House Price Forecasts in Times of Crisis: Do Forecasters Herd?

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Abstract

We used Wall Street Journal survey data for the period 2006 – 2010 to analyze whether forecasts of house prices and housing starts provide evidence of (anti-)herding of forecasters. Forecasts are consistent with herding (anti-herding) of forecasters if forecasts are biased towards (away from) the consensus forecast. We found that anti-herding is prevalent among forecasters of house prices, where anti-herding is less strong in the case of medium-term forecasts, especially in the case of housing starts.

JEL classification: E37, D84, C33
Keywords: Forecasts of house prices and housing starts; Herding

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1 Introduction

One lesson to be recalled from the recent subprime mortgage crisis concerns the major importance of the link between the housing market and macroeconomic stability. As witnessed by the U.S. subprime mortgage crisis of 2007/2008, significant macroeconomic downside risk may loom if housing markets collapse. Supporting this view, results of empirical research by Cecchetti (2006) indicate house price booms deteriorate growth prospects and create substantial risks of very bad macroeconomic outcomes. A boom in the housing market may reflect speculative exuberance and herding of investors. A natural question is whether such herding, to the extent that it occurred, was driven by herding in the forecasts of professional housing market forecasters.

We implemented a robust empirical test developed by Bernhardt et al. (2006) to study whether professional housing market forecasters did, in fact, herd. This test is easy to implement and delivers results that can be easily interpreted in economic terms. To implement the test, we used Wall Street Journal (WSJ) survey data on forecasts of house prices and housing starts for the period 2006 – 2010. The test results do not provide evidence of herding. On the contrary, we find evidence of *anti*-herding, where anti-herding is less strong in the case of medium-term forecasts, especially in the case of housing starts. Evidence of anti-herding indicates that professional housing market forecasters deliberately placed their forecasts away from the cross-sectional consensus forecast.

We go beyond earlier literature in three important ways. First, as compared to most earlier literature on forecasts of real estate indicators, our empirical study covers both house prices and housing starts. Second, our empirical study is based on recent data that cover the period of time during which

U.S. house prices boomed, and the period of time covering the eventual collapse of the house price bubble following the U.S. subprime mortgage crisis. Third, our data set contains, for different forecast horizons, forecasts of individual forecasts, allowing forecaster interactions (herding and anti-herding) to be analyzed at the micro level.

In earlier literature, Grimes et al. (2004) study housing market efficiency and overshooting of house prices based on regional data for New Zealand. Song et al. (1995) and Aggarwal and Mohanty (2000) analyze the rationality of forecasts of U.S. housing starts published in the Money Market Services Hott (2009) reports that fluctuations in actual house prices exceed fluctuations in "fundamental" house prices. None of the mentioned studies uses cross-sectional micro data on house prices and housing starts to test for herding or anti-herding of forecasters. Our empirical study closes this gap in the literature.

In Section 2, we describe the data that we used in our empirical analysis. In Section 3, we describe the test for forecaster (anti-)herding developed by Bernhardt et al. (2006), and we report our results. In Section 4, we offer some concluding remarks.

2 The Data

The WSJ conducts, usually on a monthly basis, a questionnaire survey of financial market participants. Financial market participants are asked about their forecasts of several important financial U.S. variables. When the questionnaire survey was launched in 1981, the focus was on the expected development of the Fed prime rate. In later years, the number of economic variables covered by the questionnaire survey has increased considerably.[1] Since August 2006, the questionnaire survey includes data on forecasts of house prices and forecasts of housing starts for the current year and the next year. Until December 2010, about 68 forecasters have participated in the WSJ questionnaire surveys.[2]

The WSJ survey data have been used in several earlier empirical studies. The research questions analyzed in earlier empirical studies, however, significantly differ from our research question. For example, Greer (2003) analyzes whether forecasters accurately predict the direction of change of yields on 30-year U.S. Treasury bonds correctly and finds some evidence that this is indeed the case. Cho and Hersch (1998) analyze whether the characteristics of forecasters help to explain forecast accuracy (i.e., the size of the forecast error) and/or the forecast bias (i.e., the sign of the forecast error). While the authors find that characteristics of forecasters do not help to explain forecast accuracy, some characteristics like the professional experience of a forecaster with the Federal Reserve System seem to have power for explaining forecast direction error. Kolb and Stekler (1996) report a high degree of heterogeneity of WSJ forecasts, implying that standard central moments (mean, median) do not adequately describe the rich cross-sectional structure of forecasts. Eisenbeis et al. (2002) analyze the methodology used by the WSJ to construct an overall ranking of forecasters. Because the WSJ ranks the forecasts on the sum of the weighted absolute percentage deviation from the actual realized value of each series, this methodology neglects correlations among the forecasted

