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Abhandlungen

Forecasting Changes in House Prices Under Asymmetric Loss: Evidence from the WSJ Forecast Poll*

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Abstract

The U.S. subprime mortgage crisis has witnessed that house prices may have a profound effect on the economy. A key question for researchers and policymakers is what can be learnt from forecasts of changes in house prices. We use survey data from the WSJ forecast poll to analyze this question. Forecasts of changes in U.S. house prices are consistent with cross-sectional heterogeneity across forecasters with respect to the shape of their loss function. Forecasters' loss function often appears to be asymmetric with respect to the forecast error, especially in the case of medium-term forecasts. Assuming an asymmetric loss function often (but not always) makes forecasts look rational. The asymmetry of forecasters' loss function tended to increase during the recent recession, but this increase was not persistent.

Prognose von Häuserpreisen bei asymmetrischer Verlustfunktion: Empirische Ergebnisse für die WSJ Umfragen

Zusammenfassung

Die Krise am U.S. amerikanischen Häusermarkt hat gezeigt, dass die Entwicklung der Häuserpreise starke gesamtwirtschaftliche Effekte haben kann. Eine zentrale Frage für Wissenschaftler und Wirtschaftspolitiker ist daher, was aus

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Umfragedaten über die Entwicklung von Häuserpreisen gelernt warden kann. Wir nutzen Umfragedaten des Wall Street Journal (WSJ), um diese Frage zu analysieren. Wir zeigen, dass die Prognosen der Veränderung von Häuserpreisen im Querschnitt über alle Prognostiker eine beachtliche Heterogenität aufweisen, was auf unterschiedliche Verlustfunktionen hindeutet. Prognostiker scheinen oftmals eine asymmetrische Verlaustfunktion zu haben, insbesondere für mittelfristige Prognosen. Eine asymmetrische Verlustfunktion trägt häufig (aber nicht immer) dazu bei, das die Prognosen mit dem Rationalitätskriterium vereinbar sind. In der jüngsten Krise scheint die Asymmetrie der Verlustfunktionen tendenziell zugenommen zu haben, wobei allerdings diese Zunahme eher nicht persistenter Natur war.

Keywords: Housing starts, Loss function, Rationality of forecasts
JEL Classification: D84

I. Introduction

The U.S. subprime mortgage crisis has witnessed that developments in housing markets may have a profound effect on the economy. Recent research has helped to develop a deeper understanding of these effects. On the theoretical side, researchers have studied dynamic stochastic general equilibrium models to explore how housing markets affect the dynamics of business cycles at the macroeconomic level (*Iacoviello* (2005); *Iacoviello/Neri* (2010)). On the empirical side, researchers have studied developments in housing markets by means of, for example, vector autoregressive models, cointegration and panel data models, and Markov-switching models (*Giuliodori* (2005); *Goodhart/Hofmann* (2008); *Adams/Füss* (2010); *Chang* et al. (2011), to name just a few). Still other researchers have studied speculative bubbles and market frenzies in housing markets, and the role economic fundamentals play for the development of such phenomena (*Brunnermeier/Julliard* (2008); *Fraser* et al. (2008)). Results of this theoretical and empirical research demonstrate that housing markets and the economy interact in a potentially complex way through various channels.

Given the strong links between housing markets and economic performance, many researchers have studied the predictability of developments in housing markets. Forecasts can be computed by means of the various econometric techniques that researchers have studied in earlier research (see, for example, *Brown* et al. (1997)). Alternatively, survey data of forecasts of developments in housing markets may provide a rich data environment to study the dynamics of housing markets. In recent literature, researchers have started to explore the properties of such survey data.

