Forecasting Housing Prices: Dynamic Factor Model versus LBVAR Model

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1. Introduction

Housing market is of great important for the economy. Housing construction and renovation boost the economy through an increase in the aggregate expenditures, employment and volume of house sales. They also simulate the demand for relevant industries such as household durables. The oscillation of house prices affects the value of asset portfolio for most households for whom a house is the largest single asset. Moreover, price movements influence the profitability of financial institutions and the soundness of the financial system. Recent studies further justify the necessity of housing price analysis with a conclusion that housing sector plays a significant role in acting as a leading indicator of the real sector of the economy and assets prices help forecast both inflation and output (Forni, Hallin, Lippi, and Reichlin, 2003; Stock and Watson, 2003; Das, Gupta, and Kabundi, 2009a). Thus, a timely and precise forecast for house prices can provide valuable information to policy makers and help them better control inflation and design policies. Also, these forecasts can direct individual market participants to make wise investment decisions. Under the background of economic recession started by sub-mortgage crisis, analyzing the influence of the burst of the housing price bubble and predicting its future moving trend is thus of great importance that cannot be underestimated.

Unlike the financial market, the housing market is illiquid and heterogeneous in both physical and geographical perspectives, which makes forecasting house price a difficult task. Moreover, the subtle interactions between house price and other macroeconomic fundamentals make the prediction further complicated. The change in house prices can either reflect a national phenomenon, such as the effect of monetary policy, or be attributed to local factors—circumstances that specific to each geographic market. It can either indicate the changes in the real sector variables, such as labor input and production of goods, or be affected by the activities in the nominal sector, i.e., financial market liberalization (Gupta, Miller, and Van Wyk, 2010). Many previous studies find empirical evidence supporting the significant interrelations between house price and various economic variables, such as income, interest rates, construction costs and labor market variables (Linneman, 1986; Wheaton, 1999; Quigley, 1999; Tsatsaronis and Zhu, 2004). However, quantification of these interrelationships is not enough for a precise estimation or prediction of house price, because as a leading indicator of inflation and output, house prices are expected to be interacting with a much wider range of real and nominal variables. Thus, small-scale models potentially omit information contained in the thousands of variables. In another word, a large number of economic variables help in predicting real house price growth (Rapach and Strauss, 2009).

This paper investigates the recent moving trends of house prices in 42 metropolitan areas in the United State from the perspective of large-scale models, which are Dynamic Factor Model (DFM) and Large-scale Bayesian Vector Autoregressive (LBVAR) model. These models accommodate a large panel data comprising 183 monthly series for the U.S. economy, and an in-sample period of 1980:01 to 2007:12 are used to forecast one- to twelve-months-ahead house price growth rate over the out-of-sample horizon of 2008:01 to 2010:12. According to the findings of Himmerlberg, Mayer, and Sinai (2005) and the graphs in Figure 1, those 42 metropolitan areas can be divided into three groups based on their house price patterns, which are discussed in detail in section 3. The forecasting power of these two large-scale models are examined based on their ability to predict the turning points or patterns of house prices in the three metropolitan groups during the economic recession, and it is measured in terms of the Theil *U* statistic.

The contribution of this paper can be discussed by comparing it to the previous studies in the area of housing market forecasting. Because the advantage of large-scale models over small-scale counterparts are proved and discussed by many scholars (Forni *et al*., 2005; Das, Gupta, and Kabundi, 2008, 2009b, 2011; Gupta and Kabundi, 2008a; Gupta, Kabundi, and Miller, 2009a; Stock and Watson, 2004; Bloor and Matheson, 2009), this paper is placed in the context of research using large-scale models for house price prediction. DFM, FAVAR, LBVAR (spatial or non-spatial), Dynamic Stochastic General Equilibrium (DSGE) model, and forecast combination methods are the most popular methodologies for the analysis with a large number of data. Their forecasting performances have been examined and compared in many previous studies, but the conclusions vary to a large extent.

First, the forecasting performances between DFM and LBVAR are discussed by Das, Gupta, and Kabundi (2008), Das, Gupta, and Kabundi (2009a), and Gupta and Kabundi (2008a). All these three papers examine the housing market in South Africa but with different aggregation levels. Das, Gupta, and Kabundi (2008) and Gupat and Kabundi (2008a) claim that DFM is the better model to base one's forecast on, while Das, Gupta, and Kabundi (2009a) obtain the opposite conclusion that LBVAR outperform DFM. Second, the forecasting performances between FAVAR and LBVAR are discussed in the studies of Das, Gupta, and Kabundi (2009b) and Gupta, Kabundi, and Miller (2009a, 2009b). The house price growth rate in nine census divisions of the U.S., U.S. real house price index, and the housing prices in 20 U.S. states are the study objects for these three papers respectively. The first and third papers show evidence supporting that FAVAR is better suited for forecasting house price growth. But the second paper concludes that small-scale BVAR model outperforms both FAVAR and LBVAR in terms of forecasting. Third, the comparison of forecasting power between DSGE and other large-scale models are discussed in the paper of Gupta, Kabundi, and Miller (2009a) and Gupta and Kabundi (2008b). The first and second papers are conducted under the background of U.S. and South Africa housing markets respectively. The result of the first paper shows that DSGE model forecast a turning point more accurately than FAVAR and LBVAR model do, while the second paper suggests that DFM perform significantly better than DSGE. Last, forecast combination methods are discussed by Stock and Watson (2004), the authors find the combination forecasts performed well when compared to forecasts constructed using DFM framework, but they also attribute the poor performance of the DFM forecasts to the relatively small number of series examined.

The contradictive conclusions regarding the forecasting power of these popular large-scale models indicate that no such a large-scale model that performs consistently better than its other alternatives. The superior forecasting performance of a model is defined with respect to the time period examined and the specific study object. When the examined time period and study object change, the forecasting power of a model might be strengthened or weakened. This explains why some model is best for U.S. market but not for South Africa market and why the best-suited models for data of metropolitan level, census division level and states level are different even for the same country. For the same reason, results from the studies using old data are becoming less convincing as time goes by. Since the observations of 2006:Q4 is the most recent data used in the previous papers examining U.S. housing market, the results from those papers obviously can no longer be applied to current housing market, especially after the break out of sub-prime mortgage crisis. Our paper uses the most updated data to 2010:M12, and examines the housing market by metropolitan areas. Thus, it updates and extends the understanding of U.S. housing market.

In all the reviewed papers which apply DFM framework to U.S. housing market analysis, static principal component approach (PCA) is used. This approach estimates the common component by projecting onto the static principal components of the data. However, based on contemporaneous covariances only, it fails to exploit the potentially crucial information contained in the leading-lagging relations between the elements of the panel (Forni *et al.*, 2005). In this paper, we use the dynamic component approach proposed by Forni et al. (2005). This approach obtain estimates of common and idiosyncratic variance-covariance matrices at all leads and lags as inverse Fourier transforms of the corresponding estimated spectral density matrices, and thus overcomes the limitation of static PCA.

To sum up, there are two major contributions of this paper. First, most recent data to 2010:M12 are used for the estimation, which updates the understanding of U.S. housing market and the forecast performance of these two large-scale models. Second and more important, a dynamic component approach is used which is proved to overcome the limitation of its static counterpart and have estimation error one half of the static.

The remainder of the paper is organized as follows. The second section describes these two large-scale models. The third section discusses the data. In section 4, the forecasting performance of different models are evaluated and compared. Section 5 concludes the paper and discusses the limitations of both models.

2. Models

Economy-wide forecasting models are generally formulated as VAR or VARMA models. But they have one important drawback that many parameters have to be estimated and some of them may not even significant. This overparameterization results in multicollinearity and loss of degrees of freedom that can lead to inefficient estimates and large our-of-sample forecasting errors (Dua and Ray, 1995). Thus, in the cases that the number of cross-sectional variables is very large, possibly even larger than the number of observations over time, these models are no longer appropriate. Two frameworks are proposed to overcome the overparameterization problem, which are Dynamic Factor Model (DFM) framework and Bayesian Vector Autoregressive (BVAR) framework. The rest of this section discusses these two models.