[1]For example, since January 1985, participants have also been asked to forecast the GNP growth rate and, since 1991, the GDP growth rate. The inflation rate and the unemployment rate have been incorporated into the questionnaire survey since 1989. Additionally, since 2002, the WSJ has published forecasts of the Federal Funds Rate.

[2]In our empirical analysis, we used data for those forecasters who participated in all 48 surveys. This applies to 55 forecasters yielding 2,640 forecasts. The list of forecasters and their affiliations is available upon request.

variables. Mitchell and Pearce (2007) analyze the unbiasedness and forecast accuracy of individual forecasters with respect to their interest rate and exchange rate forecasts. They find that several forecasters form biased forecasts, and that most forecasters cannot out-predict a random walk model.

The WSJ survey data have several advantages over other survey data and are, thus, less subject to some commonly debated problems one encounters when studying survey data. First, the WSJ publishes forecasts of house prices and housing starts made by a large number of individual forecasters, and not only the mean forecast used in other studies (Song et al. 1995, Aggarwal and Mohanty 2000). Second, the WSJ publishes individual forecasts together with the names of forecasters and the institutions at which they work, implying that forecaster reputation may be linked to forecast accuracy.[3] Third, unlike survey data used in earlier empirical research (see, for example, Menkhoff et al., 2008; 2009), forecasters who participate in the WSJ questionnaire survey do not only take a stance on the direction of change of a variable, but they also forecast the level of a variable. Fourth, the WSJ survey data contain information on private sector forecasts rather information on forecasts of international institutions.[4] Fifth, the WSJ conducts the questionnaire surveys at a monthly basis, implying that the data are available at a relatively high frequency, where the data are readily available to the public and the participating forecasters. This makes it possible to analyze interaction among forecasters. Sixth, the WSJ

[3]A link between forecaster reputation and forecast accuracy may strengthen incentives of survey participants to submit their best rather than their strategic forecast (Keane and Runkle 1990), or it may strengthen incentives to strategically deviate from the "consensus" forecast and to "lean against the trend". Strategic deviations from the "consensus" forecast may result in systematic "anti-herding" (Section 3). See Laster et al. (1999) for an example of a theoretical model that illustrates how "anti-herding" of forecasters arises in a game-theoretic model of forecaster interaction.

[4]Batchelor (2001) shows that the Consensus Economics forecasts are less biased and more accurate in terms of mean absolute error and root mean square error than forecasts published by the OECD and the IMF.

survey data cover the period of time of the U.S. subprime mortgage crisis, rendering it possible to analyze forecasts of house prices and housing starts in times of financial and economic distress. Finally, the WSJ survey data contain forecasts for different forecast horizons, that is, for the current year and the next year. We can, thus, analyze short-term forecasts and medium-term forecasts.

Insert Table 1 about here.

Table 1 provides summary statistics of the WSJ survey data. The sample period is August 2006 – December 2010. Because the sample period covers the period of financial market jitters following the U.S. subprime mortgage crisis, it is not surprising that forecasters expected on average house prices to decrease by about -2.7 percent (p.a.). Actual house prices decreased by -2.8 percent. Medium-term forecasts indicate on average a less severe drop in house prices by only $-.14$ percent. With regard to medium-term prospects for house prices, forecasters thus were on average slightly optimistic. Similarly, forecasters expected on average housing starts of about 0.97 million units (p.a.), where the actual number of housing starts was about 0.89 million units. The medium-term forecast (1.08 million units) again is slightly larger than the short-term forecast.

The cross-sectional, time-averaged mean values of forecasts cloud important information conveyed by the dynamics of forecasts across questionnaire surveys, and by the cross-sectional dispersion of forecasts of house price and housing starts. In order to inspect the time-series dimension and the cross-sectional dimension of the survey data, Figures 1 and 2 plot time series of (i) the cross-sectional mean values of the forecasts of changes in house prices and forecasts of housing starts (dashed lines), (ii) the actual relative change in house prices and the actual housing starts (solid lines), and, (iii) the cross-sectional heterogeneity of forecasts as measured by the cross-sectional range of forecasts (shaded areas).