Pierdzioch et al. (2012a), for example, document that survey data of forecasts of housing starts in Canada, Japan, and the United States exhibit a non-negligible degree of cross-sectional heterogeneity. They further find that forecasts of housing starts violate classic rationality and unbiasedness criteria, and that forecasters' attempts to deliberately differentiate their forecasts from the forecasts of others (so called forecaster anti-herding) which may contribute to explain the cross-sectional heterogeneity of forecasts (see also *Pierdzioch* et al. (2013a)). *Pierdzioch* et al. (2012b) replicate these results using survey data of housing approvals in Australia. In yet another recent paper, *Pierdzioch* et al. (2013b) recover the potentially asymmetric shape of forecasters' loss function from survey data of forecasts of housing starts in the United States. Asymmetry of the loss function may explain why forecasts of housing starts violate classic unbiasedness criteria, and cross-sectional heterogeneity with respect to the shape of forecasters' loss function may contribute to the cross-sectional heterogeneity of forecasts.

While housing starts are an important indicator of developments in housing markets, the dynamics of house *prices* are likely also to play a prominent role for the type of balance-sheet and collateral effects that have been studied in the macroeconomic literature on the financial accelerator. For example, *Iacoviello/Neri* (2010) report, based on an estimated and simulated dynamic stochastic general equilibrium model, that collateral effects leverage the elasticity of U.S. consumption to housing wealth (that is, the product of the quantity of houses and house prices) by 2.5 percentage points from approximately 0.11 to 0.14, and that this collateral effect has grown in importance over time. Given the prominence of such collateral effects, our research complements earlier research on survey data of forecasts of housing quantities (housing starts, housing approvals) by shedding light on the properties of survey data of forecasts of changes in house *prices*. To this end, we use monthly survey data of forecasts of changes in house prices from the Wall Street Journal (WSJ) poll. To the best of our knowledge, the WSJ is the only survey that contains data on forecasts of the dynamics of house prices. The WSJ survey comprises data for more than 6,000 forecasts of changes in house prices in the United States for two different forecast horizons (3,500 current-year and 3,000 next-year forecasts), where the sample period runs from 2006 to 2012. The sample period, thus, covers the period of time of the recent U.S. subprime mortgage market crisis and the economic and financial turbulences that were triggered by this crisis.

Following *Pierdzioch* et al. (2013b), our research focuses on the potential asymmetric shape of forecasters' loss functions. If forecasters make forecasts of changes in house prices under an asymmetric loss function, their forecasts are likely to violate classic unbiasedness criteria (*Elliott* et al. (2008)). Under an asymmetric loss function, forecasters incur a different loss of an underestimation compared to an overestimation of the same size. As a result, if one maintains the assumption of a symmetric loss function when forecasters, in fact, have an asymmetric loss function, one is likely to conclude erroneously that forecasts show systematic biases and deviations from rationality. Because unbiasedness and rationality of forecasts are important building blocks of many empirical and theoretical models, it is not surprising that in recent years researchers have studied the implications of an asymmetric loss function in various areas of economics. For example, researchers have explored whether asymmetric loss functions help to describe central banks' preferences over inflation and output growth (*Ruge-Murcia* (2003); *Surico* (2008); *Ikeda* (2010); *Pierdzioch* et al. (2012c), to name just a few). Other researchers have studied whether forecasts published by government agencies (*Auffhammer* (2007)) and international organizations (*Christodoulakis/Mamatzakis* (2008)) are consistent with an asymmetric loss function. Yet other researchers have explored the implications of asymmetric loss functions for tests of rational and unbiased forecasts (*Batchelor/Peel* (1999); *Elliott* et al. (2008)). Less is known, however, about the usefulness of asymmetric loss functions for modeling and forecasting developments in housing markets. In fact, apart from early research by *Cain/Janssen* (1995) and *Skitmore/Cheung* (2007), who use asymmetric loss functions for forecasting and modeling housing and construction prices, and the more recent research by *Pierdzioch* et al. (2013b), we are not aware of any research that uses an asymmetric loss function to model forecasts of developments in housing markets. Our research helps to close this gap in the literature.

In order to study the potentially asymmetric shape of forecasters loss function, we apply the approach advanced by *Elliott* et al. (2005) to study the properties of forecasts of changes in housing prices under an asymmetric loss function. We use their approach in our research because it is easy to implement, it informs about the type of a potential asymmetry in forecasters' loss function, and it allows the rationality of forecasts under an asymmetric loss function to be tested. Our results can be summarized as follows: We find a non-negligible degree of cross-sectional heterogeneity across forecasters with respect to the shape of their loss function.

