House Price Expectations: Unbiasedness and Efficiency of Forecasters

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Abstract

The understanding of house price expectations formation is quite limited in the housing literature. This is the first paper to rigorously test the rationality of expectations of house price change using survey data. Using a panel dataset of the Wall Street Journal economic forecasting survey from 2007 through 2012, I test for unbiasedness and efficiency by implementing the econometric methodology proposed in Davies and Lahiri (1995) in the setting of a "three-dimensional" panel dataset. I find that, after controlling for aggregate shocks, 9 out of the 47 forecasters have statistically significant biases, and their biases are all negative, indicating that they persistently predict too high of a change in house prices. The hypothesis of efficiency cannot be rejected. When the year 2012 is excluded, the unbiasedness test shows that 25 out of the 47 forecasters systematically over predicted house price changes. Again, the hypothesis of efficiency cannot be rejected.

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Introduction

House price expectations formation is of vital importance in housing economics. Expectations of house price are obviously important when individuals make decisions about buying houses, when they decide whether to default on their mortgages, and when corporations make investment decisions in real estate markets.

However, the understanding of how house price expectations are formed is quite limited. There are essentially two ways to examine how expectations are formed. One way is based on the predictions from economics models combined with assumptions about the nature of expectations formation. But the problem with this method is that it is a joint test of the assumption about the expectations formation and the correctness of the model, and therefore it involves an identification problem. For example, a rejection of the predictions may be caused by the failure of the model, not the failure of the assumption about how expectations are formed. The second way to test expectations formation is directly using survey data. Although there are a large amount of papers studying expectation surveys for major macroeconomic variables such as GDP and the inflation rate, studies of house price expectations are quite rare.[1] This is mainly because expectations about house price changes did not receive much attention until the burst of the recent housing bubble. Surveys of house price expectations generally started to be collected around or after the peak of the bubble.

This paper is the first one to rigorously examine the rationality of house price expectations using survey data.[2] Specifically, I test for the unbiasedness and efficiency of forecasters' predictions about the percentage change in house prices using the Wall Street Journal economic forecasting survey. The house price change expectation data from the Wall Street Journal survey is a "three-dimensional" panel dataset and thus errors are correlated over three dimensions. I apply the econometrics methodology proposed by Davies and Lahiri (1995) to analyze this panel dataset.

[1]Pesaran and Weale (2006) provide a comprehensive review of theoretical and empirical work on survey expectations.

[2]To the best of my knowledge, the only two papers that study house price expectation using survey data are Case, Shiller, and Thompson (2012) for U.S. housing markets and Howard and Karagedikli (2012) for New Zealand housing markets. However, the focus of their studies is different from here. Instead of testing unbiasedness and efficiency, they focus on descriptive analyses of survey answers.

The remainder of the paper is organized as follows. The next section describes the data. Then I present the methodology for the unbiasedness and efficiency tests. Next, I report the empirical results, and the last section concludes.

Data

The dataset that I use is the Wall Street Journal economic forecasting survey (hereafter, WSJ survey).[3] This survey collects, in the first half of each month, the predictions of several U.S. macroeconomic variables from 50 to 60 forecasters. This is a panel dataset, but is unbalanced because forecasters enter and leave the survey, or fail to submit answers. Since August 2006, the survey has asked the forecasters to predict the annual percentage change of the U.S. Federal Housing Finance Agency (FHFA) house price index for the current and the next year.[4]

I include in the dataset 6 target years over 2007-2012, 24 forecast horizons ranging from 24 months to 1 month, and 47 forecasters who submitted answers for at least 50% of all the possible observations. This yields a total of 4,925 observations. The dates of the forecasts submitted are from August 2006 through December 2012 (the survey was not conducted in several months during this period).

In the appendix, I describe three other surveys in U.S. that include house price expecations, and explain why the WSJ survey is chosen in this paper.

[3]The WSJ survey data can be found at http://online.wsj.com/public/resources/documents/info-flash08.html?project=EFORECAST07

[4]The WSJ survey online data source does not indicate which FHFA index forecasters were asked to predict, but it provides the "actual" percentage changes for each year. Comparing the "actual" percentage changes with all the indices available on the FHFA website, I find that the seasonally unadjusted quarterly purchase-only index is the closest. For year 2007 to 2012, the "actual" percentage changes provided on the WSJ survey website (as on 6/30/2013) are -2.4, -9.68, -2.12, -4.26, -2.38, 5.45, and the percentage changes of the seasonally unadjusted quarterly purchase-only index are -2.4, -9.65, -2.08, -4.2, -2.35, and 5.47 (based on the data downloaded from the FHFA website on 3/3/2013). Therefore, when I mention the "actual" house price index in the remainder of the paper, I refer to the seasonally unadjusted quarterly purchase-only index.

Note that the FHFA indices may have minor difference, depending on the date the data is downloaded from the website. This is because the FHFA indices are constructed by a repeated-sale methodology. Therefore, as new transactions occur and are matched with previous transactions on the same property, these new transactions will be included in the dataset used to construct the repeated-sale indices, and hence the FHFA indices are under constant minor revision.

Econometrics Methodology

The implementation of the unbiasedness test and the efficiency test requires a model of the forecast errors and an estimate of the covariance matrix. Given the estimated error covariance matrices, I then implement unbiasedness and efficiency tests.