Insert Figures 1 and 2 about here.

The cross-sectional mean values of house prices and housing starts move in tandem with the respective actual values, at least as results for end-of-year values are concerned. This result is in line with economic intuition because forecast accuracy should increase as the forecast horizon decreases. Another important information conveyed by Figures 1 and 2 is that the cross-sectional heterogeneity of forecasts is substantial. In this respect, forecasts of house prices and housing starts resemble forecasts of, for example, exchange rates.[5] To the best of our knowledge, the cross-sectional heterogeneity of house prices and housing starts has not been documented in earlier literature. Given the substantial cross-sectional heterogeneity of the WSJ data, we used in our empirical analysis individual forecasts of house prices and housing starts rather than cross-sectional mean values.

The cross-sectional heterogeneity of forecasts of changes in house prices also indicates that the expected "upside" potential, as measured by the shaded area below actual changes in house price, only slightly decreased over time in the course of the U.S. subprime mortgage crisis. In contrast, the expected "downside" potential substantially increased over time, and only stabilized at the very end of the sample period. Interestingly, the overall picture that emerges with regard to forecasts of changes in housing starts is somewhat different. While the shaded area below the actual housing starts is limited in size, the shaded area of housing prices indicates that at least some forecasters perceived some "upside" potential with regard to housing starts. The perceived "upside" potential was relatively strong in early 2009,

[5] Cross-sectional heterogeneity of forecasts of exchange rates has been widely documented in recent literature (see, for example, Benassy-Quere et al. 2003).

but thereafter became much weaker again.

3 (Anti-)Herding of Forecasters

The significant cross-sectional heterogeneity of forecasts of house prices and housing starts gives rise to the question whether herding (or anti-herding) of forecasters helps to explain this heterogeneity. Herding of forecasters arises if forecasters deliberately center their forecasts around a consensus forecast.[6] The consensus forecast can be represented by the cross-sectional mean of the forecasts made by all forecasters who participate, in a given forecasting cycle, in a questionnaire survey. Anti-herding, in contrast, arises if forecasts try to differentiate forecasts by deliberately placing their forecast farther away from the consensus forecast.

We used a test that has recently been developed by Bernhardt et al. (2006) to analyze whether forecasters (anti-)herd. Their test is easy to implement, the economic interpretation of the test results is straightforward, and the test is robust to various types of specification errors. The mechanics of the test can be illustrated by considering a forecaster who forms an efficient private forecast of house prices or housing starts. The forecaster derives her private forecast by applying her optimal forecasting model, and by using all information available to her at the time she forms the forecast. Her private forecast, thus, should be unbiased, and the probability that her unbiased private forecast overshoots or undershoots the future house price should be 0.5.

The published forecast may differ from the private forecast if the published

[6]Our analysis concerns the cross-sectional herding (or anti-herding) of forecasters. In earlier empirical research, researchers have used the term " herding" to characterize the time-series properties of forecasts. Our use of the term herding, thus, should not be confused with the terminology used by other researchers who have used the term herding to describe, for example, trend-extrapolative forecasts in a time-series contexts.

forecast is influenced by the consensus forecast. In the case of herding, a forecaster places her published forecast closer to the consensus forecast than warranted by her private forecast. The published forecast will be biased towards the consensus forecast. In case the private forecast exceeds the consensus forecast, the published forecast thus will be smaller than the private forecast. The probability of undershooting is then smaller than 0.5. In a similar vein, if the private forecast is smaller than the consensus forecast, the probability that future house prices or future housing starts overshoot the published forecast is also smaller than 0.5. In contrast, in the case of anti-herding, the published forecast will be farther away from the consensus forecast than the private forecast. The result is that the probability of undershooting and the probability of overshooting will be larger than 0.5.

