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The Role of Housing Sentiment in Forecasting US Home Sales Growth: Evidence from a Bayesian Compressed Vector Autoregressive Model

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Abstract

Accurate forecasts of home sales can provide valuable information for not only policymakers, but also financial institutions and real estate professionals. Against this backdrop, the objective of our paper is to analyze the role of consumers' home buying attitudes in forecasting quarterly US home sales growth. Our results show that the home sentiment index in standard classical and Minnesota prior-based Bayesian VARs fail to add to the forecasting accuracy of the growth of home sales derived from standard economic variables already included in the models. However, when shrinkage is achieved by compressing the data using a Bayesian compressed VAR (instead of the parameters as in the BVAR), growth of US home sales can be forecasted more accurately, with the housing market sentiment improving the accuracy of the forecasts relative to the information contained in economic variables only.

Keywords: Home Sales, Housing Sentiment, Classical and Bayesian Vector Autoregressive Models
JEL Codes: C32, R31

1. Introduction

Academics suggest that housing market follows business cycles, and housing market activity affects the economy at both macroeconomic and microeconomic levels (Leamer 2007; Hassani et al., 2017).[1] Since housing represents a large share of the total economy, from a macroeconomic perspective, movements in the housing sector spillover to the entire economy through new constructions, renovations of existing property, and the volume of home sales. At the same time, at the microeconomic level, performances of financial institutions and real estate firms depend crucially on housing market activity, as suggested by the recent financial crisis. Hence, timely and accurate forecasts of home sales can provide valuable information not only for policy makers, but also for financial institutions and real estate professionals as well as housing market participants.

In spite of the importance of home sales, the literature on forecasting home sales instead of house prices in the U.S. at the aggregate and at the regional level is, however, as far as we know, limited to five studies, namely Dua and Smyth (1995), Dua and Miller (1996), Dua et

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[1] Large number of studies has reported a strong link between the housing market and the economic activity in the US (see for example Aye et al. (2014), Nyakabawo et al. (2015) and Emirmahmutoglu et al. (2016) for detailed literature reviews in this regard).

al. (1999), Gupta et al. (2010), and Hassani et al. (2017). While Dua and Smyth (1995) used Bayesian VAR (BVAR) models to forecast home sales for the aggregate U.S. economy, Dua and Miller (1996) extended the models from Dua and Smyth (1995) to forecast home sales for the state of Connecticut. In their original model, Dua and Smyth (1995) considered home sales, price of homes, mortgage interest rate, real disposable income, unemployment rate, as well as, survey data on households' buying attitudes for homes. However, the authors showed that, the gain from including the survey data in the model is small because the efforts have been included in other economic variables.[2] Dua and Miller (1996) extended the benchmark model (containing home sales, price of homes, mortgage interest rate, real disposable income, and unemployment rate) of Dua and Smyth (1995), by including a leading index for the Connecticut economy. They showed that, by doing so, one can improve the forecast performance of the benchmark model substantially. Given this result, Dua et al., (1999) extended the model described in Dua and Smyth (1995) by adding six different leading indicators, namely housing permits authorized, housing starts, the US Department of Commerce’s composite index of eleven leading indicators, the short- and long-leading indices developed by the Center for International Business Cycle Research (CIBCR) at Columbia University, and the leading index constructed by CIBCR that focussed solely on employment related variables. They found that the benchmark BVAR model (which included, as before, home sales, price of homes, mortgage rate, real personal disposable income, and unemployment rate) supplemented by the building permits authorized as the leading indicator consistently produced the most accurate forecasts. In addition, Dua et al. (1999) noted that replacing building permits with housing starts generated equally accurate forecasts of home sales. Gupta et al. (2010) analyzed the ability of a wide array of forecasting models, which included classical and Bayesian vector-error correction (VEC) models, besides the random walk (RW), the autoregressive (AR), and BVAR models, in forecasting home sales for the four US census regions (Northeast, Midwest, South, West). In their analysis, Gupta et al. (2010) used home sales, price of homes, mortgage rate, real personal disposable income, unemployment rate, and building permits authorized, i.e., the model prescribed by Dua et al. (1999). This study found that except for the South-region, the Bayesian type models outperformed all the other models in forecasting home sales at all forecasting horizons, and were also capable of predicting the peaks and declines in home sales with tremendous accuracy. In sum, the general consensus is that the Bayesian type models are better equipped in forecasting home sales than their classical counterparts.