2-1 Dynamic Factor Model (DFM)

DFM techniques are designed especially for the analysis with a large cross-sectional dimension. Under such models, each time series in the panel is represented as the sum of two mutually orthogonal components: the common component and the idiosyncratic component. The common component is strongly correlated with the rest of the panel and has reduced stochastic dimension, while the idiosyncratic component is either mutually orthogonal or "mildly cross-correlated" across the panel. In the DFM, multivariate information are used for forecasting the common component, and the idiosyncratic can be reasonably well predicted by means of traditional univariate methods, such as AR (4) model.

The DFM used in this paper follows the framework developed by Forni *et al.* (2005), which has three desirable characteristics. First, it adopts the dynamic principal component (PC) method, which has smaller estimation errors than its static counterpart proposed by Stock and Watson (1999). Instead of basing on contemporaneous covariances only, the dynamic PC method bases its estimation on the common and idiosyncratic variance-covariance matrices at all leads and lags. Second, this DFM method obtains its *h*-step-ahead forecast as the projection of the *h* step observation onto these estimated generalized principal components, which overcome the two-sided filtering problem of the DFM method proposed by Forni *et al*. (2000). Two-sided filtering is not a problem for within-sample estimation, but it does cause some difficulties in the forecasting context due to the unavailability of future observation. Third, this DFM method allows for cross-correlation among the idiosyncratic components, because orthogonality among these components is an unrealistic assumption.

Consider a double sequence { $y_{it}, i \in \mathrm{N}, t \in \mathrm{Z}$ }. Suppose that { $x_{it}, i \in \mathrm{N}, t \in \mathrm{Z}$ } is the standardized version of { y_{it} }, i.e. the *n*-dimensional vector process $\mathbf{x}_n = \{\mathbf{x}_{nt}, t \in \mathrm{Z}\}$, where $\mathbf{x}_{nt} = (x_{1t}\ x_{2t}\ \dots x_{nt})'$, is zero mean and stationary for any *n*. According to Forni *et al*. (2005), $\mathbf{x}_{nt}$ can be written as the sum of two orthogonal components:

$$x_{it} = b_{i1}(L)u_{1t} + b_{i2}(L)u_{2t} + \dots + b_{iq}(L)u_{qt} + \xi_{it} = \chi_{it} + \xi_{it} \tag{1}$$

where $\mathbf{u}_t$ is a $q \times 1$of dynamic factors and L stands for the lag operator. The variables χ_{it} and ξ_{it} represent the common and idiosyncratic components respectively.

Because χ_{it} is unobservable, it needs to be estimated. Forni *et al*. (2000) have shown that the projection of x_{it} on all leads and lags of the first q dynamic principal components of $\mathbf{x}_n$, obtained from the population spectral density matrix $\mathbf{\Sigma}_n$, converges to χ_{it} in mean square as *n* tends to infinity. In another word, $\chi_{it,n} \xrightarrow{p} \chi_{it}$, where $\chi_{it,n}$ denoted this projection. Empirically, we construct the finite-sample counterpart of $\chi_{it,n}$, which is based on the estimated spectral density matrix $\hat{\mathbf{\Sigma}}_n$, call it $\hat{\chi}_{it,n}$. By combining the convergence of $\chi_{it,n}$ to χ_{it} with the fact that $\hat{\chi}_{it,n}$ is a consistent estimator of $\chi_{it,n}$ for any *n* as *T* goes to infinity, it can be derived that $\hat{\chi}_{it,n}$ is a consistent estimator of χ_{it} as any *n* as *T* tends to infinity. Thus, equation (1) can be re-written as:

$$\hat{x}_{it} = \hat{\chi}_{it,n} + \hat{\xi}_{it} \tag{2}$$

where $\hat{\xi}_{it}$ is a consistent estimator of ξ_{it} based on traditional univariate method.

The *h*-step ahead forecast of $y_{i,T+h|T}$ is computed as follows:

$$\hat{y}_{i,T+h|T} = \hat{\sigma}_i \hat{x}_{i,T+h|T} + \hat{\mu}_i = \hat{\sigma}_i (\hat{\chi}_{i,T+h|T} + \hat{\xi}_{i,T+h|T}) + \hat{\mu}_i \tag{3}$$

where $\hat{\sigma}_i$ and $\hat{\mu}_i$ are the sample variance and sample mean of the i^{th} variable, T is the sample size, and the second equality is obtained from equation (2). $\hat{\xi}_{i,T+h|T}$ can be estimated using a traditional univaritate method, such as AR(4). $\hat{\chi}_{i,T+h|T}$ is obtained by the dynamic PC analysis, which is presented next.

The dynamic PC analysis starts with the estimation of the sample autocovariance matrix of $\mathbf{x}_{nt} = (x_{1t}\ x_{2t}\ \ldots\ x_{nt})'$:

$$\hat{\mathbf{\Gamma}}_{n,k} = \frac{1}{T-k}\sum_{t=k+1}^{T}\mathbf{x}_{n,t}\mathbf{x}'_{n,t} \tag{4}$$

Then the spectral density matrix of $\hat{\mathbf{\Gamma}}_{n,k}$ is calculated through discrete Fourier transform:

$$\hat{\mathbf{\Sigma}}(\theta_h) = \frac{1}{2\pi}\sum_{k=-M}^{M} w_k \hat{\mathbf{\Gamma}}_{n,k} e^{-i\theta_h k} \tag{5}$$

Where w_k is Barleet-lag window estimator weight $w_k = 1 - \frac{|k|}{M+1}$, and $\theta_h = \frac{2\pi}{2M+1}h$, h=-M, …, M. To ensure the consistency of results, M is a function of T and should satisfy two conditions that $M(T) \to \infty$ as $T \to \infty$ and $\lim\sup_{T\to\infty} M^3(T)/T < \infty$ as $T \to \infty$. Empirically, $M = \sqrt{T}$ is usually used.

Then a two-step procedure proposed in the study of Forni *et al*. (2005) follows. First step is to obtain estimates of common and idiosyncratic variance-covariance matrices at all leads and lags as inverse Fourier transforms of the corresponding estimated spectral density matrices. At a given frequency θ, there exists

$$\mathbf{V}(\theta)\hat{\mathbf{\Sigma}}(\theta) = \mathbf{D}(\theta)\mathbf{V}(\theta) \tag{6}$$

where $\mathbf{D}(\theta)$ is a diagonal matrix having the eigenvalues of $\hat{\mathbf{\Sigma}}(\theta)$ on the diagonal and $\mathbf{V}(\theta)$ is the $n \times n$ matrix whose columns are the corresponding row eigenvectors. Based on the central idea of PC analysis which claims that the first few (q) largest PCs (dynamic factors) will account for most of the variation in the original variables (Jolliffe, 2002), the spectral density matrix of the common component have the following relationship with the first q largest eigenvalues and their corresponding eigenvectors:

$$\mathbf{V}_q(\theta)\hat{\mathbf{\Sigma}}_\chi(\theta) = \mathbf{D}_q(\theta)\mathbf{V}_q(\theta) \tag{7}$$

or

$$\hat{\mathbf{\Sigma}}_\chi(\theta) = \tilde{\mathbf{V}}_q(\theta)\mathbf{D}_q(\theta)\mathbf{V}_q(\theta) \tag{7'}$$

where $\tilde{\mathbf{A}}$ denotes the conjugate transpose of a matrix *A*. The spectral density matrix of the idiosyncratic component is the estimated as:

$$\hat{\boldsymbol{\Sigma}}_{\xi}(\theta) = \hat{\boldsymbol{\Sigma}}(\theta) - \hat{\boldsymbol{\Sigma}}_{\chi}(\theta) \tag{8}$$

The covariance matrices of common and idiosyncratic parts are estimated through the inverse Fourier transform of spectral density matrices as following:

$$\hat{\boldsymbol{\Gamma}}_k^{\chi} = \frac{2\pi}{2M+1} \sum_{j=-M}^{M} \hat{\boldsymbol{\Sigma}}_{\chi}(\theta_h) e^{ik\theta_h} \tag{9}$$

$$\hat{\boldsymbol{\Gamma}}_k^{\xi} = \frac{2\pi}{2M+1} \sum_{j=-M}^{M} \hat{\boldsymbol{\Sigma}}_{\xi}(\theta_h) e^{ik\theta_h} \tag{10}$$