Forecast Error Covariance Matrix

By the nature of the house price question in the survey, this panel dataset has a "three-dimensional" forecast error structure proposed by Davies and Lahiri (1995). The first dimension of error correlation is due to the fact that all forecasters would be affected at the same time by aggregate shocks. The second source of error correlation is from shocks that affect forecasting errors for the same target year at different forecasting horizons. For example, a person's forecast errors of the annual percentage change for year 2009 made at October 2009 and November 2009 are both affected by monthly shocks in November and December 2009. The third dimension of the error correlation is caused by monthly shocks that are common to adjacent target years. For example, a person's forecast errors of the annual percentage change in price for year 2009 made at December 2009 and for year 2010 made at December 2009 are both affected by the shock occurs in December 2009.

I adopt the econometric methodology developed in Davies and Lahiri (1995) to decompose the forecast errors. Following their notation, there are N individuals, T target years, and H forecast horizons. Denote F_{ith} to be the forecast made by individual i, for year t, at h months before year t ends. The forecast data are compiled in the vector $F' = (F_{11H}, \dots, F_{111}, F_{12H}, \dots, F_{121}, \dots, F_{1TH}, \dots, F_{1T1}, \dots, \dots, F_{N1H}, \dots, F_{N11}, F_{N2H}, \dots, F_{N21}, \dots, F_{NTH}, \dots, F_{NT1})$. That is, the data are sorted first by individual forecasters, then by target years, and last by forecast horizons with the forecast horizons being sorted in descending order. Denote A_t to be the actual house price percentage change for year t. The forecast errors are decomposed as

$$A_t - F_{ith} = \phi_i + \lambda_{th} + \varepsilon_{ith}, \tag{1}$$

$$\lambda_{th} = \sum_{j=1}^{h} u_{tj}. \tag{2}$$

In the above equations, ϕ_i is individual specific bias, ε_{ith} is idiosyncratic error, and λ_{th} is aggregate shock that is the accumulation of the monthly shocks u_{tj} that occur over the span of h months prior to the end of year t. ε_{ith} and λ_{th} are uncorrelated, ε_{ith} is white noise across all dimensions with $E(\varepsilon_{ith}^2) = \sigma_{\varepsilon_i}^2$, and u_{tj} is white noise with $E(u_{th}^2) = \sigma_u^2$.

A positive ϕ_i indicates that the individual is persistently underestimating house price changes and a negative ϕ_i indicates that she is persistently overestimating it, after taking account of the aggregate shocks. The monthly shocks u_{tj} could be caused by events such as the Federal Reserve unexpectedly reducing interest rates. The idiosyncratic error ε_{ith} could be the result of errors in information collection, forecasting and calculation techniques, or private information.

The covariance between two forecast errors is therefore

$$\begin{aligned}
& cov(A_{t_1} - F_{i_1t_1h_1},\, A_{t_2} - F_{i_2t_2h_2}) \qquad (3)\\
= \; & cov(\lambda_{t_1h_1} + \varepsilon_{i_1t_1h_1},\, \lambda_{t_2h_2} + \varepsilon_{i_2t_2h_2})\\
= \; & cov(\sum_{j_1=1}^{h_1} u_{t_1j_1} + \varepsilon_{i_1t_1h_1},\, \sum_{j_2=1}^{h_2} u_{t_2j_2} + \varepsilon_{i_2t_2h_2})\\
= \; & \begin{cases} \sigma_{\varepsilon_i}^2 + h\sigma_u^2, & \forall\, i_1 = i_2 = i,\, t_1 = t_2,\, h_1 = h_2 = h,\\ \min(h_1,\, h_2)\sigma_u^2, & \forall\, i_1 \neq i_2,\, t_1 = t_2, \text{ or } i_1 = i_2,\, t_1 = t_2,\, h_1 \neq h_2,\\ \min(h_1,\, h_2 - 12)\sigma_u^2, & \forall\, t_2 = t_1 + 1,\, h_2 > 12,\\ 0, & \text{otherwise.} \end{cases}
\end{aligned}$$

Applying the above equation to my case, the forecast error covariance matrix (Σ) can be written as [5]

$$\underset{(NTH \times NTH)}{\Sigma} = \begin{bmatrix} A_1 & B & ... & B \\ B & A_2 & ... & B \\ ... & & & \\ B & B & ... & A_N \end{bmatrix}_{N \times N},$$

where

$$A_i = \sigma^2_{\varepsilon_i} I_{TH} + B,$$

$$\underset{(TH \times TH)}{B} = \begin{bmatrix} b & c & 0 & 0 & ... & 0 & 0 \\ c' & b & c & 0 & ... & 0 & 0 \\ 0 & c' & b & c & ... & 0 & 0 \\ ... & & & & & & \\ 0 & & ... & 0 & c' & b & c \\ 0 & & & ... & 0 & c' & b \end{bmatrix}_{T \times T},$$

$$b = \sigma^2_u \begin{bmatrix} 24 & 23 & 22 & ... & 2 & 1 \\ 23 & 23 & 22 & ... & 2 & 1 \\ 22 & 22 & 22 & ... & 2 & 1 \\ ... & & & & & \\ 2 & 2 & 2 & ... & 2 & 1 \\ 1 & 1 & 1 & ... & 1 & 1 \end{bmatrix}_{H \times H},$$

[5] N is 47, T is 6, and H is 24 below, which are different from Davies and Lahiri, and therefore, the matrices b and c below are different from theirs.

$$
c = \sigma_u^2 \begin{bmatrix} 12 & 11 & 10 & ... & 1 & 0 & ... & 0 \\ ... & & & & & & & \\ 12 & 11 & 10 & & 1 & 0 & & 0 \\ 11 & 11 & 10 & & 1 & 0 & & 0 \\ 10 & 10 & 10 & & 1 & 0 & & 0 \\ 9 & 9 & 9 & & 1 & 0 & & 0 \\ ... & & & & & & & \\ 2 & 2 & 2 & & 1 & 0 & & 0 \\ 1 & 1 & 1 & ... & 1 & 0 & ... & 0 \end{bmatrix}_{H \times H} . \tag{4}
$$

