jushan, and Serena Ng (2007), "Determining the Number of Primitive Shocks in Factor Models". *Journal of Business and Economic Statistics* 25: 52–60.

Bai, Jushan, and Serena Ng. (2002), "Determining the Number of Factors in Approximate Factor Models". *Econometrica* 70: 191–221.

Banerji, A., Dua, P. and Miller, S. M. (2008), Performance Evaluation of the New Connecticut Leading Employment Index Using Lead Profiles and BVAR Models. *Journal of Forecasting*, 25(6), 415-437.

Bernanke B, Gertler M. (1995), "Inside the Black Box: the Credit Channel of Monetary Transmission", *Journal of Economic Perspectives*, 9:27–48.

Burger, P. and Van Rensburg, L.J (2008). "Metropolitan house prices in South Africa: Do they converge?", *South African Journal of Economics*, 76(2):291-297

Cho M. House Price Dynamics: A Survey of Theoretical and Empirical Issues. *Journal of Housing Research* 1996, **7**: 145–172.

Das, Sonali., Rangan Gupta, and Alain Kabundi (2008), "Is a DFM Well-Suited for Forecasting Regional House Price Inflation?" Forthcoming *Economic Research Southern Africa Working Paper.*

Del Negro, Marco (2001), Turn, Turn, Turn: Predicting Turning Points in Economic Activity, *Economic Review, Second Quarter*, Federal Reserve Bank of Atlanta.

Doan, Thomas, A, Robert B. Litterman, and Christopher A. Sims (1984), "Forecasting and Conditional Projections Using Realistic Prior Distributions". *Econometric Reviews* 3: 1-100.

Dua, P. and Smyth, D. J. (1995). Forecasting U. S. Home Sales using BVAR Models and Survey Data on Households' Buying Attitude for Homes. *Journal of Forecasting*, 14(3), 217-227.

Dua, P., Miller, S. M. and Smyth, D. J. (1999). Using Leading Indicators to Forecast U. S. Home Sales in a Bayesian Vector Autoregressive Framework. *Journal of Real Estate Finance and Economics*, 18(2), 191-205.

Dua, Pami, and Stephen M. Miller (1996), "Forecasting Connecticut Home Sales in a BVAR Framework Using Coincident and Leading Indexes". *Journal of Real Estate Finance and Economics* 13: 219-235.

Dua, Pami, and Subhash C. Ray (1995), "A BVAR Model for the Connecticut Economy". *Journal of Forecasting*, 14: 167-180.

Elliott G, Rothenberg TJ, Stock J. (1996), "Efficient Tests for an Autoregressive Unit Root", *Econometrica* ,64: 813–836.

Forni, Mario., Marc Hallin, Marco Lippi, and Lucrezia Reichlin (2005), "The Generalized Dynamic Factor Model, One Sided Estimation and Forecasting". *Journal of the American Statistical Association* 100: 830–840.

Forni M, Hallin M, Lippi M, Reichlin L.(2003), " Do financial variables help forecasting inflation and real activity in the euro area*?",* *Journal of Monetary Economics* , 50: 1243-1255.

Forni, Mario., Marc, Hallin, Marco, Lippi, and Lucrezia Reichlin (2000), "The Generalized Dynamic Factor Model: identification and estimation", *Review of Economics and Statistics* 82: 540–554.

Gupta, R. (2008). Bayesian Methods of Forecasting Inventory Investment in South Africa**.** Forthcoming *South African Journal of Economics*.

Gupta, Rangan, and Sonali Das (2008a), "Spatial Bayesian Methods for Forecasting House Prices in Six Metropolitan Areas of South Africa". *Forthcoming South African Journal of Economics.*

[16] For a detailed review of the literature on the use of DSGE models for forecasting, see Liu and Gupta (2007) and Liu *et al*. (2007, 2008).