The probabilities of undershooting and overshooting can be used to develop a simple test of herding and anti-herding. Under the null hypothesis that forecasters neither herd nor anti-herd, the probability, P, that the forecast of future house prices or housing starts ($E_{i,t}[s_{t+1}]$) made by forecaster i overshoots (undershoots) future house prices or housing starts (s_{t+1}) should be 0.5, regardless of the consensus forecast ($\bar{E}_t[s_{t+1}]$). The conditional probability of undershooting in case a forecast exceeds the consensus forecast should be

$$P(s_{t+1} < E_{i,t}[s_{t+1}] \,|\, E_{i,t}[s_{t+1}] > \bar{E}_t[s_{t+1}], s_{t+1} \neq E_{i,t}[s_{t+1}]) = 0.5, \quad (1)$$

and the conditional probability of overshooting in the case a forecast is smaller than the consensus forecast should be

$$P(s_{t+1} > E_{i,t}[s_{t+1}] \,|\, E_{i,t}[s_{t+1}] < \bar{E}_t[s_{t+1}], s_{t+1} \neq E_{i,t}[s_{t+1}]) = 0.5. \quad (2)$$

In the case of herding, published forecasts will center around the consensus forecast, implying that the conditional probabilities should be smaller than 0.5. In the case of anti-herding, the published forecast will be farther away from the consensus forecast, and the conditional probabilities should be larger than 0.5. The test statistic, S, defined as the arithmetic average of the sample estimates of the two conditional probabilities, should assume the value $S = 0.5$ in case of unbiased forecasts, the value $S < 0.5$ in case of herding, and the value $S > 0.5$ in case of anti-herding. Bernhardt et al. (2006) show that the test statistic S, asymptotically has a normal sampling distribution. They also demonstrate that, due to the averaging of conditional probabilities, the test statistic, S, is robust to phenomena like, for example, correlated forecast errors and optimism or pessimism among forecasters. Such phenomena make it more difficult to reject the null hypothesis of unbiased forecasts.

Please insert Table 2 about here.

The results summarized in Table 2 show that the test statistic, S, significantly exceeds the value 0.5, thereby, provide strong evidence of anti-herding. The test statistic, S, yields evidence of anti-herding in the case of short-term forecasts irrespective of whether one analyzes data on house prices or housing starts. This results is supported in Table 3 where we used the consensus of the previous period to account for the information set of the forecasters.[7] Again the evidence of anti-herding is strong regardless of the forecast horizon and whether looking at house prices or housing starts.

4 Conclusions

We have used the monthly WSJ survey data on forecasts of house prices and housing starts for the period August 2006 − December 2010 to study

[7] More precisely, we combined short-term and medium-term forecasts. For instance, to detect herding for the short-term January forecasts, we used the consensus of the medium-term forecast of December. Since we do not have a consensus for the medium-term forecast in January, we skipped these forecasts from the herding test.

(anti-)herding of forecasters. Our empirical results show that anti-herding is prevalent among forecasters of house prices, where anti-herding is less strong in the case of medium-term forecasts of housing starts. This key results of our empirical analysis does not only provide insights into how forecasters form forecasts, but it may also be useful for recent policy debates. One such policy debate concerns the relevance of house prices for monetary policy. Because house prices play a major role for the transmission of monetary policy, a natural question is whether central banks should account for housing market developments in their inflation projections. Inflation projections can be formed by using, for example, VAR-based forecasts of house prices and housing starts, or by using private-sector forecasts of house prices and housing starts. Our key result demonstrates that, when monetary policy uses private-sector forecasts, it becomes important to take into consideration heterogeneity and scattering of forecasts caused by anti-herding of forecasters.

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Table 1: Summary Statistics of the Survey Data (2006 – 2010)

Panel A: Forecasts of House Prices (in p.a.)

	Short-Term	Medium-Term	Actual
Mean	-2.6939	-.14066	-2.8577
Standard Deviation	(0.0807)	(0.0684)	
Observations	2640	2640	48

Panel B: Forecasts of Housing Starts (in mns.)

	Short-Term	Medium-Term	Actual
Mean	0.963	1.084	0.887
Standard Deviation	(0.0076)	(0.0066)	
Observations	2640	2640	48

Note: The short-term (medium-term) forecasts refer to the forecasts for the current (next) year. The actual values were taken from Federal Housing Finance Agency.