Therefore, the forecast error covariance matrix is fully characterized by $N+1$ parameters σ_u^2 and $\sigma_{\varepsilon i}^2$. To estimate this matrix (Σ), Davies and Lahiri (1995) propose the consistent estimates:

$$
\frac{1}{TH} \sum_{t=1}^{T} \sum_{h=1}^{H} (A_t - F_{ith}) = \widehat{\phi}_i, \tag{5}
$$

$$
\frac{1}{N} \sum_{i=1}^{N} (A_t - F_{ith} - \widehat{\phi}_i) = \widehat{\lambda}_{th}, \tag{6}
$$

$$
A_t - F_{ith} - \widehat{\phi}_i - \widehat{\lambda}_{th} = \widehat{\varepsilon}_{ith}. \tag{7}
$$

Consistent estimates of $\sigma_{\varepsilon_i}^2$ are obtained by regressing $\widehat{\varepsilon}_{ith}^2$ on N individual dummies because $E(\varepsilon_{ith}^2) = \sigma_{\varepsilon_i}^2$, and a consistent estimate of σ_u^2 is obtained by regressing $\widehat{\lambda}_{th}^2$ (a $TH \times 1$ vector) on a horizon index ranging from 24 to 1 because $E(\lambda_{th}^2) = h\sigma_u^2$.

Because this dataset is unbalanced, the data matrix and forecast error covariance matrix are compressed by deleting each row and column if the corresponding observation in the forecast vector is missing. These compressed matrices are used in the regressions below.

Test for Unbiasedness

With the consistent estimate of the forecast error covariance Σ mentioned above, the test for unbiasedness is to run an OLS regression of Equation (1) to get estimates of the ϕ_i's. The covariance of the estimators is given by the formula $(Z'Z)^{-1}Z'\Sigma Z(Z'Z)^{-1}$ where Z is the matrix of regressors.

Test for Efficiency

The test for efficiency is determining if the forecast error and variables in the information set known by the forecasters at the time the forecast is made are correlated. That is, the forecasters are efficient if those available information cannot improve forecast accuracy. Specifically, rejecting the null hypothesis of $\delta = 0$ in the regression below indicates a rejection of the efficiency hypothesis

$$A_t - F_{ith} = \delta X_{t,h+1} + \phi_i + \lambda_{th} + \varepsilon_{ith}, \tag{8}$$

where the $X_{t,h+1}$ represents information known by the forecaster when she makes the forecast F_{ith}, and $X_{t,h+1}$ contains any publicly available economic variables or previous forecasts made by the forecaster.

Davies and Lahiri (1995) propose to take the first difference of (8) to eliminate the individual dummies ϕ_i and get the following regression equation for the efficiency test:

$$F_{ith} - F_{i,t,h+1} = -\delta(X_{t,h+1} - X_{t,h+2}) + u_{t,h+1} - \varepsilon_{ith} + \varepsilon_{i,t,h+1}, \tag{9}$$

where $(X_{t,h+1} - X_{t,h+2})$ should be uncorrelated with the error term $u_{t,h+1} - \varepsilon_{ith} + \varepsilon_{i,t,h+1}$.

To estimate δ in (9), I first need to estimate the error covariance matrix for (9).

A typical element in the covariance matrix Ω in (9) is

$$cov(u_{t_1,h_1+1} - \varepsilon_{i_1 t_1 h_1} + \varepsilon_{i_1,t_1,h_1+1},\, u_{t_2,h_2+1} - \varepsilon_{i_2 t_2 h_2} + \varepsilon_{i_2,t_2,h_2+1}) \tag{10}$$
$$= \begin{cases} \sigma_u^2 + 2\sigma_{\varepsilon_i}^2, & \forall\ i_1 = i_2 = i,\ t_1 = t_2,\ h_1 = h_2, \\ \sigma_u^2, & \forall\ i_1 \neq i_2,\ t_1 = t_2,\ h_1 = h_2, \\ -\sigma_{\varepsilon_i}^2, & \forall\ i_1 = i_2 = i,\ t_1 = t_2,\ |h_1 - h_2| = 1, \\ 0, & \text{otherwise.} \end{cases}$$

Therefore, the covariance matrix Ω can be written as

$$\underset{(NTH \times NTH)}{\Omega} = \begin{bmatrix} A_1 & B & ... & B \\ B & A_2 & ... & B \\ ... & & & \\ B & B & ... & A_N \end{bmatrix}_{N \times N},$$

where

$$\underset{(TH \times TH)}{A_i} = 2\sigma_{\varepsilon_i}^2 I_{TH} + B + \begin{bmatrix} C & 0 & ... & 0 \\ 0 & C & & 0 \\ ... & & & \\ 0 & 0 & ... & C \end{bmatrix}_T,$$

$$B = \sigma_u^2 I_{TH},$$

$$C_{H \times H} = -\sigma_{\varepsilon_i}^2 \begin{bmatrix} 0 & 1 & 0 & ... & 0 & 0 \\ 1 & 0 & 1 & & 0 & 0 \\ 0 & 1 & 0 & & 0 & 0 \\ ... & & & & & \\ 0 & & & 1 & 0 & 1 \\ 0 & & & ... & 1 & 0 \end{bmatrix}_{H \times H}. \tag{11}$$

After obtaining the consistent estimates of $\sigma^2_{\varepsilon_i}$ and σ^2_u as previously mentioned, I obtain a consistent estimate of Ω. I then apply OLS to (9) with the covariance of the estimators given by the formula $(Z'Z)^{-1}Z'\Omega Z(Z'Z)^{-1}$ where Z is the matrix of regressors.