The second step is to use these estimates to construct the contemporaneous linear combinations of x_{it} 's that minimize the idiosyncratic-common variance ratio, and the linear combination gives the estimate of $\hat{\chi}_{it,n}$. The resulting aggregates can be obtained as the solution of a generalized principal component problem:

$$\mathbf{V}_G \hat{\boldsymbol{\Gamma}}_0^{\chi} = \mathbf{D}_G \mathbf{V}_G \hat{\boldsymbol{\Gamma}}_0^{\xi} \tag{11}$$

where D_G is a diagonal matrix having the generalized eigenvalues of the pair ($\hat{\boldsymbol{\Gamma}}_0^{\chi}, \hat{\boldsymbol{\Gamma}}_0^{\xi}$) on the diagonal and $\mathbf{V}_G$ is the $n \times n$ matrix whose columns are the corresponding row eigenvectors. The j^{th} generalized PCs are defined as

$$\hat{\mathbf{P}}_{t,j}^{G} = \mathbf{v}_{G,j} \mathbf{x}_{nt} \tag{12}$$

where $\mathbf{v}_{G,j}$ is the j^{th} generalized row eigenvector corresponding to the j^{th} largest generalized eigenvalues. Based on the PC theory, the *r* aggregates $\hat{\mathbf{P}}_{t,j}^{G}$, j=1, …, *r*, preserves most of the information of $\mathbf{x}_n$. Consider a space Δ_r spanned by these *r* aggregates, $\hat{\chi}_{it}$ is the projection of x_{it} onto this space. In another word,

$$\hat{\chi}_{it} = proj(x_{it} \mid \Delta_r) \tag{13}$$

The *h*_step ahead forecast $\hat{\chi}_{i,T+h|T}$ is based on the information available at time *T* and is estimated as the projection of x_{iT} on to the space spanned by the *r* aggregates $\hat{\mathbf{P}}_{T,j}^{G}$, j=1, …, *r*. Thus, the estimates of $\hat{\chi}_{i,T+h|T}$ is:

$$\hat{\chi}_{i,T+h|T} = \hat{\boldsymbol{\Gamma}}_h^{\chi} \tilde{\mathbf{V}}_{Gr} (\mathbf{V}_{Gr} \hat{\boldsymbol{\Gamma}}_0 \tilde{\mathbf{V}}_{Gr})^{-1} \mathbf{V}_{Gr} \mathbf{x}_{nT} \tag{14}$$

where $\mathbf{V}_{Gr}$ is the $n \times r$ matrix whose columns are the generalized row eigenvectors corresponding to the *r* largest generalized eigenvalues. The $\hat{y}_{i,T+h|T}$ can be obtained by plugging $\hat{\chi}_{i,T+h|T}$ into equation (3).

2-2 Large-scale BVAR (LBVAR) Model

LBVAR is another alternative of VAR to accommodate large-scale variables and overcome the overparameterization problem. As described in Litterman (1981), Doan, Litterman, and Sims (1984), Todd (1984), Litterman (1986), and Spencer (1993), instead of estimating longer lags and/ or less important variables, the Bayesian technique imposes restrictions on these coefficients by assuming that these are more likely to near zero than the coefficients on shorter lags and/or more important variables. If, however, there are strong effects from longer lags and/or less important variables, the data can override this assumption. This method supplements the data with prior information on the distribution of the coefficients. With each restriction, the number of observations and degrees of freedom are increased by one in an artificial way. Therefore, the loss of degrees of freedom due to overparameterization associated with a VAR model is not a concern in LBVAR model.

The restrictions are imposed by specifying normal prior distributions with means zero and small standard deviations for all coefficients with decreasing standard deviations on increasing lags. The exception is the coefficient on the first own lag of a variable that has a mean of unity. This prior is called the "Minnesota prior", which takes the following form:

$$\beta_i \sim N(1, \sigma_{\beta_i}^2) \text{ and } \beta_j \sim N(1, \sigma_{\beta_j}^2) \tag{15}$$

where β_i represents the coefficients associated with the lagged dependent variables in each equation of the LBVAR, while β_j represents any other coefficient. The standard deviation of the prior distribution for lag *m* of variables *j* in equation *i* for all *i*, *j*, and *m*--$\sigma(i, j, m)$--is specified as follows:

$$\sigma(i, j, m) = [w \times g(m) \times f(i, j)] \frac{\hat{\sigma}_i}{\hat{\sigma}_j} \tag{16}$$

$$f(i,j)=\begin{cases}1, \ if \ \ i=j \\ k, \ other \ wise \ (0<k<1)\end{cases} \tag{17}$$

$$g(m)=m^{-d}, \ d>0 \tag{18}$$

where $\hat{\sigma}_i$ is the standard error of a univariate autoregression for variable i. The ratio $\hat{\sigma}_i / \hat{\sigma}_j$ scales the variables to account for differences in units of measurement and allows the specification of the prior without consideration of the magnitudes of the variables. The parameter w is the standard deviation on the first own lag and describes the overall tightness of the prior. The tightness on lag m relative to lag 1 is given by the function $g(m)$, assumed to have a harmonic shape with decay factor d. The tightness of variable j relative to variables i in equation i is represented by the function $f(i, j)$. The value of $f(i, j)$ determines the importance of variable j relative to variable i, higher values implying greater interaction. A tighter prior occurs by decreasing w, increasing d, and/or decreasing $f(i, j)$.

Next, the appropriate values for these hyperpapermeters are discussed. In the analysis, both regional and national data are used. Realizing that national variables affect both national and regional variables, while regional variables primarily influence only other regional variables, the LBVAR should be estimated with asymmetric priors. Following Das, Gupta, and Kabundi (2009b), the weight, i.e. $f(i, j)$, of a national variable in a national equation, as well as a regional equation, is set at 0.6. The weight of a regional variable in other regional equation is fixed at o.1 and that in a national equation at 0.01. Last, the weight of the regional variables in its own equation is 1.0. In the standard Minnesota-type prior, the overall tightness (w) takes the values of 0.1, 0.2, 0.3, while the lag decay (d) is generally chosen to be equal to 0.5, 1.0, and 2.0.

2.3 Forecast Accuracy

The out-of-sample forecast accuracy for 2008:M1 through 2010:M12 is estimated by the Theil U-statistics for one-through six-month-ahead forecasts. Let A_{t+n} denotes the actual value of a variable in period (t+n), and F_{t+n} denotes the forecast value made in period t for (t+n), then the Theil U statistic is define as follows:

$$U = \sqrt{\frac{\sum (A_{t+n} - F_{t+n|t})^2}{\sum (A_{t+n} - A_t)^2}} \tag{19}$$

Thus, the U-statistic measures the ratio of the root mean square error (RMSE) of the model forecasts to the RMSE of na ïve, no-change forecasts. Therefore, the U-statistic compares forecasts to the na ïve model. When the U-statistic equals to one, the model's forecast match the na ïve, no-change forecasts on average. A U-statistic greater than one implies that the na ïve forecasts outperform the model forecasts. A U-statistic less than one indicates that the model's forecast outperform the na ïve forecasts.

We estimate the models for the initial period 1981:M1 through 2007:M12 and forecasts up to six months ahead. We then add one more observation to the sample, re-estimate the models, and again forecast the up to six months ahead. This process continues ahead until the end of our sample is reached. Based on the out-of-sample forecasts, we compute the Theil U-statistics for one- through six-month-ahead forecasts.

The "optimal" Bayesian priors for the LBVAR models are selected by comparing Theil U-statistics for out-of-sample forecasts, following procedures outlined in Dua and Ray (1995). The average of U-statistics for one- through six-month-ahead forecasts is examined. The superparameters are changed, and a new set of U-statistics is generated. The combination of the superparameters producing the lowest average U-statistic is chosen.