More recently, Hassani et al. (2017) build on this line of literature, by comparing the ability of two different versions of Singular Spectrum Analysis (SSA) methods, namely, Recurrent SSA (RSSA) and Vector SSA (VSSA), in univariate and multivariate frameworks, in forecasting seasonally unadjusted home sales for the aggregate U.S. economy and its four census regions. Given the dominance of VAR models in the home sales forecasting literature, Hassani et al. (2017) compared the performance of the SSA-based models with classical and Bayesian variants of the autoregressive and vector autoregressive models. The authors found that the univariate VSSA was the best performing model for the aggregate US home sales,

[2] Interestingly, recent papers by Baghestani et al. (2013) and Baghestani (2017) have highlighted the role of consumers' home buying attitudes in predicting in-sample movements of US home sales, while, the importance of financial variables (Federal funds rate, mortgage rate, and term-spread) in doing the same has been stressed by Baghestani and Kaya (2016). But, it is well-known that in-sample predictability does not necessarily translate into out-of-sample forecasting gains, with Campbell (2008) pointing out that, the ultimate test of any predictive model is its out-of-sample performance. However, this positive result in favour of consumers' home buying attitudes (as well as financial variables) in predicting home sales could be a result of the fact that the models used in these studies are only bivariate in nature, consisting of home sales and consumers' home buying attitudes or financial variables.

while the multivariate versions of the RSSA was the outright winner in forecasting home sales for all the four census regions. In the process, their results highlighted the superiority of the nonparametric SSA approach.

Following this backdrop, the objective of our paper is to revisit the role of including consumers' home buying attitudes. The benchmark model suggested in a literature typically includes home sales, price of homes, mortgage rate, real personal disposable income, unemployment rate, building permits authorized, and housing starts as potential regressors. In doing so, we forecast quarterly U.S. home sales, over an out-of-sample period of 1995:1 to 2014:3, by using an in-sample training period of 1975:3 to 1994:4. For our purpose, we use the newly developed housing sentiment index of Bork et al., (2017), which is constructed based on household responses to questions regarding house buying conditions from the consumer survey of the University of Michigan. The decision to use this broad housing sentiment index in forecasting home sales emanates from the favourable out-of-sample evidence provided by Bork et al. (2017) who showed that the housing sentiment explains a large share of the time-variation in house prices during both boom and bust cycles and it strongly outperforms several macroeconomic variables typically used to forecast house prices.[3]

Regarding our econometric framework, we rely on both classical and Bayesian VAR models for analysing the ability of housing sentiment in forecasting home sales of the U.S. economy. However, unlike the existing studies on home sales forecasting using BVARs, which imposes the popular Minnesota prior shrinkage on the parameters to overcome issues of over-parameterization in classical VARs (resulting in the favourable performance of the former), we use a Bayesian Compressed VAR (BCVAR) framework. In the BCVAR model, shrinkage is achieved by compressing the data instead of the parameters. A crucial aspect of this method is that the projections used to compress the data are drawn randomly in a data oblivious manner. Then, through Bayesian model averaging (BMA), different weights are assigned to the projections where the weights are determined according to the explanatory power of the compressed variables on the dependent variable. In other words, the projections do not involve the data, and thus, compute trivially, which is not often the case with BVAR models based on priors other than the Minnesota prior. To the best of our knowledge, this is the first paper to forecast U.S. home sales by using a BCVAR model, based on a housing sentiment index, which summarizes a broader set of information on consumers' home buying attitudes. In the process, our paper aims to analyze the role of both a new measure of housing sentiment and a new econometric framework in forecasting home sales. The remainder of the paper is organized as follows: Section 2 presents the basics of the econometric models used, while Section 3 discusses the data and results, with Section 4 concluding the paper.