Empirical Results

Figure 1 provides a descriptive view of the forecasters' performance. The graphs show the box-and-whisker plots of the forecasts of house price changes in each month for every target year. The bottom and top of the box are the first and third quartiles, and the band inside the box is the median. The vertical lines extending from the box are called whiskers and cover most or all the remaining data. The upper (lower) whisker is restricted to the upper (lower) quartile plus (minus) 1.5 times the interquartile range. Dots outside the whiskers are outliers.

Three patterns appear here. First, the forecasters seem generally conservative when the aggregate shocks are not controlled. During the 2007-2011 period when house price is declining, the predictions of house price changes are higher than the actual changes, except for the predictions for target year 2009 made during year 2009. During this period, the forecasters are overly pessimistic about 2009 house price changes. During 2012, house price changes become positive, but the forecasters predicted lower house price appreciation. Second, as forecasting horizons approach zero, the forecast error generally diminishes, although they still deviate from the actual values for some years. Third, boxes for target years 2007 to 2009 are bigger than boxes for target years 2011 and 2012, indicating that the disagreement among forecasters was larger during the housing bust, and their disagreement was smaller when the housing market reached the bottom and recovered.

Unbiasedness

Table 1 provides estimates of the variance of the idiosyncratic error $\sigma^2_{\varepsilon_i}$, the individual bias ϕ_i, and the standard errors of $\widehat{\phi_i}$ for the 47 forecasters. The estimate of the variance of the monthly aggregate shock σ^2_u is 0.84. Note that, when I take account of the aggregate shocks, the majority of the forecasters have negative bias, meaning that their predictions of house price changes are systematically higher than the actual changes. Only 9 out of the 47 forecasters have biases that are statistically significant, and the bias of all of these 9 forecasters are negative, that is, they are persistently predicting too high house price changes.

The estimates of $\sigma^2_{\varepsilon_i}$ and σ^2_u reveal some information about the sources of forecasting error, that is, the relative contributions of the idiosyncratic error and the aggregate shock to the forecasting error. According to Equation (1) and (2), the variance of the accumulated aggregate shock decreases as the forecast horizon decreases (24 times σ^2_u when the horizon is 24 and just σ^2_u when the horizon is 1). In my result, the average of the estimates of the variance of the idiosyncratic error $\sigma^2_{\varepsilon_i}$ over i is 5.71, the variance of the accumulated aggregate shock is 20.16 (24 times 0.84) when it is 24 months prior to the end of the target year and it decreases to 0.84 when it is only one month before the target year ends. Therefore, about 78 percent (20.16/(5.71+20.16)) of the average variance of the forecasting error is contributed by the accumulated aggregated shock when it is 24 months before the target year ends, and the contribution of aggregate shock one month before the target year ends decreases to only 13 percent (0.84/(5.71+0.84)).

Efficiency

I run separate regressions for (9), including one of the following variables as the exogenous regressor ($X_{t,h+1} - X_{t,h+2}$) at each time: (1) the individual's forecast revision, lagged two months; (2) change in the percentage change of the monthly FHFA house price index over the past 12 months, lagged three months; (3) change in the conventional conforming 30-year fixed mortgage rate released in the last week each month, lagged two months; (4) change in NAHB/Wells Fargo national Housing Market Index, lagged two months; and (5) change in housing starts, lagged two months.

The above five variables are chosen as the latest information that are "available to the forecasters $h+1$ months prior to the end of the year t", as in Davies and Lahiri (1995), so they are contemporaneously uncorrelated with the error term. The sources and descriptions of these five variables are listed below.

(1) Because the individual's own previous forecast should be in her information set, I use the two months lagged forecast revision ($F_{i,t,h+2} - F_{i,t,h+3}$) as an exogenous regressor

$(X_{t,h+1} - X_{t,h+2})$. I do not use the change in one period lagged forecast revision $(F_{i,t,h+1} - F_{i,t,h+2})$ because it is correlated with the error terms ($F_{i,t,h+1}$ is correlated with $\varepsilon_{i,t,h+1}$). Therefore, $(F_{i,t,h+1} - F_{i,t,h+2})$ is not a valid exogenous regressor.

(2) The monthly FHFA house price index is released at the end of two months later.[6] For example, January's index is released in late March. Therefore, when forecasters make predictions in early April, January's house price index is in their information set.

(3) The data of the conventional conforming 30-year fixed mortgage rate is released by Freddie Mac weekly on Thursday.[7] I use the change in the mortgage rate released on the last Thursday lagged two months as the exogenous regressor. I do not use the rate released late last month because although it is in the forecasters' information set, it is correlated with $u_{t,h+1}$ in the error term.

(4) The NAHB/Wells Fargo national Housing Market Index (HMI) is a seasonally adjusted series derived from a monthly survey of NAHB members.[8] It reflects builders' views of housing market conditions. Each month's index is released around the 16th-20th of the same month, and I use the change in the HMI lagged two months as the exogenous regressor, due to the same reason as in (3).

(5) The housing starts measure is a monthly data which is released around the 16th-20th of the next month.[9] When forecasters answer the survey in, say, early April, the housing starts in February is in their information set, so I use the change in housing starts lagged two month as the regressor.