Gupta, Rangan, and Sonali Das (2008b), "Predicting Downturns in the US Housing Market". *Forthcoming Journal of Real Estate Economics and Finance.*
Gupta, R. and Kabundi, A. (2008a). A Dynamic Factor Model for Forecasting Macroeconomic Variables in South Africa. *Working Paper* No. 200815, Department of Economics, University of Pretoria.
Gupta, R. and Kabundi, A. (2008b). Forecasting Macroeconomic Variables using Large Datasets: Dynamic Factor Model vs Large-Scale BVARs. *Working Paper* No. 200816, Department of Economics, University of Pretoria.
Gupta, R. and Kabundi, A. (2008c). Forecasting Macroeconomic Variables in a Small Open Economy: A Comparison between Small- and Large-Scale Models. *Working Paper* No. 200830, Department of Economics, University of Pretoria.
Gupta, Rangan (2006), "Forecasting the South African Economy with VARs and VECMs". *South African Journal of Economics* 74, 611-628.
Gupta, Rangan, and Moses, Sichei (2006), "A BVAR Model for the South African Economy". *South African Journal of Economics* 74: 391-409.
Iacoviello, Matteo, and Stefano Neri, (2008), "Housing Market Spillovers: Evidence from an Estimated DSGE Model", Paper provided by Boston College Department of Economics in its series Boston College Working Papers in Economics with number 659.
International Monetary Fund. World Economic Outlook: Asset Prices and the Business Cycle, 2000.
Johnes G, Hyclak T. (1999), " House Prices and Regional Labor Markets". *Annals of Regional Science*, **33**:33–49.
Kinal, T. and Ratner, J. (1986). A VAR Forecasting Model of a Regional Economy: Its Construction and Comparison. *International Regional Science Review*, 10(2), 113-126.
Kwiatowski D, Phillips PCB, Schmidt P, Shin Y. (1992) Testing the Null Hypothesis of Stationarity Against the Alternative of a Unit Root: How Sure Are We That Economic Time Series Have a Unit Root? *Journal of Econometrics*; **54**: 159–178.
Litterman, Robert B. (1981), "A Bayesian Procedure for Forecasting with Vector Autoregressions". Working Paper, Federal Reserve Bank of Minneapolis.
Litterman, Robert B. (1986), "Forecasting with Bayesian Vector Autoregressions – Five Years of Experience". *Journal of Business and Economic Statistics* 4 (1):25-38.
Liu, G. and Gupta, R. (2007). A Small-Scale DSGE Model for Forecasting the South African Economy. *South African Journal of Economics*, 75(2), 179-193.
Liu, G., Gupta, R. and Schaling, E. (2007b). Forecasting the South African Economy: A DSGE-VAR Approach. *Working Paper* No. 200724, Department of Economics, University of Pretoria.
Liu, G., Gupta, R. and Schaling, E. (2008). A New Keynesian DSGE Model for Forecasting the South African Economy. Forthcoming *Journal of Forecasting*.
LUCAS, Jr., R. E. (1976). Econometric Policy Evaluation: A Critique. *Carnegie Rochester Conference Series on Public Policy*, vol. 1, 19–46.
Rapach, David .E. and Jack K. Strauss. (2008), "Differences in Housing Price Forecast ability Across U.S. States" . Mimeo, Department of Economics, St. Louis University.
Rapach, David .E. and Jack K. Strauss. (2007), "Forecasting Real Housing Price Growth in the Eighth District States". *Federal Reserve Bank of St. Louis. Regional Economic Development*. 3(2): 33–42.
Shoesmith, G. L. (1992). Co-integration, Error Correction and Medium-Term Regional VAR Forecasting. *Journal of Forecasting*, 11(1), 91-109.
Sims, C. A., Stock, J. H. and Watson, M. W. (1990). Inference in Linear Time Series Models with Some Unit Roots. *Econometrica*, 58(1), 113-144.
Sims, Christopher A. (1980), "Macroeconomics and Reality". *Econometrica* 48:1-48.
Spencer, David E. (1993), "Developing a Bayesian Vector Autoregression Model". *International Journal of Forecasting"*, 9: 407-421.
Stock, James H., and Mark W. Watson (2003), Forecasting Output and Inflation: The Role of Asset Prices". *Journal of Economic Literature*, 41(3), 788-829.
Theil, Herni (1971), *Principles of Econometrics*. New York, John Wiley.
Todd, Richard M. (1984), "Improving Economic Forecasting with Bayesian Vector Autoregression". *Quarterly Review*, Federal Reserve Bank of Minneapolis, Fall, 18-29.
Topel, RH, Rosen S. (1988), "Housing Investment in the United States". *Journal of Political Economy*, **96**:718–740.
Vargas-Silva C. (2008), "The Effect of Monetary Policy on Housing: A Factor Augmented
Vector autoregression (FAVAR) Approach". Applied Economics Letters 2008, 15: 749-752.
Zellner, Arnold (1986), "A Tale of Forecasting 1001 Series: The Bayesian Knight Strikes Again". *International Journal of Forecasting* 2:494-494.