3. Data

The DFM and LBVAR models are estimated based on 183 monthly series, which comprise of 42 house price index series and 141 macroeconomic series. The house rice index figures for the 42 metropolitan areas are obtained from the Office of Federal Housing Enterprise Oversight (OFEO). The data for these macroeconomic indicators are taken from the DRI/McGraw Hill Basic Economics Database provided by IHS Global Insight. Data between 1981:M1 and 2007:M12 are used for the in-sample estimation, and the data between 2008:M1 and 2010:M12 are used for the out-of-sample forecast of the house price growth of the 42 metropolitan areas in the US. The out-of-sample forecast is done for one to six months ahead. With the motivation to examine the housing market of

U.S. during the economic recession began with the sub-prime mortgage crisis, the choice of 2008:M1 as the onset of forecast horizon emerges naturally.

According to Himmerlberg, Mayer, and Sinai (2005), over the 1980-2004 periods, the 42 metropolitan area house prices have followed one of three patterns. In about one-half of the cities, including Boston, New York, and San Francisco, house price peaked in the late 1980s, fell to a trough in the 1990s, and rebounded by 2004. Price in 18 metropolitan areas, including Miami and Denver, have a "U" shape history: high in the early 1980s and high again by the end of the sample. A few cities, such as Houston and New Orleans, follow a third pattern: real house prices have declined since 1980 and have not fully recovered. The 42 metropolitan areas are divided into three groups with each group following one of the three patterns respectively, and they are reported in Table 1.

The 141 macroeconomic indicators are selected based on the data set used by Boivin, Giannoni, and Mihov (2009). The most recent data available are those of 2010:M12, and this time point is automatically chosen to be the endpoint of our sample. The data set contains a broad range of macroeconomic variables, which provide different perspectives on the economy. They can be summarized into the following categories: industrial production, income, employment, housing starts, inventories, orders, stock prices, exchange rates, interest rates, money aggregates, producer and consumer prices, earnings, and consumer expectations.

All series are seasonally adjusted and covariance stationary. DFGLS test of Elliott, Rothenberg, and Stock (1996) is used to assess the degree of integration of all series. All nonstationary series are made stationary through differencing. The Schwarz information criterion is used in selecting the optimal lag length so that no serial correlation is left in the stochastic error term.

The number of dynamic factors (q) in the DFM is determined using the criterion proposed by Forni *et al*. (2000). The criterion suggests the optimal q should make the average over θ of the first q empirical eigenvalues diverges, whereas the average of the $(q+1)^{th}$ one relatively stable. In another word, there should be a substantial gap between the variance explained by the q^{th} principal component and the variance explained by $(q+1)^{th}$ one. A preassigned minimum, such as 5%, for the explained variance, could be used as a practical criterion for the determination of the number of dynamic factors to be retained. A 5% limit is suggested by Forni *et al*. (2000) in empirical exercise.

4. Results

Given the specifications of DFM and LBVAR models, we estimate them over the period of 1981:M1 to 2007:M12, and compute the out-of-sample one- through six-month-ahead forecasts for the period of 2008:M1 to 2010:M12. Then we compare the forecast performances of the alternative models. For the DFM model, the optimal number of dynamic factors is reported as 10. The LBVAR model is estimated with 3 lags, which is chosen based on the Akaike information criterion (AIC) and the Schwarz information criterion (SIC). Because in the standard Minnesota-type prior the overall tightness (w) takes the values of 0.1, 0.2, 0.3, while the lag decay (d) is generally chosen to be equal to 0.5, 1.0, and 2.0, there are nine combination of w and d. In order to find out which combination is optimal for the analysis, the LBVAR model is estimated nine times, each time with a different (w, d) combination. The forecasting accuracy results are reported in Table 2 through Table 5. For each table, the first row gives the six Theil U-statistics for one- through six-month-ahead forecasts made by DFM model, and the other rows shown the Theil U-statistics for forecasts made by LBVAR model with different (w, d) combinations. The results of Table 2 are estimated based on that forecasts for all the 42 metropolitan areas, while those of Table 3 to Table 5 are based only on the forecasts for the metropolitan areas in one of the three metro groups. The model that produces the lowest average value for the Theil U-statistic is selected as the best model for a specific metro group. There are five major findings derived from the four Tables:

(i) For all four sets of data, the Theil U-statistics for one- through six-month-ahead forecasts made by DFM are quite similar to each other. They are the same if only accurate to four decimal places. This implies the forecast power of DFM does not decrease as the number of forecasted period ahead increases;

(ii) The two-month-ahead forecasts using LBVAR always have the lowest Theil U-statistics among other forecasts with LBVAR, no matter what (w, d) combination is used. For the three- through six-month-ahead forecasts with LBVAR, the Theil

U-statistics are increasing with the number of forecasted time period ahead, which indicates a declining forecasting power of LBVAR model;

(iii) Except for the results from third metro group, the superparameter combination of w=0.2 and d=0.5 produces the lowest average Theil U-statistics, and thus it is most likely the optimal combination for LBVAR analysis of U.S. housing market. The third metro group has the optimal combination of w=0.3 and d=1.0, which indicates a flatter overall distribution and a faster lag decay. This means, compared to the overall housing market and the other metro groups, the housing price growth in the third metro group are affected by the near lags to a larger extent.

(iv) Comparing the average Theil U-statistics for forecasts of DFM with those of LBVAR, DFM has a much better forecasting performance than its LBVAR alternative. Except for the third metro group, the U-statistics of DFM are almost only half of those for LBVAR model. The U-statistic measures the ratio of the root mean square error (RMSE) of the model forecasts to the RMSE of naïve, no-change forecasts. Thus the results imply that the RMSE of DFM is about only half of the RMSE of LBVAR. The superiority of DFM over its alternative is also easy to see from Figure 1, which plots the out-of-sample forecasts of both DFM and LBVAR, and compares them to the actual series for all 42 metropolitan areas.

(v) Comparing across the four Tables, DFM predicts the house price growth rates of the second metro group the most accurately, and the ones of the third metro group most poorly. However, LBVAR model performs best in analyzing the third metro group—the average U-statistic of the optimal LBVAR model for this group is the lowest among the entire average U-statistics for LBVAR.

(vi) According to Figure 1, DFM can predict the turning points well, but it tends to overestimate the vibration at the turning point, and also tends to undersmooth the original data. LBVAR does poorly in turning point prediction.

In summary, DFM consistently outperforms its LBVAR alternative for both the overall U.S. housing market and the three metro groups. The forecasting power of DFM does not decrease as the number of forecasted period ahead increases, while LBVAR has its best performance for two-month-ahead forecast and then its forecasting accuracy decays. The housing price growth rates in the third metro group are affected by the near lags to a larger extent than the than those in the other two metro groups and the overall U.S. housing market. DFM can predict turning points well for all metropolitan areas, but it tends to undersmooth the original data and overestimate the vibration at the turning points.

5. Conclusion

This paper investigates the recent moving trends of house prices in 42 metropolitan areas in the United State from the perspective of large-scale models, which are Dynamic Factor Model (DFM) and Large-scale Bayesian Vector Autoregressive (LBVAR) model. These models accommodate a large panel data comprising 183 monthly series for the U.S. economy, and an in-sample period of 1980:01 to 2007:12 are used to forecast one- to six-months-ahead house price growth rate over the out-of-sample horizon of 2008:01 to 2010:12. The 42 metropolitan areas can be divided into three groups based on their house price patterns. The forecasting power of these two large-scale models are examined based on their ability to predict the turning points and patterns of house prices in the three metropolitan groups during the economic recession, and it is measured in terms of the Theil *U* statistic.

Our results show that DFM consistently outperforms its LBVAR alternative for both the overall U.S. housing market and three metropolitan (metro) groups. The forecasting power of DFM does not decrease as the number of forecasted period ahead increases, while LBVAR has its best performance for two-month-ahead forecast and then its forecasting accuracy decays. The housing price growth rates of the third metro group are affected by the near lags to a larger extent than the than those in the other two metro groups and the overall U.S. housing market. DFM can predict turning points well for all metropolitan areas, but it tends to undersmooth the original data and overestimate the vibration at the turning points.