While some forecasters seem to forecast under a symmetric loss function, the symmetry assumption cannot be retained for other forecasters. The asymmetry of the loss function appears to be somewhat stronger for medium-term forecasts than for short-term forecasts. Assuming an asymmetric loss function often (but not always) makes forecasts look rational when invoking a symmetric loss function leads to a rejection of forecast rationality. Results further show that the asymmetry of forecasters' loss function tended to increase during the recent recession, but this increase was not persistent.

We organize the remainder of our analysis as follows. In Section II, we describe the approach developed by *Elliott* et al. (2005) to study the shape of forecasters' loss function. Because their approach has been used extensively in earlier research (see *Pierdzioch* et al. (2013b)), our description is relatively brief. In Section III, we summarize our empirical analysis. In Section IV, we offer some concluding remarks.

II. Modeling an Asymmetric Loss Function

The approach developed by *Elliott* et al. (2005) to modeling an asymmetric loss function rests on the assumption that the loss function, $\mathcal{L}$, of forecasters can be described in terms of the following general functional form:

$$\mathcal{L} = \alpha + \left[(1-2\alpha) I\left(s_{t+1} - f_{t+1} < 0 \right) \right] \left| s_{t+1} - f_{t+1} \right|^{p}, \tag{1}$$

where $s_{t+1}\left(f_{t+1}\right)$ reflects the (period-t forecast of) changes in house prices in period $t+1$ and I reflects an indicator function. For $p = 1$, Equation (1) refers to a linear-linear (lin-lin) loss function and for $p = 2$ to a quadratic-quadratic (quad-quad) loss function. The parameter $\alpha \in \left(0,1\right)$ governs the degree of asymmetry of the loss function. The general functional form given in Equation (1) implies that, in the case of $\alpha = 0.5$ the loss function is symmetric. The standard symmetric quadratic loss function obtains for $\alpha = 0.5$ and $p = 2$. In this case, the loss forecasters incur increases in the squared forecast error. For $\alpha = 0.5$ and $p = 1$, the loss increases in the absolute forecast error.

Elliott et al. (2005) show that, given the general functional form of the loss function (as defined in terms of the parameter p), the asymmetry parameter, α, can be consistently estimated by means of the Generalized Methods of Moments as

(2) $$\hat{\alpha} = \frac{\widehat{\gamma'}_1 \hat{s}^{-1} \hat{\gamma}_2}{\widehat{\gamma'}_1 \hat{s}^{-1} \hat{\gamma}_1}$$

where $\hat{\alpha}$ denotes the estimate, and where we define

(3) $$\hat{\gamma}_1 = \frac{1}{T} \sum_{t=\tau}^{T+\tau-1} \upsilon_t \left| s_{t+1} - f_{t+1} \right|^{p-1}$$

and

(4) $$\hat{\gamma}_2 = \frac{1}{T} \sum_{t=\tau}^{T+\tau-1} \upsilon_t \, I\left(s_{t+1} - f_{t+1} < 0 \right) \left| s_{t+1} - f_{t+1} \right|^{p-1}$$

and the vector of instruments, υ_t, is used to estimate a weighting matrix given by $\hat{S} = \frac{1}{T} \sum_{t=\tau}^{T+\tau-1} \upsilon_t \upsilon_t' \left(I\left(s_{t+1} - f_{t+1} < 0 \right) - \hat{\alpha} \right)^2 \left| s_{t+1} - f_{t+1} \right|^{2p-2}$, and $I(.)$ denotes the indicator function, and T denotes the number of forecasts available, starting in period $\tau + 1$. With the weighting matrix depending on $\hat{\alpha}$, estimation is done iteratively.