2. Methodology

Following Koop et al. (forthcoming), we use the following framework based on Bayesian compressed VAR (BCVAR) model, as our main focus:

$$Y_t = \beta Y_{t-1} + \varepsilon_t \tag{1}$$

where Y_t (t=1,…,T) represents an $n \times 1$ vector containing observations on n time 1 series of variables, ϵ_t is i.i.d. $N(0, \Omega)$ and β is an $n \times n$ matrix of coefficients. In order to compress the

[3] In-sample evidence, in this regard, can also be found in Dua (2008).

explanatory variables in the VAR, we can use the projection matrix Φ as described in Koop, et al. (forthcoming), where Φ is a $m \times k$ matrix drawn from the following distribution:

$$\begin{aligned} &\Pr\left(\phi_{ij} = \frac{1}{\sqrt{\varphi}}\right) = \varphi^2 \\ &\Pr(\phi_{ij} = 0) = 2(1-\varphi)\,\varphi \ , \\ &\Pr\left(\phi_{ij} = \frac{1}{\sqrt{\varphi}}\right) = (1-\varphi)^2 \end{aligned} \tag{2}$$

where φ and m are unknown parameters. Next, they rely on BMA to average across the different random projections. Treating each Φ^r (r=1,….,R) as defining a new model, we first calculate the marginal likelihood for each model. Thereafter, we average across the various models by using weights proportional to the marginal likelihoods. We also note that both m and φ can be estimated as part of the BMA exercise. With the estimated projection matrix, we can compress the explanatory variables in the VAR and define the compressed VAR model as follows:

$$Y_t = \beta^c(\Phi Y_{t-1}) + \varepsilon_t \ , \tag{3}$$

subjected to the normalization $\Phi'\Phi = \mathrm{I}$. Finally, the full predictive density $p(Y_{t+h}|M_r D^t)$ (i.e., $M_1,\ldots,M_R$) is obtained for each compressed VAR model by using the predictive simulation method as descripted in Koop, et al. (forthcoming). Therefore, the final BMA forecast for each forecast at horizon h can be represented as:

$$\mathrm{p}(Y_{t+h}|D^t) = \sum_{r=1}^{R} \omega_r \, \mathrm{p}(Y_{t+h}|M_r, D^t) \ , \tag{4}$$

where D^t is the information set available at time t, $\omega_r = \exp(-.5\Psi_r) \,/\, \sum_{r=1}^{R} \exp(-.5\Psi_r)$ is the model M_r weight, and $\Psi_r = BIC_r - BIC_{min}$, with BIC_r be the value of the Bayesian Information Criterion (BIC) of model M_r and BIC_{min} be the minimum value of the BIC among all R models.

Besides the BCVAR, we also estimate the standard classical VAR and BVAR models, with the latter based on the popular Minnesota-prior shrinkage. Our implementation of the BVAR, which involves a single prior shrinkage parameter (ω), follows closely the approach used by Banbura et al. (2015). However, different from Banbura et al. (2015), we modify the approach used by Giannone, et al. (2015) to estimate ω in a data-based fashion. As in Koop et al. (forthcoming), we choose a grid of values for the inverse of the shrinkage factor ω^{-1} ranging from $0.5\times\sqrt{np}$ to $10\times\sqrt{np}$, in increments of $0.1\times\sqrt{np}$. At each point in time, the BIC is used to choose the optimal degree of shrinkage. All remaining specification and forecasting choices are exactly the same as in Banbura et al (2010), and hence, we skip reporting the procedure.

3. Data and Results

As discussed in the introduction, our data set covers the quarterly period of 1975:3 to 2014:3, with the start and end date being purely driven by the availability of the housing sentiment index developed by Bork et al., (2017). The authors use time series data from the consumer surveys of the University of Michigan to generate the housing sentiment index, with housing sentiment defined based on the general attitude of households about house buying conditions. In particular, Bork et al. (2017) consider the underlying reasons households to provide their views about all the house buying conditions. The part of University of Michigan's consumer survey related to house buying conditions starts with the question: "Generally speaking, do you think now is a good time or a bad time to buy a house?", with the follow-up question: "Why do you say so?". In constructing the index, Bork et al. (2017) focuse on the responses to the follow-up question as the idea is to draw on the information in the underlying reasons why households believe that it is a bad or good time to buy a house. Specifically, the housing sentiment index is based on the following ten time series: good time to buy ; prices are low, good time to buy ; prices are going higher, good time to buy;interest rates are low, good time to buy; borrow-in-advance of rising interest rates, good time to buy; good investment, good time to buy; times aregood, bad time to buy; prices are high, bad time to buy; interest rates are high, bad time to buy;cannot afford, and bad time to buy; uncertain future. Then Bork et al., (2017) used partial least squares (PLS) to aggregate the information contained in each of the ten time series into an easy-to-interpret index of housing sentiment, with PLS filtering out idiosyncratic noise from the individual time series and summarizing the most important information in a single index.[4]

