Forecasting house prices using dynamic model averaging approach: Evidence from China

Yu Wei, Yang Cao
School of Economics & Management, Southwest Jiaotong University, China

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ABSTRACT

Forecasting house price has been of great interest to macroeconomists, policy makers and investors in recent years. To improve the forecasting accuracy, this paper introduces a dynamic model averaging (DMA) method to forecast the growth rate of house prices in 30 major Chinese cities. The advantage of DMA is that this method allows both the sets of predictors (forecasting models) as well as their coefficients to change over time. Both recursive and rolling forecasting modes are applied to compare the performance of DMA with other traditional forecasting models. Furthermore, a model confidence set (MCS) test is used to statistically evaluate the forecasting efficiency of different models. The empirical results reveal that DMA generally outperforms other models, such as Bayesian model averaging (BMA), information-theoretic model averaging (ITMA) and equal-weighted averaging (EW), in both recursive and rolling forecasting modes. In addition, in recent years it is found that the Google search index, instead of fundamental macroeconomic or monetary indicators, has developed greater predictive power for house price in China.

1. Introduction

House prices are important indicators of the real estate market's health and stability. Forecasting the changes in house prices can help investors, real estate developers and government regulators always pay great attention to the trends in house prices. Forecasting house prices accurately can not only help the government to regulate the real estate market more effectively, but it can also help real estate developers to make their investment decisions properly. House investors' decisions also depend largely on predictions of future house prices. The more accurate the predictions of future house prices, the more rational the buyers can be in allocating their current and future consumptions.

A number of scholars have conducted extensive research in predicting house prices. For example, DiPasquale and Wheaton (1994) explore the dynamic mechanism of house prices in the United States during the 1980s. These authors apply several macroeconomic variables for the first time to forecast house prices, and they find that these macroeconomic variables can improve the accuracy of house price forecasts. Brown et al. (1997) use the time-varying parameter (TVP) model to forecast quarterly changes in house prices in the U.K. from 1968 to 1992. They show that the TVP model performs better than several traditional constant parameter regression models, e.g., the error correction mechanism, the vector autoregressive and the autoregressive time series regression models. Crawford and Fratantoni (2003) forecast quarterly house prices in five U.S. states from 1979 to 2001 by using the ARIMA, GARCH and transition matrix methods. Their study reveals that according to the in-sample goodness-of-fit test, the transition matrix model performs better than other models, as it allows the variable parameters to change over time. However, for out-of-sample forecasting, the traditional ARIMA model is superior to the others. Hadavandi et al. (2011) investigate the annual changes in house prices in 20 regions of Iran since 2001 by using a fixed effects model with panel data. They find that the forecast accuracy of the panel data model is better than that of the ordinary OLS regression. Rapach and Strauss (2009) study the quarterly house prices of the top 20 major cities in the U.S. from 1995 to 2006, and then compare the differences in predictions produced by auto-regression (AR) models and ARDL models that incorporate information from numerous economic variables. Rapach and Strauss find that the AR models often provide relatively accurate house price forecasts in a number of interior states. However, all of the forecasting models tend to perform poorly for a group of primarily coastal states that have experienced especially strong growth in house prices. Ghysels et al. (2013) classify the recent literature on house price forecasting, and summarize the defects and problems of traditional forecasting models.

However, those traditional house price forecasting models face at
least one or two main problems as follows: first, it has been documented in the recent literature that the effects of the determinants (predictors) on house prices change over time (Ghysels et al., 2013). Lots of factors such as macroeconomic cycles or policy adjustments on real estate industry may lead to the structural break in the relationship between fundamentals and house price dynamics. Furthermore, the influence of each determinant on house prices may not be identical during different periods of time and (or) under different market conditions (Rapach and Strauss, 2009; Ghysels et al., 2013; Nneji et al., 2013; Plakandaras et al., 2015). Second, it is found that one specific model with a fixed set of predictors might not perform well consistently over time. To handle this issue, a model selection procedure may be carried out at each point in time, but with a huge computational task. For example, if there are n predictors in hand, that is, 2^n models are needed to be assessed at each point in time and a total number of models to be assessed over the evaluation period of T is 2^nT. If both n and T are large, this task seems unachievable. Thus the model averaging method such as forecast combination is adopted to improve the forecasting accuracy. When considering different sets of predictors as separate models, model averaging is simply a weighted average of all possible combinations of predictors. However, the weights assigned by either simple forecast combination or Bayesian model averaging (BMA) to combine different models are constant over time, which is not flexible enough to capture the time-variation of the contribution from each model (Pröchniak and Witkowski, 2013; Man, 2015). Recently, Kapetanios et al. (2008) propose a new model combination method, named as information-theoretic model averaging (ITMA). This method adopts Akaike information criterion (AIC) of each individual model in previous observations to update the model probability by the ordinary BMA. The ITMA method is found to be a powerful alternative to Bayesian averaging schemes (Piegorsch et al., 2013).