Testing whether $\hat{\alpha}$ differs from α_0 is done by using the following z-test $\sqrt{T}\left(\hat{\alpha} - \alpha_0 \right) \to \mathcal{N}\left(0, \left(\hat{h}' \hat{S}^{-1} \hat{h} \right)^{-1} \right)$, where $\hat{h} = \frac{1}{T} \sum_{t=\tau}^{T+\tau-1} \upsilon_t \left| s_{t+1} - f_{t+1} \right|^{p-1}$. *Elliott* et al. (2005) further prove that a test for rationality of forecasts, given a loss function of the lin-lin or a quad-quad type $\left(p = 1.2 \right)$, can be performed by computing

(5) $$J\left(\hat{\alpha} \right) = \frac{1}{T}\left(x_t' \hat{S}^{-1} x_t \right) \sim \chi^2_{d-1},$$

Where $x_t = \sum_{t=\tau}^{T+\tau-1} \upsilon_t \left[I\left(s_{t+1} - f_{t+1} < 0 \right) - \hat{\alpha} \right] \left| s_{t+1} - f_{t+1} \right|^{p-1}$ and d denotes the number of instruments. In the case of a symmetric loss function, the rationality test is given by $J\left(0.5 \right) \sim \chi^2_d$.

The statistic $J\left(0.5 \right)$ answers the question of whether forecasters under the maintained assumption of a symmetric loss function form rational forecasts of changes in house prices. The statistic $J\left(\hat{\alpha} \right)$ answers the question of whether forecasters form rational forecasts of changes in house prices, given an estimated asymmetric loss function of the lin-lin or quad-quad functional form. A comparison of $J\left(\hat{\alpha} \right)$ with $J\left(0.5 \right)$ shows whether an asymmetric loss function helps to remedy a potential failure of rationality of forecasts of changes in house prices observed under a symmetric loss function.

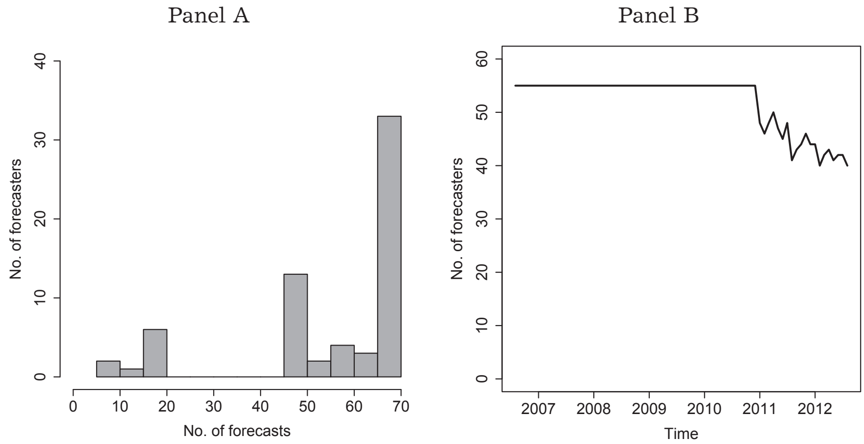
III. Empirical Analysis

Section 1 contains a description of the WSJ survey data on forecasts of changes in house prices. Section 2 summarizes the estimates of the asymmetry parameter and the results of rationality tests. Section 3 lays out the results of a rolling-window analysis that helps to trace out changes in the asymmetry parameter over time.

1. The Data

The WSJ conducts, usually on a monthly basis, a questionnaire survey of forecasters who work at universities, banks and other private companies, and research institutes. Forecasters are asked about their forecasts of several important financial and economic U.S. variables. The questionnaire survey was launched in 1981 and, at that time, focused on forecasts of the dynamics of the Fed prime rate. Later on, the scope of the questionnaire survey has increased considerably to include forecasts of the growth rate of GNP (since 1985), the inflation rate and the unemployment rate (since 1989), the growth rate of GDP (since 1991), and the Federal Funds rate (since 2002). In view of the broad set of financial and economic variables that the WSJ survey data cover, it is not surprising that much significant research has been undertaken based on this survey data. *Greer* (2003), for example, analyzes the directional accuracy of forecasts of yields on 30-year U.S. Treasury bonds. *Cho/Hersch* (1998) and *Frenkel* et al. (2009) explore whether forecaster characteristics help to explain forecast accuracy and forecast bias. *Kolb/Stekler* (1993) 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. *Mitchell/Pearce* (2007) analyze the unbiasedness and accuracy of interest-rate and exchange-rate forecasts. The potential asymmetry of forecasts of changes of house prices, however, has not been analyzed, to the best of our knowledge, in earlier research.