Table 2: Test for Herding

Panel A: Short-Term Forecasts of House Prices

	$E_{i,t}[s_{t+1}] < \bar{E}_t[s_{t+1}]$	$E_{i,t}[s_{t+1}] > \bar{E}_t[s_{t+1}]$
$s_{t+1} < E_{i,t}[s_{t+1}]$	289 / 22.7 %	1187 / 87.0 %
$s_{t+1} > E_{i,t}[s_{t+1}]$	984 / 77.3 %	177 / 13.0 %
Sum	1273 / 100.0 %	1364 / 100.0 %
S-Stat	0.82	
Stand. Dev.	0.0097	
Lower 99 %	0.80	
Upper 99 %	0.85	

Panel B: Medium-Term Forecasts of House Price

	$E_{i,t}[s_{t+1}] < \bar{E}_t[s_{t+1}]$	$E_{i,t}[s_{t+1}] > \bar{E}_t[s_{t+1}]$
$s_{t+1} < E_{i,t}[s_{t+1}]$	467 / 38.3 %	1064 / 74.8 %
$s_{t+1} > E_{i,t}[s_{t+1}]$	751 / 61.7 %	358 / 25.2 %
Sum	1218 / 100.0 %	1422 / 100.0 %
S-Stat	0.68	
Stand. Dev.	0.0098	
Lower 99 %	0.66	
Upper 99 %	0.71	

Panel C: Short-Term Forecasts of Housing Starts

	$E_{i,t}[s_{t+1}] < \bar{E}_t[s_{t+1}]$	$E_{i,t}[s_{t+1}] > \bar{E}_t[s_{t+1}]$
$s_{t+1} < E_{i,t}[s_{t+1}]$	884 / 67.3 %	1233 / 93.0 %
$s_{t+1} > E_{i,t}[s_{t+1}]$	430 / 32.7 %	93 / 7.0 %
Sum	1314 / 100.0 %	1326 / 100.0 %
S-Stat	0.63	
Stand. Dev.	0.0097	
Lower 99 %	0.60	
Upper 99 %	0.65	

Panel D: Medium-Term Forecasts of Housing Starts

	$E_{i,t}[s_{t+1}] < \bar{E}_t[s_{t+1}]$	$E_{i,t}[s_{t+1}] > \bar{E}_t[s_{t+1}]$
$s_{t+1} < E_{i,t}[s_{t+1}]$	960 / 71.0 %	980 / 76.1 %
$s_{t+1} > E_{i,t}[s_{t+1}]$	392 / 29.0 %	307 / 23.9 %
Sum	1352 / 100.0 %	1287 / 100.0 %
S-Stat	0.53	
Stand. Dev.	0.0097	
Lower 99 %	0.50	
Upper 99 %	0.55	

Table 3: Test for Herding using the previous consensus

Panel A: Short-Term Forecasts of House Prices

	$E_{i,t}[s_{t+1}] < \bar{E}_t[s_{t+1}]$	$E_{i,t}[s_{t+1}] > \bar{E}_t[s_{t+1}]$
$s_{t+1} < E_{i,t}[s_{t+1}]$	357 / 26.3 %	1119 / 87.5 %
$s_{t+1} > E_{i,t}[s_{t+1}]$	1001 / 73.7 %	160 / 12.5 %
Sum	1358 / 100.0 %	1279 / 100.0 %
S-Stat	0.81	
Stand. Dev.	0.0097	
Lower 99 %	0.78	
Upper 99 %	0.83	

Panel B: Medium-Term Forecasts of House Price

	$E_{i,t}[s_{t+1}] < \bar{E}_t[s_{t+1}]$	$E_{i,t}[s_{t+1}] > \bar{E}_t[s_{t+1}]$
$s_{t+1} < E_{i,t}[s_{t+1}]$	551 / 41.3 %	980 / 75.0 %
$s_{t+1} > E_{i,t}[s_{t+1}]$	782 / 58.7 %	327 / 25.0 %
Sum	1333 / 100.0 %	1307 / 100.0 %
S-Stat	0.67	
Stand. Dev.	0.0097	
Lower 99 %	0.64	
Upper 99 %	0.69	