Besides using the index measuring consumers' home buying attitudes, the other variables used include: sales of new and single-family houses, median sale prices of new and single-family houses, 30-year conventional mortgage rate, real disposable personal income (in chained 2009 dollars), civilian unemployment rate, new private housing units authorized by building permits, and new privately owned housing units started. Data on home sales and prices are obtained from the Census Bureau of the US, while the other variables are derived from the FRED database of the Federal Reserve Bank of St. Louis. All the variables are seasonally adjusted, and are converted into quarterly data based on temporal aggregation when it is available at a higher frequency. Following Koop et al. (forthcoming), we ensure that all variables are approximately mean-reverting which, in turn, requires us to use growth rates of home sales and prices, and that of real disposable personal income. In the Appenidix of the paper, Figure A1 plots the eight variables of our concern while Table A1 provides the summary statistics for the variables.

To avoid forward-looking bias, we follow Bork et al. (2017) to compute the housing sentiment index in a recursive manner over 1995:1-2014:3. Thereafter, we use the same time-frame as the out-of-sample period in our forecasting exercise, with our models being estimated recursively over this period as well producing one- to twelve-quarters-ahead forecasts. The lag-length chosen for the VAR models is 1, based on the BIC.

For our forecasting, we estimate two-versions of the classical VAR model: BVAR model and the BCVAR model. In the first case, we use home sales, price of homes, mortgage rate, real personal disposable income, unemployment rate, building permits authorized, and housing starts. Building on the results of the first model, we include the housing sentiment index in the second approach along with all the previous mentioned variables. Hence, we end up with six models, three for each case. We then compare the mean squared forecast errors (MSFEs) from each of the models, relative to the MSFE of the naïve (no-change) forecasting model, which we call the relative MSFE (RMSFE). Understandably, a RMSFE value of less (greater) than one, would suggest that the particular model analyzed performs better (worse) than the naïve model. The RMSFE for each model is reported in Table 1 for forecasting horizons 1 to 12, along with the average values of the same, over all these forecasting horizons – a metric

[4] The data is available for download from: https://www.dropbox.com/s/al3sddq1026xci2/Online%20data.xlsx?dl=0.

that has been used widely in the abovementioned home sales forecasting literature to decide on the optimal forecasting model.

We can make the following observations from Table 1: (1) The various VARs considered consistently outperform the naïve model for all horizons, with the exception of eight-, and twelve-quarters-ahead forecasts. At horizon h=8, the naïve model performs better than all the VAR models, while at h=12, the same holds true relative to the VARs and the BVARs, but not the BCVARs; (2) On average, adding information of the housing sentiment index does not have any value added to forecasting accuracy of home sales growth derived from the VAR and BVAR models. This result is consistent with of Dua and Smyth (1995); (3) Based on the average value of the RMSFE, the BVAR models outperform their corresponding classical counterparts, but the BCVAR models performs better than both VAR and BVAR models, and; (4) Within the BCVAR models, the BCVAR2 model outperforms the BCVAR1 model based on the average RMSFE, producing a gain of 6.7457 percent. In sum, we observe that when shrinkage is achieved by compressing the data (as done in the BCVAR) instead of the parameters (as implemented in the BVAR), growth of U.S. home sales can be forecasted more accurately. In addition, in this (BCVAR) framework, the housing market sentiment tends to improve the accuracy of the forecasts for home sales growth, when compared to the information contained in economic variables only.[5]

[INSERT TABLE 1]