The WSJ survey data contain forecasts of changes in house prices since August 2006. To the best of our knowledge, the WSJ is the only prominent survey covering forecasts of changes in house prices. Other widely studied survey data like, for example, the data compiled and published by Consensus Economics only contain information on housing starts and housing approvals. Forecasts are available for the current year (short-term forecasts) and the next year (medium-term forecasts). The forecast horizon

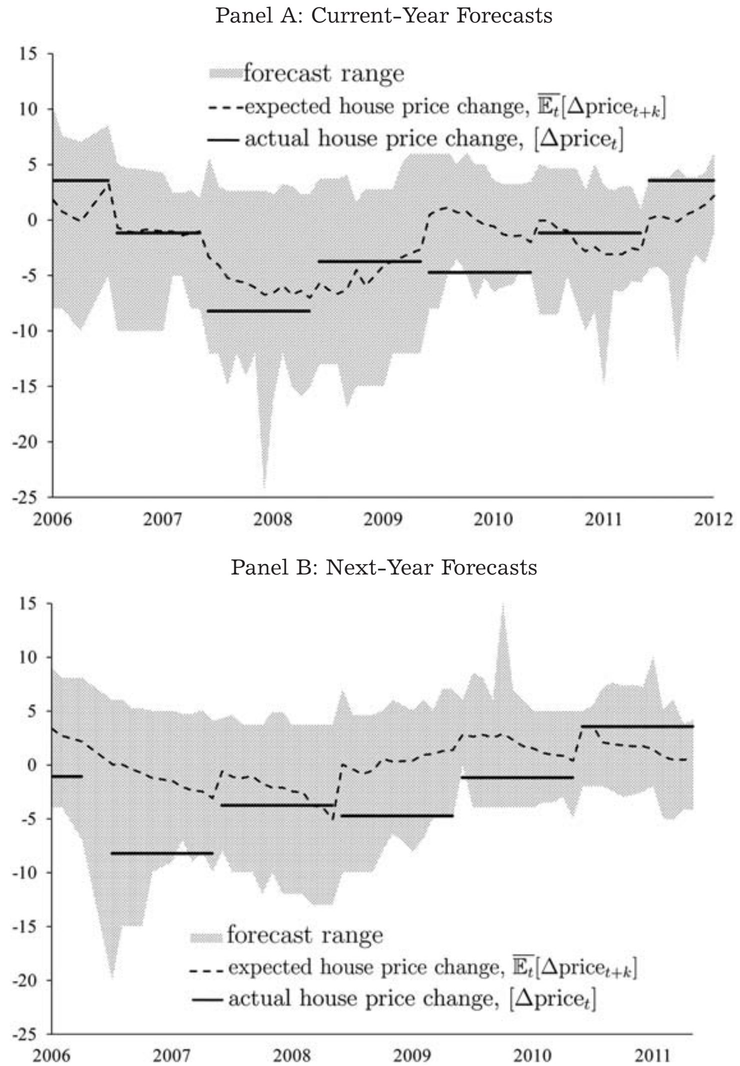


Notes: Panel A shows a histogram of the number of short-term forecasts made by the forecasters. Panel B shows how many forecasters participated in the surveys.

Figure 1: Distribution of Forecasts Across Forecasters and Across Time

varies between one and 12 months for short-term forecasts and between 13 and 24 months for medium-term forecasts. Until August 2012, a total of 64 forecasters have contributed to the WSJ survey, yielding more than 3,000 forecasts of changes in house prices. We, thus, can analyze the shape of the loss function at the level of individual forecasters. Moreover, because the WSJ survey data cover the period of time of the U.S. subprime mortgage crisis, we can study how the shape of forecasters loss function has changes in times of financial and economic distress.