Zita, S. E. and Gupta, R. (2008). Modelling and Forecasting the Metical-Rand Exchange Rate. Forthcoming ICFAI Journal of Monetary Economics.

Table 1. Large Middle-Segment (2001:01-2006:4)

	QA	1	2	3	4	Average
	UOLS	7.6251	11.1535	12.4930	14.6719	11.4859
	VAR	8.2894	13.2600	16.3651	21.7194	14.9085
	DFM	10.7001	11.8895	12.3906	13.6091	12.1473
w=0.3,d=0.5	**UBVAR**	7.6507	10.8855	12.3250	14.0990	11.2400
	SBVAR	7.1261	10.0614	11.5019	13.6714	10.5902
	LBVAR	2.5138	0.8128	1.7729	0.9020	1.5003
w=0.2,d=1	**UBVAR**	7.6156	10.2381	11.5509	13.1236	10.6320
	SBVAR	7.8267	10.7540	12.1414	13.6428	11.0912
	LBVAR	2.3499	0.3116	2.1669	1.0100	1.4596
w=0.1,d=1	**UBVAR**	7.7395	10.3749	11.4148	12.8624	10.5979
	SBVAR	7.7199	10.3497	11.3774	12.8060	10.5633
	LBVAR	2.5542	0.4357	1.7550	0.7009	1.3614
w=0.2,d=2	**UBVAR**	7.9524	10.8216	12.2585	13.7656	11.1995
	SBVAR	7.8224	10.3813	11.6917	13.1564	10.7630
	LBVAR	1.7410	0.2447	2.2942	1.0257	1.3264
w=0.1,d=2	**UBVAR**	7.7368	10.2601	11.2240	12.6499	10.4677
	SBVAR	7.7718	10.3328	11.3300	12.7285	10.5408
	LBVAR	2.1479	0.2178	1.7364	0.5203	1.1556

UBVAR: Univariate BVAR; SBVAR: Small-Scale BVAR; LBVAR: Large-Scale BVAR

Table 2. Medium Middle-Segment (2001:01-2006:4)

	QA	1	2	3	4	Average
	UOLS	6.6699	11.1283	13.7053	15.9012	11.8512
	VAR	7.6226	13.2491	17.7929	22.7807	15.3613
	DFM	11.0542	12.3504	13.1730	14.5277	12.7764
w=0.3,d=0.5	**UBVAR**	6.6217	10.8245	13.5545	15.5817	11.6456
	SBVAR	6.5071	10.5573	13.2145	15.4633	11.4355
	LBVAR	1.3811	1.7065	0.3441	1.2291	1.1652
w=0.2,d=1	**UBVAR**	6.5061	10.4036	13.0992	15.1067	11.2789
	SBVAR	6.5437	10.4656	13.2209	15.1911	11.3553
	LBBAR	1.345286	1.668599	0.215229	1.421703	1.1627
w=0.1,d=1	**UBVAR**	6.2777	9.8641	12.4356	14.3960	10.7434
	SBVAR	6.2935	9.9233	12.5298	14.5264	10.8183
	LBVAR	1.228055	1.45676	0.252001	1.29891	1.0589
w=0.2,d=2	**UBVAR**	6.4954	10.2068	12.8802	14.8433	11.1064
	SBVAR	6.4512	10.1520	12.7567	14.7452	11.0263
	LBVAR	0.808409	1.32817	0.125094	1.331778	0.8984
w=0.1,d=2	**UBVAR**	6.2212	9.6563	12.1248	14.0596	10.5155
	SBVAR	6.2391	9.7022	12.2007	14.1637	10.5764
	LBVAR	0.731027	1.00139	0.002744	0.933318	0.6671

UBVAR: Univariate BVAR; SBVAR: Small-Scale BVAR; LBVAR: Large-Scale BVAR

Table 3. Small Middle-Segment (2001:01-2006:4)