Table 2 reports the separate regressions for the efficiency test using each of the above regressors. None of the regression can reject the efficiency hypothesis. This result indicates that none of the available information improve the forecast accuracy. The forecasters fully incorporate this information when they make predictions.

I further conduct a joint test of efficiency by estimating equation (9), including all the variables (1) to (5) in the regression at the same time. Results are presented in Table 3. None

[6] I use seasonally unadjusted national purchase-only index.

[7] http://www.freddiemac.com/pmms/

[8] http://www.nahb.org/reference_list.aspx?sectionID=134

[9] I use seasonally adjusted housing starts series. The number of housing units are measured in thousands. The data can be found at http://www.census.gov/construction/nrc/historical_data/

of the coefficients are significantly from zero. The null hypothesis that the five coefficients are jointly zero cannot be rejected by the χ^2 statistic.[10] Therefore, the efficiency hypothesis cannot be rejected.

Excluding Year 2012

I also conduct the unbiasedness test and the efficiency test limited to target years 2007 to 2011, excluding 2012. As shown in Figure 1, 2012 is the only year that has positive house price changes, and is the only year that the forecasts are lower than the actual value.

Table 4 presents the unbiasedness test results for year 2007 to 2011. A noticeable point is that many more forecasters have statistically significant bias than the case that includes 2012, and all those biases are negative. Now 25 out of the 47 forecaster are systematically over predicting house price changes from 2007 through 2011.

Table 5 reports the efficiency test results that include only one regressor in each regression. Table 6 reports the joint efficiency test results that include all the regressors at the same time. Similar to the case that includes 2012, none of the coefficients is significant, and the χ^2 statistic indicates that we cannot reject the null hypothesis that the coefficients are jointly zero. Therefore, efficiency cannot be rejected, indicating that the forecasters fully incorporate this information when they made predictions during 2007-2011.

Conclusions

This paper examines the unbiasedness and efficiency of forecasters when they predict house price changes. Using the Wall Street Journal economic forecasting survey that covers 2007-2012, and implementing the econometric methodology proposed in Davies and Lahiri (1995) to deal with a "three-dimensional" panel dataset, I find that, after controlling for aggregate shocks, 9 out of the 47 forecasters have statistically significant biases, and the biases are all negative, indicating that they persistently predict higher than the actual house price changes. For the efficiency test, I examine whether the following information can improve forecast

[10]Under the null hypothesis $H_0 : \delta = (\delta_1, ..., \delta_5)' = 0$, we have $\widehat{\delta}'[(Z'Z)^{-1}Z'\Omega Z(Z'Z)^{-1}]^{-1}\widehat{\delta}$ being approximately $\chi^2(5)$.

accuracy: the forecaster's own forecast lagged two months; change in FHFA monthly house price index over the past 12 months lagged three months; mortgage rate lagged two months; NAHB/Wells Fargo national Housing Market Index lagged two months; and housing starts lagged two month. The hypothesis of efficiency cannot be rejected in any case, indicating that the forecasters have fully incorporated these information when they make predictions. If the target year 2012 is excluded, 25 out of the 47 forecasters have significant biases and all these biases are negative. The efficiency tests results are similar to the case that includes 2012, that is, the hypothesis of efficiency cannot be rejected.

References

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Appendix: House Price Expectation Surveys

In the appendix, I describe three other surveys about or that include house price expectations in U.S., and explain why I chose the WSJ survey to study.

The "House Price Expectations Survey" conducted by Pulsenomics surveys a panel of around 100 to 110 economists and industry professionals in the housing field.[11] The individuals are asked to predict the annual house price percentage changes ("on a Q4-over-preceding

[11] This survey can be found at https://pulsenomics.com/Home-Price-Expectations.html

Q4 basis") of the S&P/Case-Shiller U.S. national home price index, for the current year and the next five years. This survey began in May 2010 and was conducted monthly through Dec 2010. Beginning at 2011, the survey has been collected quarterly.

Case and Shiller conduct surveys in the year 1988 and then annually from 2003 to 2012, for recent homebuyers in four U.S. cities: Boston, Los Angeles, San Francisco, and Milwaukee. The number of survey answers returned are 886 in 1988, 705 in 2003, but declines to 328 in 2012. The relevant questions in their survey that are closely related to my study are the two questions asking about the expectation of future house price changes. Question 6: "How much of a change do you expect there to be in the value of your home over the next 12 months?" Question 7: "On average over the next ten years how much do you expect the value of your property to change each year?"

Figure 5 in Case and Shiller's paper plots actual and expected house price changes and shows that the respondents in their survey (the recent homebuyers) are much more optimistic than the forecasters in the WSJ survey. Their figure shows that the only negative one-year expectations for house price changes occur in 2008 in SF, Boston, and LA. In Milwaukee, there is never a negative expectation. This indicates that, either forecasters are making better predictions, or the recent homebuyers in their sample are not a random sample of the population. Rather, people who buy homes are generally optimistic about housing markets. Case and Shiller also run regressions testing the hypothesis of rational expectations. But since individuals are predicting their own property's value changes, only the mean expectations for each city in each year can be used. This gives only 9 observations for each of the 4 cities. They implement a efficiency test by regressing the actual subsequent one-year home price change on the expectation of one-year home price change, the lagged actual own-city one-year home price change, and the lagged actual U.S. one-year home price change. Both of the last two variables have insignificant coefficients, and therefore "this confirms the rational expectations for the 12-month forecasts. Respondent do appear to incorporate this other information in making the 12-month forecasts."