4. Conclusion

The housing market activity in the U.S. has been shown to affect the economy at both the macroeconomic and the microeconomic level. Hence, timely and accurate forecasts of home sales can provide valuable information not only, for policy makers, but also for housing market participants (financial institutions and real estate professionals). Given this, we analyze the role of including consumers' home buying attitudes, in a model that contains information on lagged economic variables (such as, price of homes, mortgage rate, real personal disposable income, unemployment rate, building permits authorized and housing starts, besides home sales itself), for forecasting quarterly US home sales, over an out-of-sample period of 1995:1 to 2014:3. In doing so, we rely on both classical and Bayesian VAR models for analysing the ability of a newly developed broad housing sentiment index in forecasting growth of home sales of the US economy. Besides using the popular Minnesota prior shrinkage on the parameters to overcome issues of over-parameterization in classical VARs, we also consider a Bayesian Compressed VAR (BCVAR) model. In the BCVAR model, shrinkage is achieved by compressing the data instead of the parameters. Our results show that, when shrinkage is achieved by compressing the data instead of the parameters, the growth rate of U.S. home sales can be forecasted more accurately. In addition, the housing market sentiment capturing consumers' home buying attitudes, included in the BCVAR model, tends to improve the accuracy of the forecasts for home sales growth, when compared to the information contained in economic variables only. Our results thus highlight the importance of compressing the data over the parameters in Bayesian models, when forecasting home sales based on housing sentiment, over and above standard economic variables.

[5] However, it is also important to qualify this statement a bit. If we compare the forecasting performance of the BCVAR1 with that of the BCVAR2 model by leaving out h=8, where both these models perform poorly relative to the naïve model (with BCAVR1 performing worst amongst all the models), then the former ends up being the preferred model, with an average RMSFE of 0.1829 compared to 0.2132.

Given that Bork et al., (2017) has shown that the national housing sentiment index can also accurately forecast regional housing price growth rates, as part of future research, it would be interesting to check, whether the same hold for regional home sales growth rates as well.

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Table 1. Forecasting Performance of Alternative VAR Models:

	Forecasting Models					
Forecast Horizon (*h*)	VAR1	BVAR1	BCVAR1	VAR2	BVAR2	BCVAR2
1	0.4952	0.4888	**0.0267**	0.4916	0.4918	0.0288
2	0.3601	0.3464	**0.0973**	0.3560	0.3503	0.2108
3	0.5321	0.5013	**0.0492**	0.5425	0.5091	0.1198
4	2.6433	2.4992	0.4672	2.6806	2.5129	**0.4641**
5	0.5169	0.4836	0.0084	0.5043	0.4827	**0.0034**
6	0.3425	0.3241	**0.4360**	0.3368	0.3247	0.6161
7	0.5373	0.5170	**0.0648**	0.5366	0.5181	0.1503
8	1.9184	1.8736	5.4171	1.9344	1.8746	4.5827
9	0.4724	0.4637	**0.1558**	0.4668	0.4622	0.2324
10	0.3108	0.3098	**0.0000**	0.3055	0.3091	0.0097
11	0.4736	0.4809	**0.0202**	0.4683	0.4793	0.0628
12	1.7479	1.7846	0.6859	1.7373	1.7780	**0.4464**
Average	0.8625	0.8394	0.6191	0.8634	0.8411	**0.5773**

Note: Entries are relative mean square forecast errors of a specific model against the naïve (random walk) model (RMSFE); VAR1 (VAR2), BVAR1 (BVAR2), and BCVAR1 (BCVAR2) represent the typical VAR without housing sentiment (with housing sentiment included), the Bayesian VAR based on the Minnesota prior without housing sentiment (with housing sentiment included), and the Bayesian compressed VAR without housing sentiment (with housing sentiment included); Bold entries indicate when the model performs the best in terms of the RMSFE; For h=8, the naïve model performs the best.

APPENDIX:

Figure A1. Data Plot

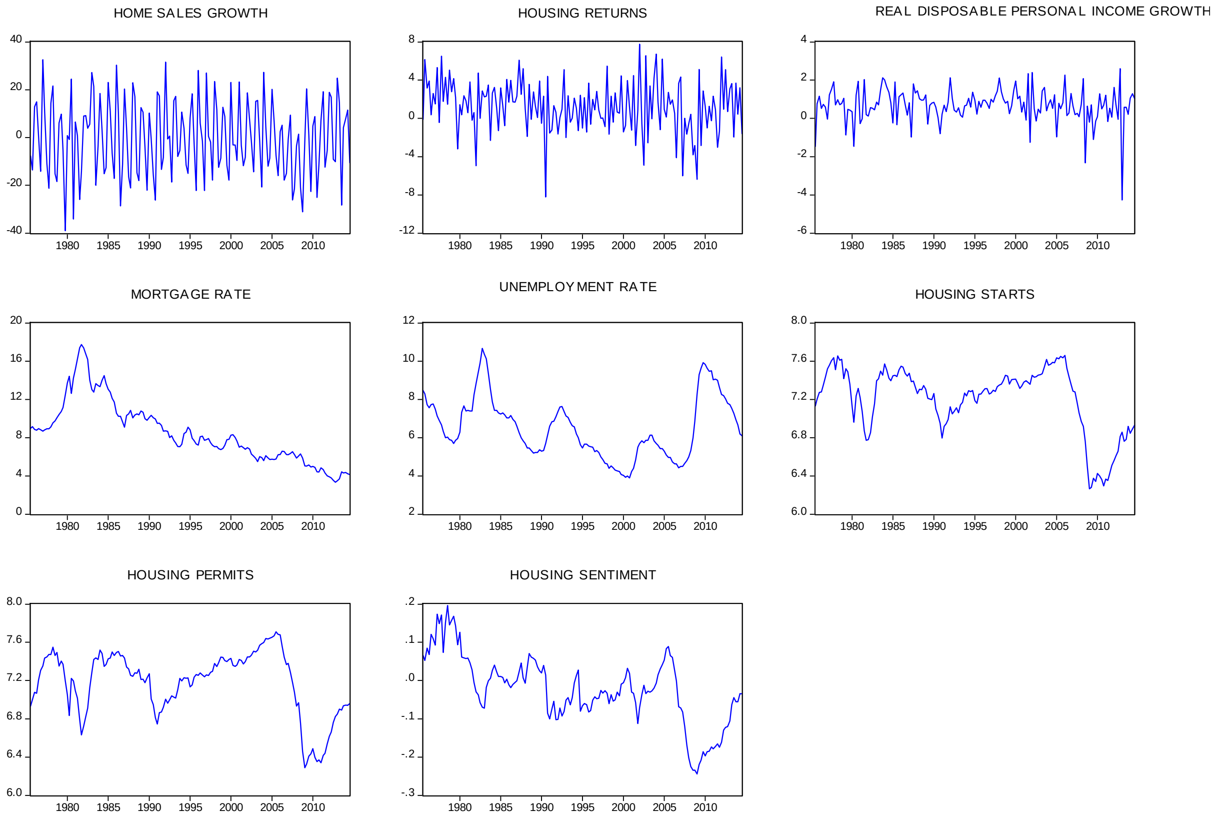

Table A1. Summary Statistics

Statistic	HOME SALES GROWTH	HOUSING RETURNS	REAL DISPOSABLE PERSONAL INCOME GROWTH	MORTGAGE RATE	UNEMPLOYMENT RATE	HOUSING STARTS	HOUSING PERMITS	HOUSING SENTIMENT
	Variable							
Mean	-0.2583	1.2529	0.6856	8.5151	6.5057	7.2035	7.1766	-0.0231
Median	-0.6557	1.2679	0.7169	8.0100	6.1333	7.2971	7.2572	-0.0263
Maximum	32.5054	7.7731	2.5925	17.7333	10.6667	7.6593	7.7090	0.1958
Minimum	-38.9961	-8.1952	-4.2652	3.3600	3.9000	6.2647	6.2891	-0.2441
Std. Dev.	15.8673	2.7665	0.8764	3.2005	1.5766	0.3454	0.3369	0.0910
Skewness	-0.0052	-0.3538	-1.4574	0.7933	0.5420	-1.1086	-0.8899	-0.1816
Kurtosis	2.1780	3.4672	9.4030	3.2773	2.6277	3.5104	3.1166	3.0846
Jarque-Bera	4.4211	4.7038	323.7811	16.9697	8.5935	33.8597	20.8111	0.9093
Probability	0.1096	0.0952	0.0000	0.0002	0.0136	0.0000	0.0000	0.6347
Observations	157							

Note: Std. Dev. stands for standard deviation, while probability is the p-value for the Jarque-Bera test, with the null hypothesis of normality.