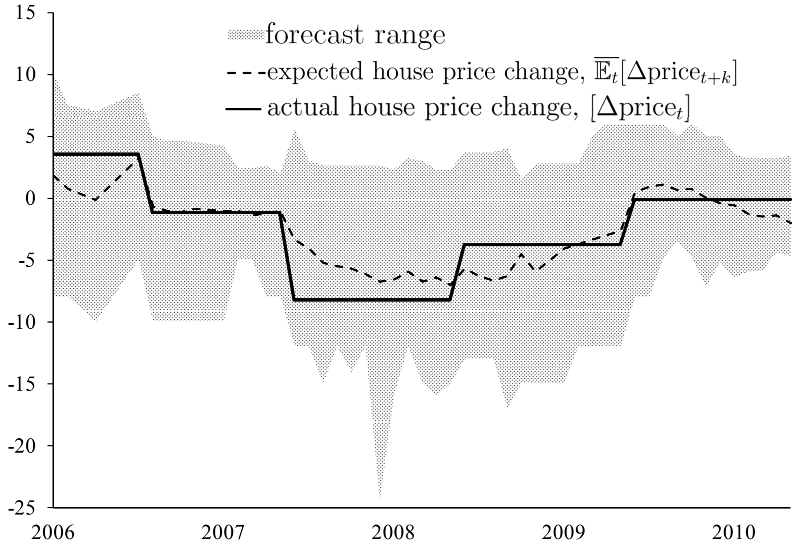
Panel C: Short-Term Forecasts of Housing Starts

	$E_{i,t}[s_{t+1}] < \bar{E}_t[s_{t+1}]$	$E_{i,t}[s_{t+1}] > \bar{E}_t[s_{t+1}]$
$s_{t+1} < E_{i,t}[s_{t+1}]$	967 / 69.2 %	1150 / 92.6 %
$s_{t+1} > E_{i,t}[s_{t+1}]$	431 / 30.8 %	92 / 7.4 %
Sum	1398 / 100.0 %	1242 / 100.0 %
S-Stat	0.62	
Stand. Dev.	0.0097	
Lower 99 %	0.59	
Upper 99 %	0.64	

Panel D: Medium-Term Forecasts of Housing Starts

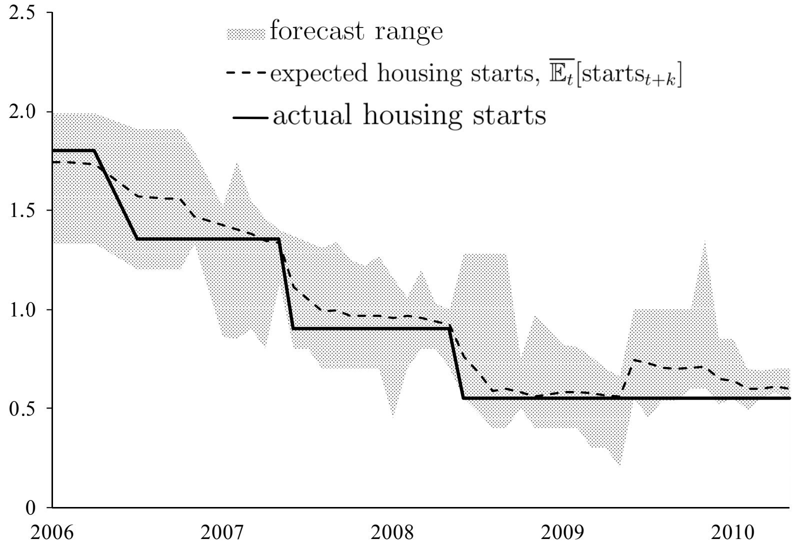
	$E_{i,t}[s_{t+1}] < \bar{E}_t[s_{t+1}]$	$E_{i,t}[s_{t+1}] > \bar{E}_t[s_{t+1}]$
$s_{t+1} < E_{i,t}[s_{t+1}]$	1034 / 71.1 %	906 / 76.6 %
$s_{t+1} > E_{i,t}[s_{t+1}]$	421 / 28.9 %	276 / 23.4 %
Sum	1455 / 100.0 %	1182 / 100.0 %
S-Stat	0.53	
Stand. Dev.	0.0098	
Lower 99 %	0.50	
Upper 99 %	0.55	

Figure 1: Expected and Actual Change in House Prices



Notes: This figure shows the mean of the short-term forecasts of the relative change in house price (dashed line), the actual change in house prices (solid line), and the forecast range (shaded area). The vertical distance between the expected and the actual house price captures the forecast error.

Figure 2: Expected and Actual Housing Starts



This figure shows the mean of the short-term forecasts of housing starts (dashed line), the actual housing starts (solid line), and the forecast range (shaded area). The vertical distance between the mean forecast and the actual housing starts captures the forecast error.