	QA	1	2	3	4	Average
	UOLS	7.1218	10.9471	13.3339	16.0891	11.8730
	VAR	7.9998	13.5224	18.1246	23.6199	15.8167
	DFM	11.3963	11.6307	12.1631	14.2256	12.3539
w=0.3,d=0.5	**UBVAR**	7.0812	10.9023	13.4321	15.8916	11.8268
	SBVAR	6.7764	10.6527	13.4899	16.2816	11.8001
	LBVAR	2.2690	5.2247	3.5924	3.7260	3.7030
w=0.2,d=1	**UBVAR**	7.0021	10.7143	13.2513	15.5501	11.6295
	SBVAR	7.1894	10.9627	13.4611	15.6902	11.8259
	LBVAR	1.6219	3.9732	2.3725	2.8725	2.7100
w=0.1,d=1	**UBVAR**	7.1012	10.6804	12.9729	15.2257	11.4951
	SBVAR	7.0560	10.6301	12.9526	15.2829	11.4804
	LBVAR	1.6947	3.8056	2.6036	2.8698	2.7434
w=0.2,d=2	**UBVAR**	7.2474	10.9464	13.3839	15.5598	11.7844
	SBVAR	7.0765	10.6763	13.1243	15.3775	11.5637
	LBVAR	1.0821	3.0972	2.1133	3.0300	2.3307
w=0.1,d=2	**UBVAR**	7.0911	10.5807	12.8007	15.0435	11.3790
	SBVAR	7.0804	10.5700	12.8116	15.1174	11.3948
	LBVAR	1.2918	3.1277	2.1990	2.6840	2.3256

UBVAR: Univariate BVAR; SBVAR: Small-Scale BVAR; LBVAR: Large-Scale BVAR

Figure 1: Real House Price Growth Rates (Middle-Segment, 2007:01-2008:02)

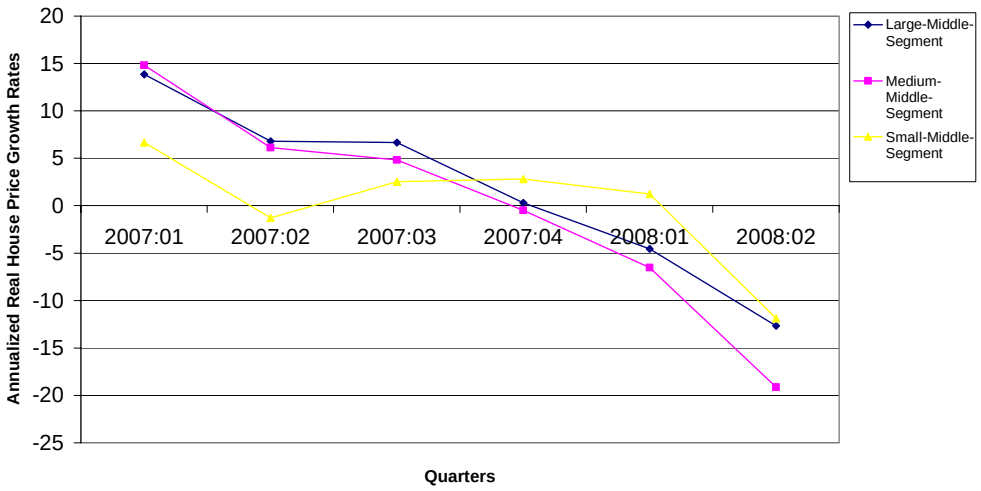

Figure 2: Predicting the Turning points in Real House Price Growth (Large Middle-Segment, 2007Q1-2008Q2)