The third survey is the Surveys of Consumers conducted by the Survey Research Center at the University of Michigan.[12] 500 individuals are randomly selected each month. Starting

[12]Its information can be found at http://press.sca.isr.umich.edu/

from May 2007, one-year and five-year house price expectations changes have been asked in the survey: "By about what percent do you expect prices of homes like yours in your community to go (up/down), on average, over the next 12 months?" "..., over the next 5 years or so?"

The advantages of the WSJ survey compared to the above three surveys are the following.

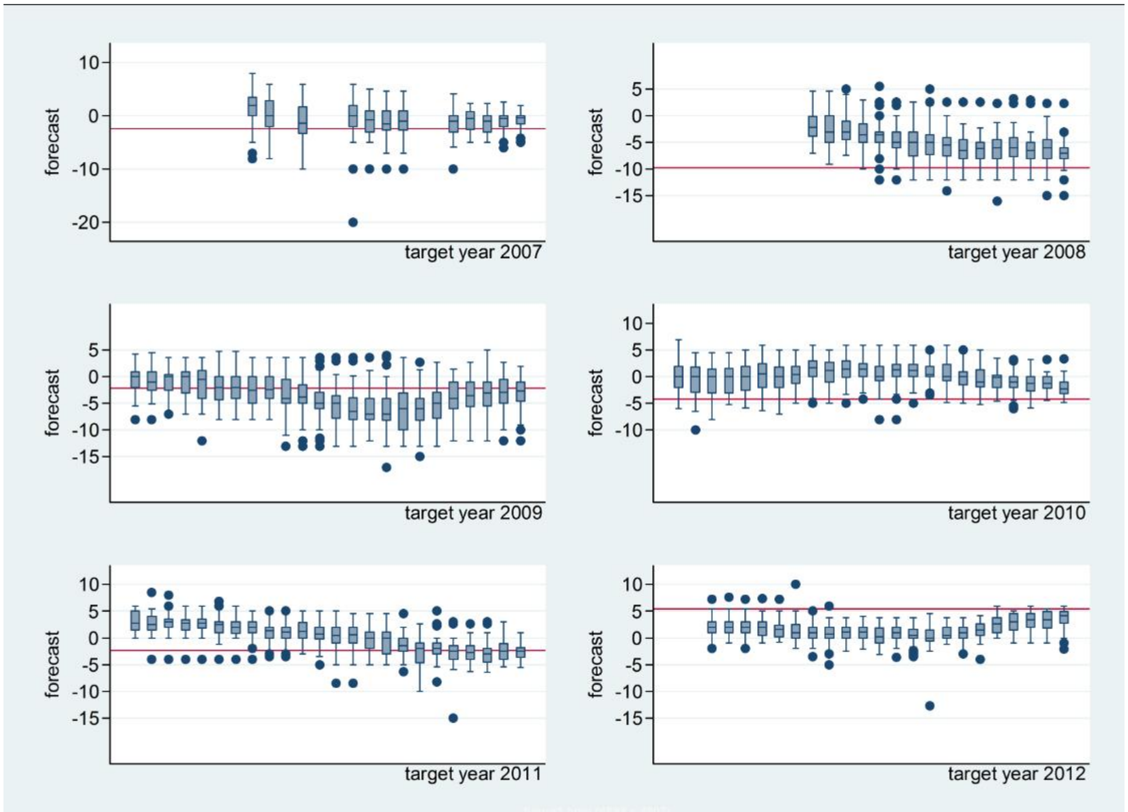
First, the WSJ survey has the largest number of observations. It is monthly and begins four year before the Pulsenomics survey, which is quarterly. The Case-Shiller survey and Michigan survey are not panel datasets, and the questions are about the individual's own house or houses in her community, so to test for expectation formations, only aggregated mean value can be used. This yields 36 annual observations for the Case-Shiller survey, and around 70 monthly observations for the Michigan survey.[13]

The second advantage is that the WSJ survey is a panel dataset. The tests for individuals' expectation formation using a panel dataset are more reliable than using the aggregated mean values. The rationality of the mean of forecasts does not imply the rationality of the individual forecasts. For example, individuals may have different forecasts with some being positively biased and others being negatively biased, but the mean of these individual forecasts may be unbiased when they offset each other. Moreover, a panel dataset allows for controlling the aggregate shocks, which is impossible using the aggregated mean value data.

Its login is at http://www.sca.isr.umich.edu/

[13]The Michigan/Reuters survey also releases mean values of the expectation of house price changes for four regions, that would yield 280 observations.

Figure 1. Box-and-Whisker plots for each target year



Notes: The solid lines are the actual annual percentage changes of house price (FHFA). The graphs show the distribution of forecasts made in each month. The bottom and top of the box are the first and third quartiles, and the band inside the box is the median. The upper (lower) whisker is restricted to the upper (lower) quartile plus (minus) 1.5 times the interquartile range. Dots outside the whiskers are outliers. Several outliers are dropped from the graphs: one observation that is under -20 in 2008, one that is under -30 in 2010, and one that is above 10 in 2011.