The poor forecasting performance of LBVAR model may be due to the two major limitation of this method. First, the forecast accuracy is sensitive to the choice of the priors. So if prior is not well specified, an alternative model used for forecasting may perform better. Secondly, 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 (Das, Gupta, and Kabundi, 2008, 2009a)

Although DFM is the better model to base one’s forecasts on, there are two caveats in its application. First, structural changes of the economy, whether in or out of the sample, would make the models inappropriate. Second, the estimation procedures used are linear in nature, and hence, they fail to take into account of the nonlinearities in the data (Das, Gupta, and Kabundi, 2009a).

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Table 1: Metropolitan areas with three price patterns

Group One

Markets where house prices peaked in the late 1980s and had a trough in the 1990s:

Atlanta, GA	Nashville, TN	Richmond, VA
Austin, TX	New York, NY	Sacramento, CA
Baltimore, MD	Oakland, CA	San Diego, CA
Boston, MA	Philadelphia, PA	San Francisco, CA
Dallas, TX	Phoenix, AZ	San Jose, CA
Jacksonville, FL	Portland, OR	Seattle, WA
Los Angeles, CA	Raleigh-Durham, NC	

Group Two

Markets where house prices were high in the early 1980s and rebounded in the 2000s:

Charlotte, NC	Detroit, MI	Milwaukee, MN
Chicago, IL	Fort Lauderdale, FL	Minneapolis, MN
Cincinnati, OH	Indianapolis, IN	Orlando, FL
Cleveland, OH	Kansas City, KS	Pittsburgh, PA
Columbus, OH	Memphis, TN	St. Louis, MO
Denver, CO	Miami, FL	Tampa, FL

Group Three

Markets where house prices have declined since the early 1980s and never fully rebounded:

Fort Worth, TX	New Orleans, LA	San Antonio, TX
Houston, TX		

Table 2: One- to Six-Months-Ahead Theil U-statistics for All the Metropolitan Areas

	Model	1	2	3	4	5	6	Average
	DFM	0.3440	0.3440	0.3440	0.3440	0.3440	0.3440	0.3440
w=0.1, d=0.5	LBVAR	0.7037	0.6802	0.7235	0.7877	0.8120	0.8163	0.7539
w=0.1, d=1.0	LBVAR	0.7113	0.6889	0.7322	0.7945	0.8171	0.8207	0.7608
w=0.1, d=2.0	LBVAR	0.7065	0.6833	0.7233	0.7835	0.8047	0.8072	0.7514
w=0.2, d=0.5	LBVAR	0.6911	0.6653	0.7071	0.7737	0.8034	0.8147	0.7426*
w=0.2, d=1.0	LBVAR	0.6978	0.6735	0.7176	0.7818	0.8090	0.8177	0.7496
w=0.2, d=2.0	LBVAR	0.7127	0.6924	0.7377	0.7970	0.8187	0.8239	0.7637
w=0.3, d=0.5	LBVAR	0.6956	0.6692	0.7089	0.7739	0.8059	0.8249	0.7464
w=0.3, d=1.0	LBVAR	0.6933	0.6669	0.7093	0.7745	0.8054	0.8205	0.7450
w=0.3, d=2.0	LBVAR	0.7104	0.6886	0.7358	0.7967	0.8218	0.8312	0.7641

Table 3: One- to Six-Months-Ahead Theil U-statistics for Metro Group One

	Model	1	2	3	4	5	6	Average
	DFM	0.3150	0.3150	0.3150	0.3150	0.3150	0.3150	0.3150
w=0.1, d=0.5	LBVAR	0.7004	0.6872	0.7302	0.8008	0.8364	0.8325	0.7646
w=0.1, d=1.0	LBVAR	0.7082	0.6956	0.7385	0.8066	0.8402	0.8357	0.7708
w=0.1, d=2.0	LBVAR	0.7034	0.6896	0.7294	0.7946	0.8246	0.8178	0.7599
w=0.2, d=0.5	LBVAR	0.6872	0.6727	0.7143	0.7916	0.8371	0.8429	0.7576*
w=0.2, d=1.0	LBVAR	0.6936	0.6805	0.7251	0.7977	0.8388	0.8408	0.7628
w=0.2, d=2.0	LBVAR	0.7105	0.7014	0.7474	0.8130	0.8465	0.8437	0.7771
w=0.3, d=0.5	LBVAR	0.6967	0.6830	0.7218	0.7989	0.8480	0.8631	0.7686
w=0.3, d=1.0	LBVAR	0.6900	0.6750	0.7175	0.7938	0.8415	0.8523	0.7617
w=0.3, d=2.0	LBVAR	0.7078	0.6976	0.7461	0.8153	0.8552	0.8580	0.7800

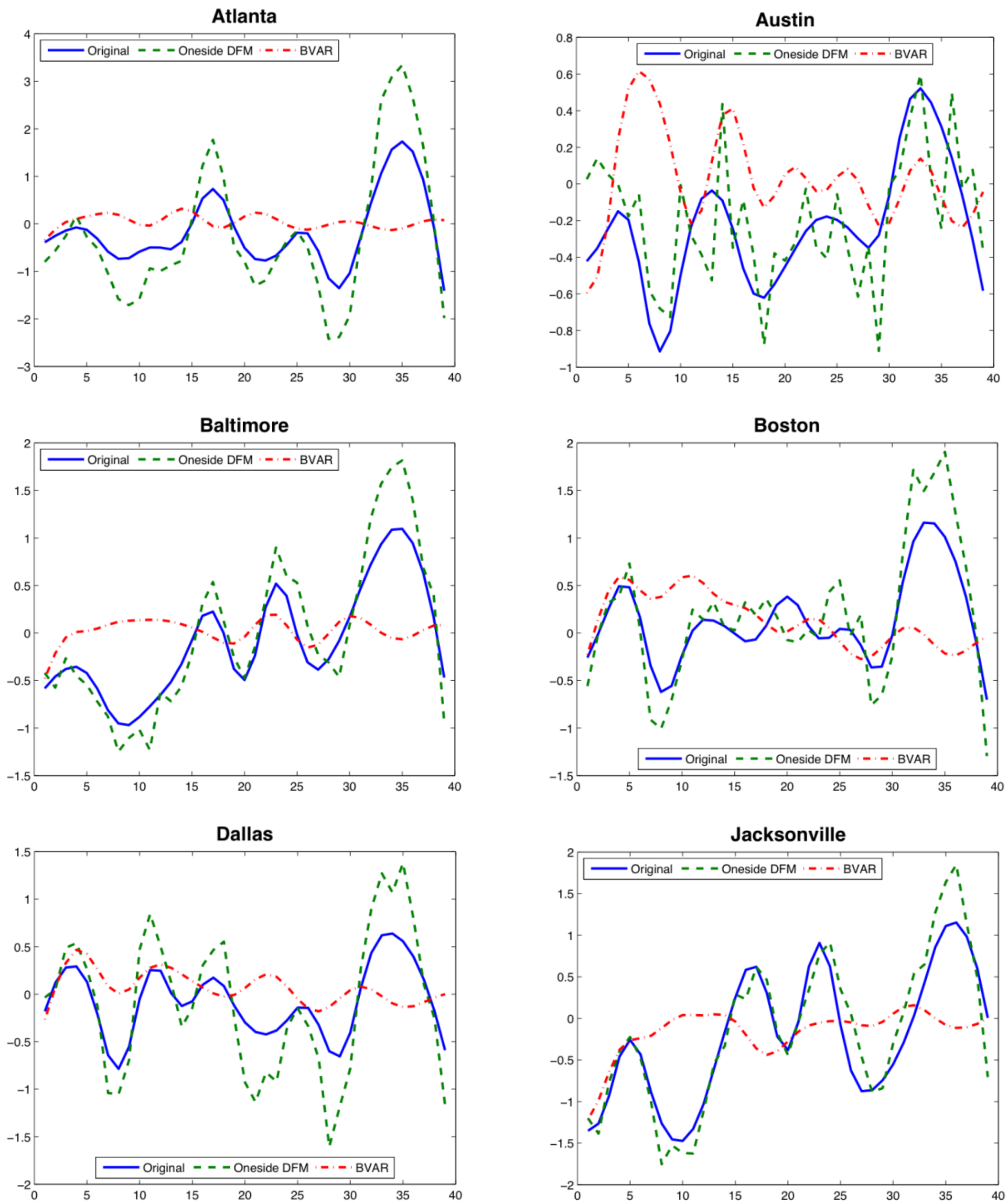
Table 4: One- to Six-Months-Ahead Theil U-statistics for Metro Group Two