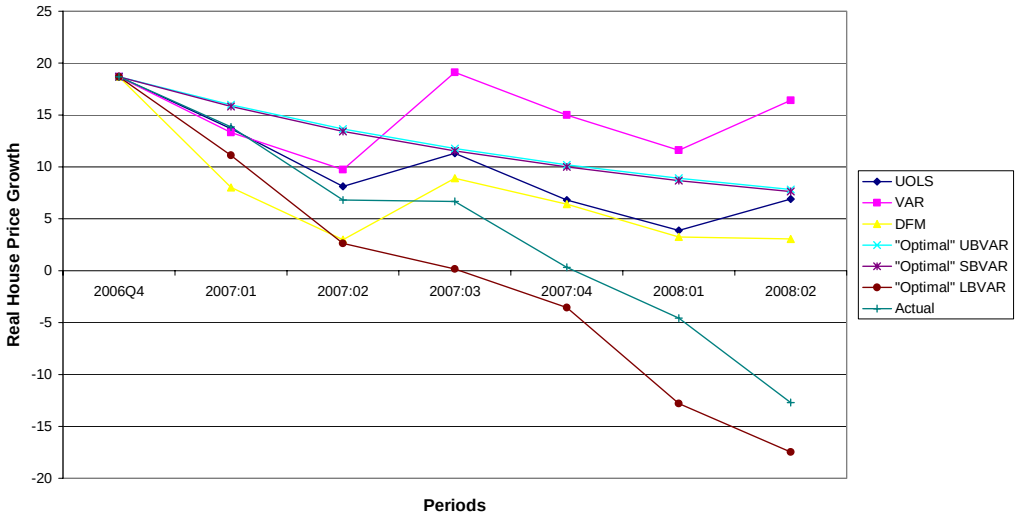

Figure 3: Predicting the Turning points in Real House price Growth (Medium Middle-Segment, 2007Q1-2008Q2)

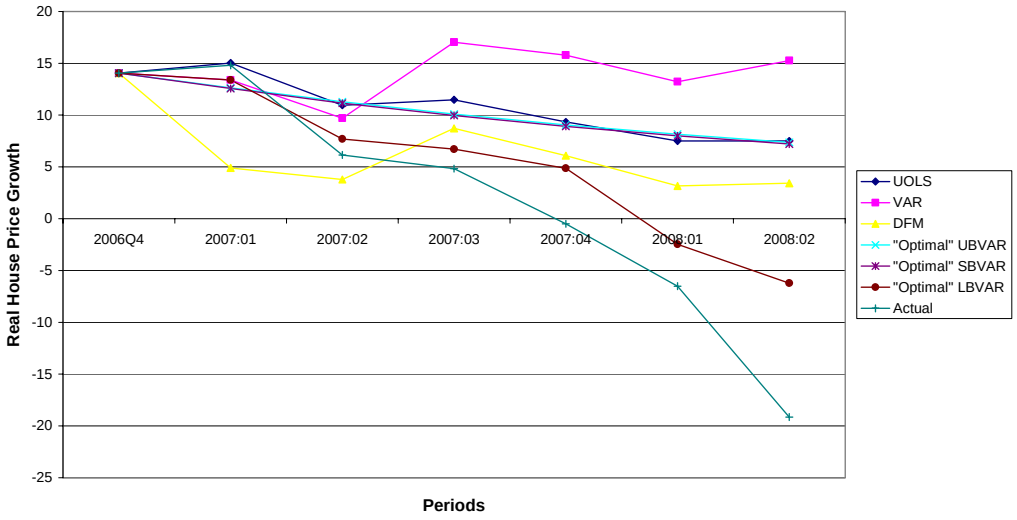
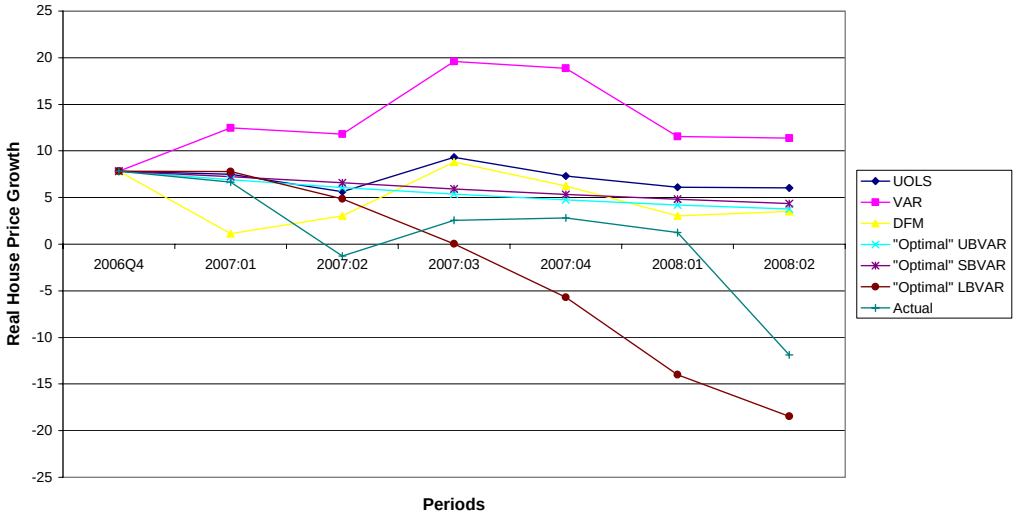
Figure 4: Predicting the Turning points in Real House Price Growth (Small MIddle-Segment, 2007Q1-2008Q2)