Table 1. Test for Unbiasedness, 2007-2012

Forecasters	Institute	$\sigma^2_{\varepsilon_i}$	ϕ_i	s.e. of ϕ_i
Bart van Ark	The Conference Board	6.21	0.53	1.52
Paul Ashworth	Capital Economics	6.60	0.20	1.39
Nariman Behravesh	Global Insight	6.79	1.02	1.36
Richard Berner/David Greenlaw	Morgan Stanley	6.81	0.47	1.62
Ram Bhagavatula	Combinatorics Capital	9.54	0.64	1.38
Jay Brinkmann	Mortgage Bankers Association	3.72	-0.61	1.49
Joseph Carson	AllianceBernstein	2.45	-1.40	1.34
Mike Cosgrove	Econoclast	3.18	-1.13	1.35
Lou Crandall	Wrightson ICAP	2.77	-2.10	1.34
J. Dewey Daane	Vanderbilt University	5.68	-1.61	1.35
Richard DeKaser	National City Corporation	5.20	-3.17	1.64*
Douglas Duncan	Mortgage Bankers Association	3.67	-0.52	1.34
Stephen Gallagher	Societe Generale	6.60	-4.52	1.69***
Ethan S. Harris	Lehman Brothers	5.36	-1.02	1.46
Maury Harris	UBS	11.60	0.16	1.43
Tracy Herrick	The Private Bank	11.80	-0.04	1.38
Stuart Hoffman	PNC Financial Services Group	1.91	-0.30	1.48
Gene Huang	FedEx Corp.	5.21	-1.31	1.36
William B. Hummer	Wayne Hummer Investments LLC	26.04	0.15	1.42
Dana Johnson	Comerica Bank	3.29	-4.40	1.55***
Bruce Kasman	JP Morgan Chase & Co.	3.68	-0.86	1.35
Paul Kasriel	The Northern Trust	11.10	0.20	1.50
Joseph LaVorgna	Deutsche Bank Securities, Inc.	13.35	-1.09	1.68
Edward Leamer	UCLA Anderson Forecast	4.03	0.02	1.34
John Lonski	Moody's Investors Service	2.27	-1.12	1.34
Dean Maki	Barclays Capital	2.92	-1.04	1.40
David Malpass	Encima Global LLC	3.52	-2.04	1.60
Jim Meil/ Tianlun Jian	Eaton Corp.	4.82	-1.51	1.35

Table 1. (Continued)

Forecasters	Institute	$\sigma^2_{\varepsilon_i}$	ϕ_i	s.e. of ϕ_i
Mark Nielson	MacroEcon Global Advisors	7.05	-2.55	1.47*
Michael P. Niemira	International Council of Shopping Centers	4.05	-2.14	1.35
Nicholas S. Perna	Perna Associates	2.68	-0.28	1.33
Joel Prakken/ Chris Varvares	Macroeconomic Advisers	3.97	-0.48	1.47
Arun Raha	Economic and Revenue Forecast Council	4.83	-1.71	1.77
David Resler	Nomura Securities International Inc.	4.66	-1.10	1.39
John Ryding	Bear Stearns & Co. Inc.	3.06	-0.83	1.35
Ian Shepherdson	High Frequency Economics	3.40	0.01	1.39
John Silvia	Wachovia Corp.	4.07	-1.14	1.35
Allen Sinai	Decision Economics Inc.	4.37	-0.16	1.35
James F. Smith	Western Carolina Univ & Parsec Financial Mgmt	5.34	-5.90	1.35***
Sung Won Sohn	Hanmi Bank	4.67	-1.51	1.39
Stephen Stanley	Pierpont Securities	2.83	-2.29	1.36*
Susan M. Sterne	Economic Analysis	7.24	-3.38	1.37**
Diane Swonk	Mesirow Financial	4.56	-0.26	1.34
Brian S. Wesbury	First Trust Advisors, L.P.	2.32	-2.75	1.34**
William T. Wilson	Keystone Business Intelligence India	6.82	-3.06	1.67*
David Wyss	Standard and Poor's	8.37	-0.40	1.59
Lawrence Yun	National Association of Realtors	3.90	-2.17	1.43

Notes: Listed are the estimates of the variance of the idiosyncratic error $\sigma^2_{\varepsilon_i}$, the individual bias ϕ_i, and the standard errors of $\widehat{\phi}_i$ for the 47 forecasters. Since Feb 2012, Arun Raha moved job and joined Jim Meil. *, **, and *** indicates significance at the 10%, 5%, and 1%, respectively.

Table 2. Test for Efficiency, 2007-2012

Regressor $(X_{t,h+1} - X_{t,h+2})$	$-\delta$	s.e. of δ
(1) Forecast revision lagged 2 months	-0.045	0.046
(2) Change in percentage change in FHFA index over the past 12 months lagged 3 months	0.163	0.115
(3) Change in mortgage rate lagged 2 months	0.448	0.422
(4) Change in HMI lagged 2 months	0.035	0.045
(5) Change in housing starts lagged 2 months	0.0013	0.0015

Notes: The coefficient and its standard error are obtained from running separate regressions for (9), including only one of the variables (1)-(5) as the exogenous regressor $(X_{t,h+1} - X_{t,h+2})$ at each time.

Table 3. Joint Test for Efficiency, 2007-2012

	coff.	s.e.
Forecast revision lagged 2 months	-0.051	0.046
Change in percentage change in FHFA index		
over the past 12 months lagged 3 months	0.141	0.13
Change in mortgage rate lagged 2 months	0.476	0.494
Change in HMI lagged 2 months	0.017	0.05
Change in housing starts lagged 2 months	0.0004	0.002
χ^2 statistic		3.856

Notes: Coefficient and their standard errors are obtained from running the regression (9), including all the variables (1) to (5) in the regression at the same time. The 1%, 5%, and 10% critical values for the $\chi^2(5)$ are 15.086, 11.070, and 9.236.