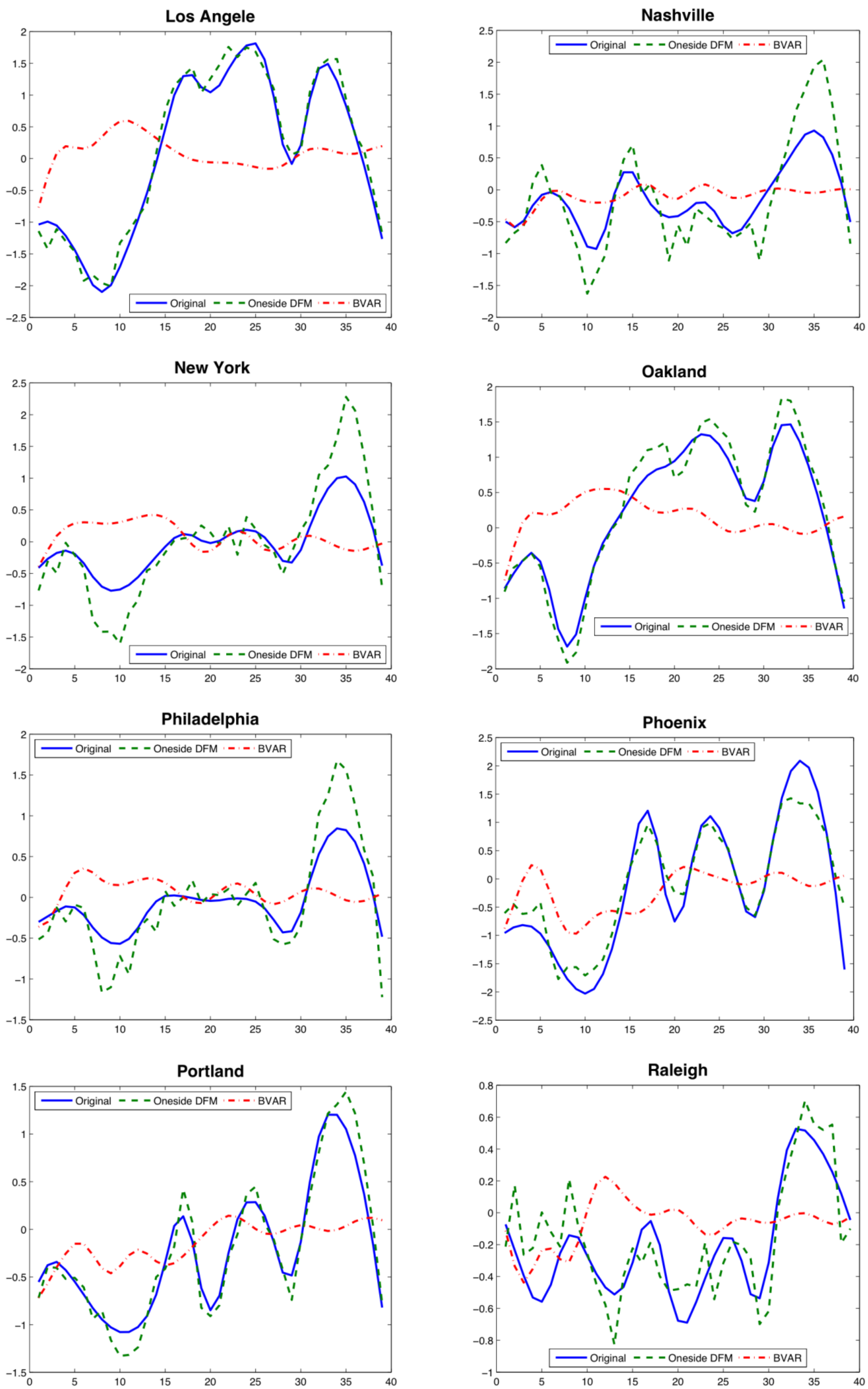
	Model	1	2	3	4	5	6	Average
	DFM	0.3419	0.3419	0.3419	0.3419	0.3419	0.3419	0.3419
w=0.1, d=0.5	LBVAR	0.6965	0.6670	0.7162	0.7852	0.8050	0.8159	0.7476
w=0.1, d=1.0	LBVAR	0.7040	0.6762	0.7258	0.7933	0.8117	0.8220	0.7555
w=0.1, d=2.0	LBVAR	0.6989	0.6708	0.7171	0.7841	0.8029	0.8125	0.7477
w=0.2, d=0.5	LBVAR	0.6832	0.6512	0.6991	0.7667	0.7885	0.8045	0.7322*
w=0.2, d=1.0	LBVAR	0.6913	0.6606	0.7101	0.7769	0.7972	0.8112	0.7412
w=0.2, d=2.0	LBVAR	0.7049	0.6784	0.7290	0.7929	0.8094	0.8211	0.7559
w=0.3, d=0.5	LBVAR	0.6815	0.6487	0.6955	0.7604	0.7837	0.8067	0.7294
w=0.3, d=1.0	LBVAR	0.6848	0.6526	0.7011	0.7665	0.7882	0.8070	0.7334
w=0.3, d=2.0	LBVAR	0.7041	0.6759	0.7276	0.7905	0.8075	0.8221	0.7546

Table 5: One- to Six-Months-Ahead Theil U-statistics for Metro Group Three

	Model	1	2	3	4	5	6	Average
	DFM	0.6354	0.6354	0.6354	0.6354	0.6354	0.6354	0.6354
w=0.1, d=0.5	LBVAR	0.8461	0.7777	0.7393	0.7075	0.6923	0.6943	0.7429
w=0.1, d=1.0	LBVAR	0.854	0.7852	0.7447	0.7097	0.6928	0.6947	0.7468
w=0.1, d=2.0	LBVAR	0.8516	0.7799	0.7322	0.6913	0.6731	0.6801	0.7347
w=0.2, d=0.5	LBVAR	0.8518	0.7713	0.727	0.6948	0.6794	0.6828	0.7345
w=0.2, d=1.0	LBVAR	0.8431	0.7668	0.7282	0.7004	0.6888	0.6934	0.7368
w=0.2, d=2.0	LBVAR	0.8515	0.7796	0.7411	0.7074	0.692	0.695	0.7444
w=0.3, d=0.5	LBVAR	0.8764	0.7836	0.7329	0.6967	0.6785	0.6802	0.7414
w=0.3, d=1.0	LBVAR	0.8536	0.7668	0.7219	0.6941	0.6822	0.6874	0.7343*
w=0.3, d=2.0	LBVAR	0.8347	0.7593	0.7272	0.7044	0.6961	0.7011	0.7371

Figure 1: Original data and forecasts from DFM and LBVAR model for the 42 metropolitan areas from 2008:M1-2010M12