To address the problems mentioned above, Raftery et al. (2010) propose a novel method known as dynamic model averaging (DMA). It is found that this approach works quite well in macroeconomic forecasting (see, e.g., Koop and Korobilis, 2011, 2012). There are several obvious advantages of the DMA approach. It allows both the sets of predictors (forecasting models) and the coefficients of predictors to change over time. Furthermore, DMA method combines models in a dynamic way using two forgetting factors to approximate the evolution of model parameters and model switching probabilities, respectively. These two forgetting factors make the heavy computational task of model selection procedure manageable.

Motivated by the work of Raftery et al. (2010) and Koop and Korobilis (2012), a study by Bork and Moller (2015) is the first application using the dynamic model averaging (DMA) and dynamic model selection (DMS) methods in forecasting house price. Their study investigates the predictability of quarterly house price data in 50 U.S. states from 1976 to 2012. Unlike the traditional constant parameter or TVP forecasting models, the DMA and DMS methods allow changes over time in both the forecasting models and their coefficients. Bork and Moller (2015) also find that the forecasting precision of the DMA model is about 30% better than that of the traditional time series methods such as the AR and OLS regression models. More recently, Akinsoimi et al. (2016) use DMA to forecast the growth rates of U.S. real estate investment trusts (REITs) from January 1991 to December 2014. They find that compared to the traditional predictors, the sentiment and uncertainty indicators can better predict changes in REITs. DMA can also outperform other models such as Bayesian model averaging (BMA) and AR, as DMA produces smaller forecasting errors. Their results suggest that economy-wide indicators, monetary policy instruments and sentiment indicators are among the most powerful predictors of REIT returns. However, it is very interesting to note that besides those fundamental macroeconomic and monetary policy indicators, with the recent dramatic development of Internet information and big-data technology, there is growing evidence that Internet online search indexes can be useful in predicting some future economic variables, social population features and even outbreaks of epidemic diseases. However, to the best of our knowledge, there is no direct research focusing on the relationship between Internet search indexes and changes in house prices. A relevant paper by Das et al. (2015) examines the association between online apartment rental searches and several fundamental real estate market variables. These researchers find that consumers’ online Google search indexes are significantly associated with vacancy rates, rental rates and U.S. REIT returns.

It is also important to note that in most of the previous house price forecasting studies, different models are evaluated simply by a single loss function, e.g., the mean squared forecast error (MSFE) or mean absolute forecast error (MAFE). However, when a particular loss function value is smaller for model A than it is for model B, we cannot arbitrarily conclude that the forecasting performance of model A is superior to that of model B. Such a conclusion cannot be made on the basis of a single loss function or a single data sample.

Recent work has focused on a testing framework that can determine whether one particular model outperforms another (Diebold and Mariano, 1995; West, 1996; White, 2000). Hansen et al. (2011) propose a new statistical test for forecast errors, namely the model confidence set (MCS) test. The MCS test has several attractive advantages over conventional tests such as the super predictive ability test of Hansen (2005) or the reality check test by White (2000). First, the MCS test does not require a benchmark model to be specified, which is very useful in applications without an obvious benchmark. Second, the MCS test acknowledges the influence of measurement or calculation errors in a data sample by using a bootstrap sampling technique. Third, the MCS procedure allows for the possibility of more than one “best” model.

Since 2007, the real estate market in large and medium-sized Chinese cities has entered a stage of high-speed growth in which house prices have risen sharply. For example, the national average of house prices has increased by 7.6% per year, and some developed cities have even seen sustained double-digit growth in prices. The overheated real estate industry with its high house prices not only traps the economic capital of property-owning entities, but it also brings the disadvantages of excessive dependence on land finance for government income and other economic or social problems. In 2013, the government began to introduce control measures to prevent house prices from rising too quickly, but these measures appear to have little effect. The “China City Life Quality Report 2013” issued by the Experimental Research Institute of Chinese Economy, indicated that more than 40% of China’s urban residents felt the city house prices were unacceptably high. Thus accurate forecasting of house price in China is of great importance for policy makers and different market participants.

As discussed above, this paper contributes to the literature in four ways. First, we forecast house price in major Chinese cities using dynamic model averaging (DMA) for the first time, and compare its performance with that of Bayesian model averaging (BMA), information-theoretic model averaging (ITMA) and other commonly-used forecasting models. Second, unlike the method used by Bork and Moller (2015) and Akinsoimi et al. (2016), this investigation applies both recursive forecasting and rolling-window prediction in the DMA forecast to enhance the robustness of empirical performance for different models. Although the recursive method is usually used in DMA forecasting and the forgetting factor approach is able to play a role in discarding early observations and giving more weights to the most recent ones, it cannot handle the problem of possible structural break in house price dynamics. Third, this paper is the first to use a Google online search index as an additional predictor, along with several fundamental macroeconomic and real estate market indicators, to forecast house price changes in major Chinese cities. Fourth, instead of depending on one single loss function criterion, this paper applies a newly developed model comparison technique, the MCS test, which is proposed by Hansen et al. (2011) to assess the forecasting performance of different models using a number of criteria and test statistics.
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