Table 4. Test for Unbiasedness, 2007-2011

Forecasters	Institute	$\sigma^2_{\varepsilon_i}$	ϕ_i	s.e. of ϕ_i
Bart van Ark	The Conference Board	6.46	-0.42	1.31
Paul Ashworth	Capital Economics	7.46	-0.80	1.18
Nariman Behravesh	Global Insight	4.11	0.57	1.14
Richard Berner/David Greenlaw	Morgan Stanley	6.91	0.32	1.28
Ram Bhagavatula	Combinatorics Capital	10.39	0.06	1.17
Jay Brinkmann	Mortgage Bankers Association	4.10	-1.87	1.28
Joseph Carson	AllianceBernstein	2.84	-2.39	1.14**
Mike Cosgrove	Econoclast	3.30	-2.52	1.13**
Lou Crandall	Wrightson ICAP	3.28	-3.35	1.13***
J. Dewey Daane	Vanderbilt University	4.85	-3.24	1.14***
Richard DeKaser	National City Corporation	3.86	-3.17	1.25**
Douglas Duncan	Mortgage Bankers Association	4.19	-1.77	1.13
Stephen Gallagher	Societe Generale	5.42	-4.52	1.30***
Ethan S. Harris	Lehman Brothers	5.49	-1.73	1.15
Maury Harris	UBS	12.39	-0.25	1.17
Tracy Herrick	The Private Bank	13.46	-0.73	1.18
Stuart Hoffman	PNC Financial Services Group	2.03	-1.04	1.24
Gene Huang	FedEx Corp.	6.18	-2.36	1.15**
William B. Hummer	Wayne Hummer Investments LLC	27.26	-0.74	1.23
Dana Johnson	Comerica Bank	2.45	-4.60	1.20***
Bruce Kasman	JP Morgan Chase & Co.	4.05	-1.81	1.13
Paul Kasriel	The Northern Trust	10.99	-0.07	1.20
Joseph LaVorgna	Deutsche Bank Securities, Inc.	16.08	-2.29	1.53
Edward Leamer	UCLA Anderson Forecast	4.58	-0.88	1.14
John Lonski	Moody's Investors Service	2.55	-2.35	1.13**
Dean Maki	Barclays Capital	2.11	-2.06	1.17*
David Malpass	Encima Global LLC	3.94	-3.34	1.33**
Jim Meil/ Tianlun Jian	Eaton Corp.	5.63	-2.52	1.14**

Table 4. (Continued)

Forecasters	Institute	$\sigma^2_{\varepsilon_i}$	ϕ_i	s.e. of ϕ_i
Mark Nielson	MacroEcon Global Advisors	6.87	-4.27	1.25***
Michael P. Niemira	International Council of Shopping Centers	3.56	-3.62	1.13***
Nicholas S. Perna	Perna Associates	2.86	-1.39	1.12
Joel Prakken/ Chris Varvares	Macroeconomic Advisers	4.17	-1.61	1.21
Arun Raha	Economic and Revenue Forecast Council	4.97	-2.92	1.42**
David Resler	Nomura Securities International Inc.	5.08	-2.28	1.16**
John Ryding	Bear Stearns & Co. Inc.	3.11	-2.31	1.14**
Ian Shepherdson	High Frequency Economics	3.77	-0.79	1.14
John Silvia	Wachovia Corp.	4.33	-2.47	1.14**
Allen Sinai	Decision Economics Inc.	4.96	-1.31	1.14
James F. Smith	Western Carolina Univ & Parsec Financial Mgmt	4.64	-7.58	1.13***
Sung Won Sohn	Hanmi Bank	4.97	-2.88	1.17**
Stephen Stanley	Pierpont Securities	3.10	-3.56	1.14***
Susan M. Sterne	Economic Analysis	8.15	-4.69	1.16***
Diane Swonk	Mesirow Financial	4.78	-1.52	1.13
Brian S. Wesbury	First Trust Advisors, L.P.	2.69	-3.74	1.13***
William T. Wilson	Keystone Business Intelligence India	5.39	-3.06	1.28**
David Wyss	Standard and Poor's	7.35	-0.50	1.23
Lawrence Yun	National Association of Realtors	4.69	-3.44	1.22***

Notes: Listed are the estimates of the variance of the idiosyncratic error $\sigma^2_{\varepsilon_i}$, the individual bias ϕ_i, and the standard errors of $\widehat{\phi}_i$ for the 47 forecasters. *, **, and *** indicates significance at the 10%, 5%, and 1%, respectively.

Table 5. Test for Efficiency, 2007-2011

Regressor $(X_{t,h+1} - X_{t,h+2})$	$-\delta$	s.e. of δ
(1) Forecast revision lagged 2 months	-0.05	0.05
(2) Change in percentage change in FHFA index		
over the past 12 months lagged 3 months	0.17	0.11
(3) Change in mortgage rate lagged 2 months	0.46	0.36
(4) Change in HMI lagged 2 months	0.04	0.04
(5) Change in housing starts lagged 2 months	0.002	0.001

Notes: The coefficient and its standard error are obtained from running separate regressions for (9), including only one of the variables (1)-(5) as the exogenous regressor $(X_{t,h+1} - X_{t,h+2})$ at each time.

Table 6. Joint Test for Efficiency, 2007-2011

	coff.	s.e.
Forecast revision lagged 2 months	-0.05	0.05
Change in percentage change in FHFA index over the past 12 months lagged 3 months	0.16	0.12
Change in mortgage rate lagged 2 months	0.48	0.44
Change in HMI lagged 2 months	0.01	0.05
Change in housing starts lagged 2 months	0.0005	0.002
χ^2 statistic		4.971

Notes: Coefficient and their standard errors are obtained from running the regression (9), including all the variables (1) to (5) in the regression at the same time. The 1%, 5%, and 10% critical values for the $\chi^2(5)$ are 15.086, 11.070, and 9.236.