Los Angele
Original
Oneside DFM
BVAR
Nashville
Original
Oneside DFM
BVAR
New York
Original
Oneside DFM
BVAR
Oakland
Original
Oneside DFM
BVAR
Philadelphia
Original
Oneside DFM
BVAR
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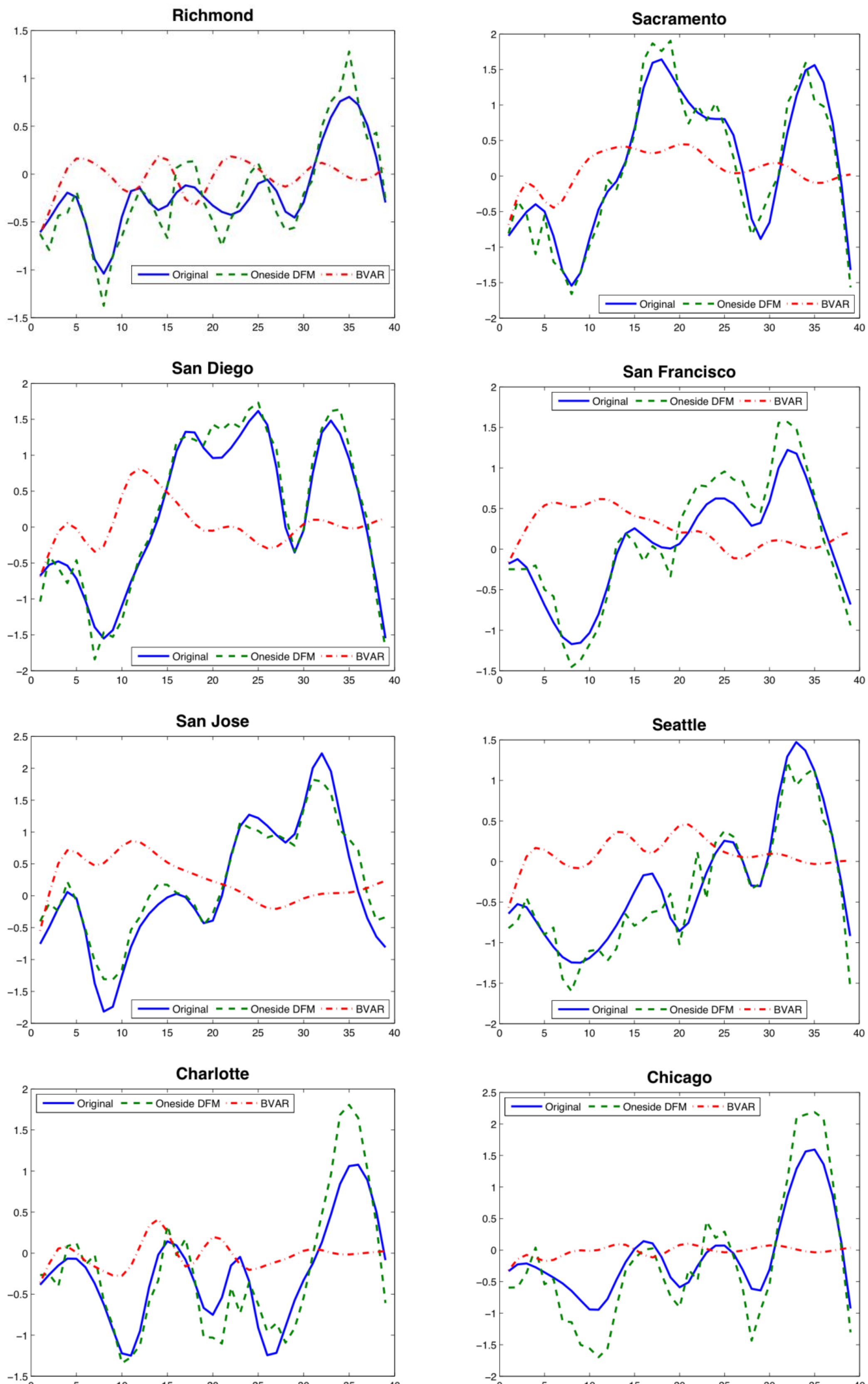
Oneside DFM
BVAR
Portland
Original
Oneside DFM
BVAR
Raleigh
Original
Oneside DFM
BVAR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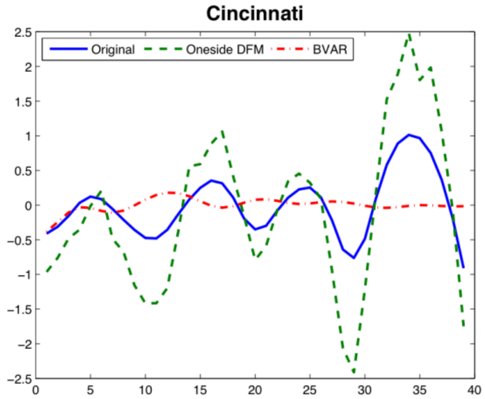
Original
Oneside DFM
BVAR
Sacramento
San Diego
San Francisco
San Jose
Seattle
Charlotte
Chicago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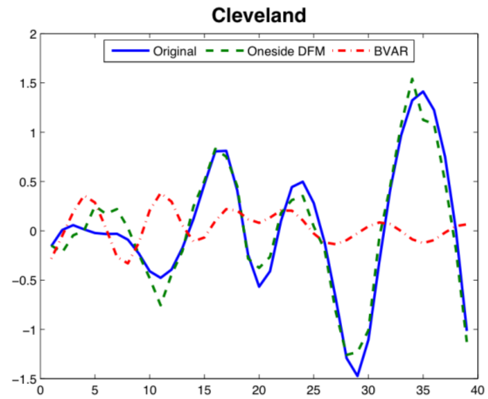
Original
Oneside DFM
BVAR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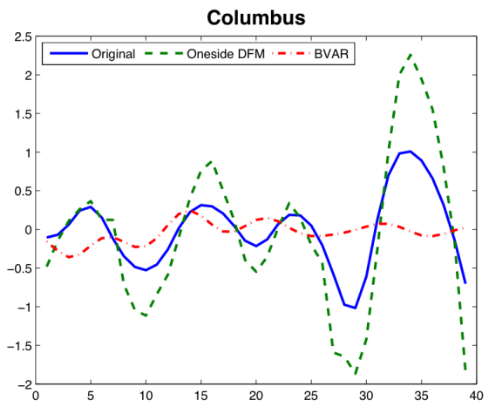
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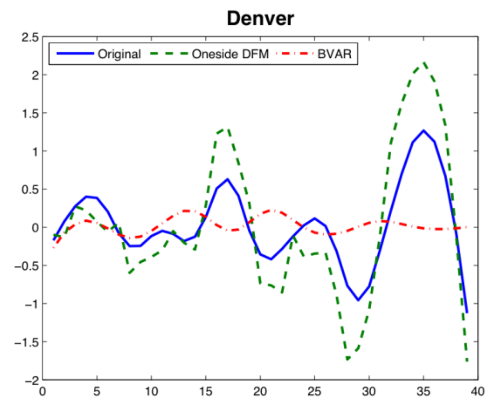
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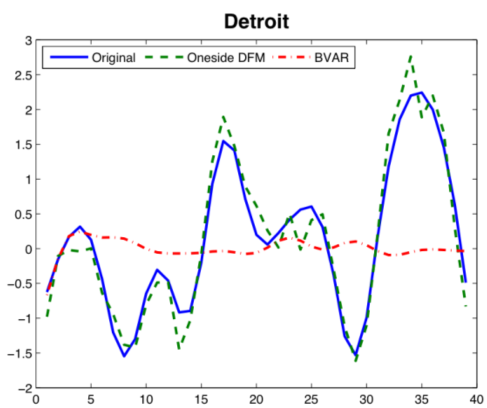
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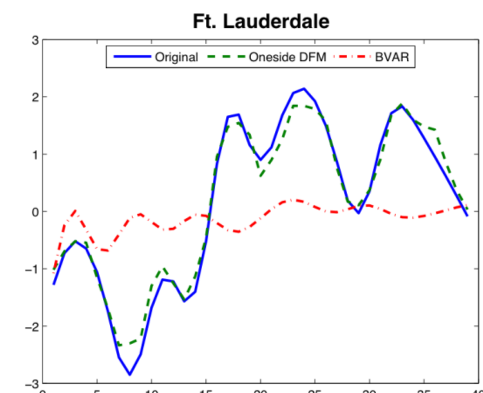
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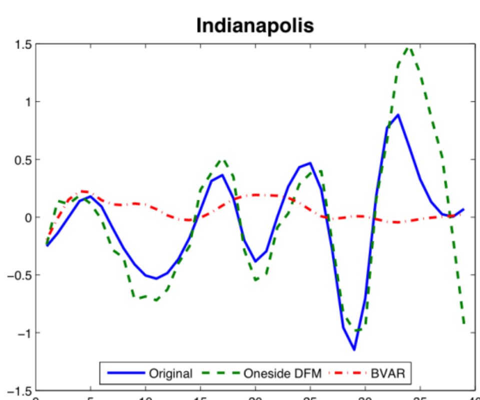
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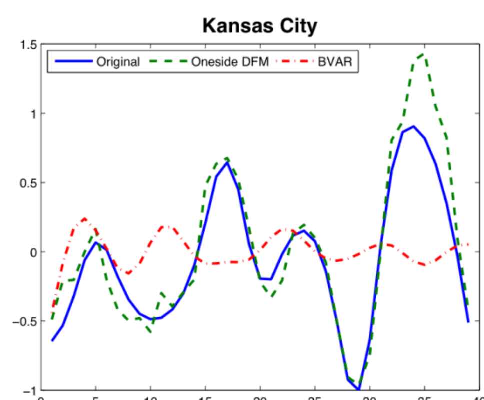
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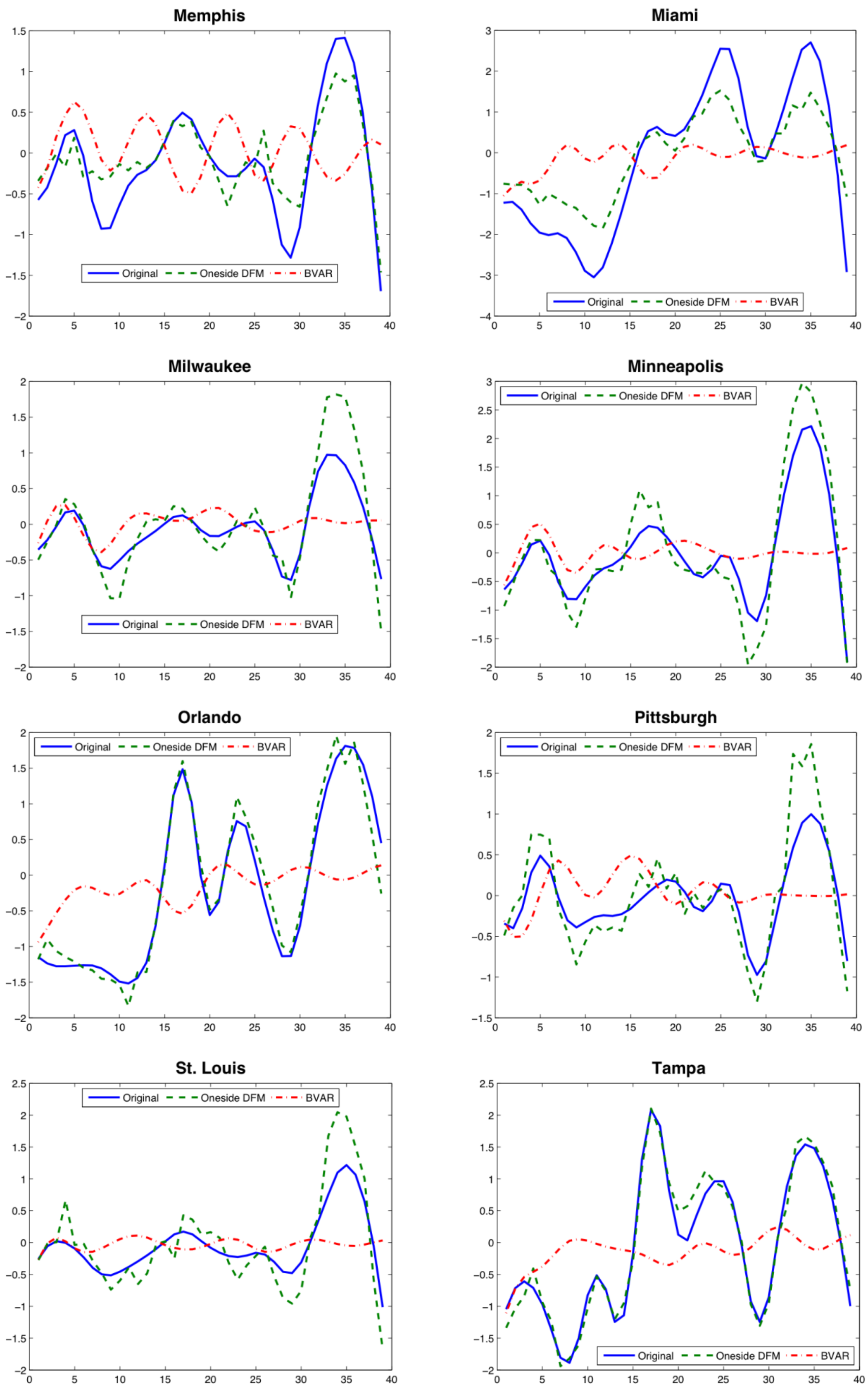
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BVAR
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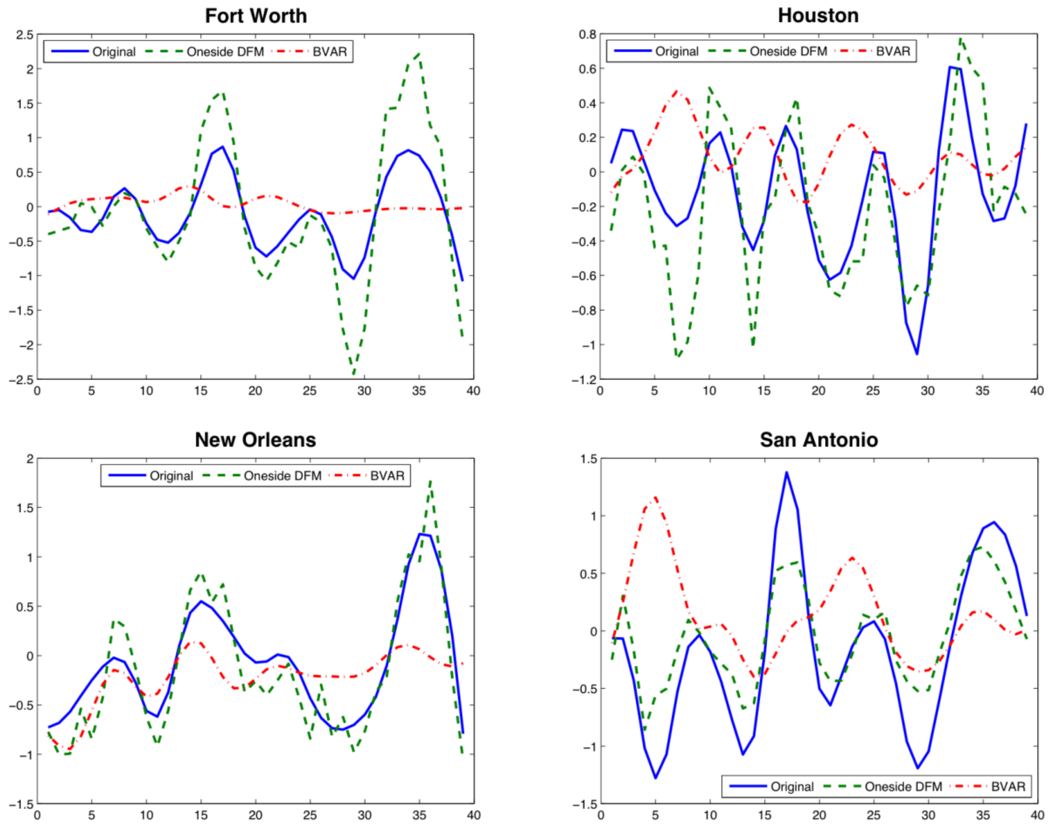
Milwaukee
Minneapolis
Orlando
Pittsburgh
St. Louis
Tampa


Fort Worth
Houston
New Orleans
San Antonio
Original
Oneside DFM
BVAR