Figure 1 shows in Panel A how often forecasters contributed to the survey (time-series dimension), and in Panel B how many forecasters participated in the surveys (cross-sectional dimension). The cross-sectional dimension of the WSJ survey data was relatively stable across time. Only since approximately 2010/2011 the number of forecasts per survey has started slightly to decrease, but has never dropped below 40 forecasts per survey. That is, not all forecasters always contributed their forecasts to the WSJ questionnaire study. The WSJ survey data, thus, is an unbalanced panel dataset. In total, forecasts are available from 64 forecasters, where some forecasters published only a few forecasts, and 55 forecasters published at least 45 forecasts. In our empirical analysis in Sections 2 and 3 below, we shall focus on these forecasters. We excluded additional seven forecasters from our empirical analysis because their forecasts did not show enough variability to permit estimation.



Notes: This figure shows the consensus forecast (dotted line) as well as the forecast range (shaded area) of the change in house price for short-term and medium-term forecasts. The realized value (solid line) is taken from the Federal Housing Finance Agency (http://www.fhfa.gov).

Figure 2: Expected and Actual Change in House Prices (in % p.a.)

Figure 2 plots our data for the short-term forecasts (Panel A) and the medium-term forecasts (Panel B), where the solid line represents actual changes in house prices, the dashed lines represents the cross-sectional mean value of forecasts (that is, the consensus forecast), and the shaded

Table 1

Forecast Errors of Changes in House Prices

Period/Horizon	Short-term	Medium-term
Crisis Period	–0.824*	–2.608*
Standard Error	(.128)	(.119)
No. Of observations	1,045	1,045
Full sample	–0.598*	–3.054*
Standard Error	(.065)	(.073)
No. Of observation	3,524	3,093

Note: This table reports the cross-sectional forecast error and its standard deviation. An asterisk (*) denotes significance at the one percent level. The forecast error is defined as $s_{t+k} - f_{t+k}$. The Crisis period is defined using the NBER dating of the recession as the period of time between December 2007 and June 2009 (see http://www.nber.org/cycles.html).

area visualizes the cross-sectional range of forecasts. The shaded area, thus, represents the cross-sectional heterogeneity of forecasts. *Pierdzioch* et al. (2012a) and (2012b) report a similar cross-sectional heterogeneity for forecasts of housing starts and housing approvals. The cross-sectional heterogeneity of forecasts was particularly large during the recent financial and economic crisis, as defined using the NBER dating of the recession as the period of time between December 2007 and June 2009 (see http://www.nber.org/cycles.html). On balance, it seems that the larger proportion of the shaded area more often can be found above than below the solid lines. This effect is more pronounced for medium-term forecasts than for short-term forecasts. When averaged across forecasters and across time, it thus seems that forecasters overpredict changes in house prices more often than they underpredict changes in house prices. Results plotted in Table 1 confirm this impression.

Table 1 reports the average forecast errors for both short-term and medium-term forecasts for the full sample period and the recession period from December 2007 to June 2009. Results show that the forecasters systematically overestimated the change in house prices, implying that forecasts were, on average, biased. This bias is stronger for medium-term forecasts compared to short-term forecasts. The bias also tends to be stronger, as far as short-term forecasts are concerned, during the recession period as compared to the rest of the sample period. Given the systematic bias in forecasts of changes in house prices, classic tests of forecast rationality (*Mincer/Zarnowitz* (1969); *Ito* (1990)) would indicate

Table 2

Wilcoxon Test for an Asymmetric Distribution of Forecast Errors

No.	Obs.	Statistic	p value	No.	Obs.	Statistic	p value
1	68	1149.0	0.8858	25	48	562.0	0.7936
2	61	314.0	0.0000	26	48	269.0	0.0011
3	67	1221.0	0.6106	27	68	479.0	0.0000
4	68	308.5	0.0000	28	48	699.0	0.2568
5	68	918.0	0.1198	29	48	638.0	0.6111
6	48	18.0	0.0000	30	68	481.0	0.0000
7	67	713.0	0.0078	31	68	946.0	0.1662
8	65	920.5	0.4261	32	67	1959.5	0.0000
9	48	158.0	0.0000	33	68	1306.0	0.4181
10	57	1223.5	0.0016	34	68	1132.0	0.8043
11	68	630.5	0.0009	35	56	826.0	0.8223
12	68	1329.0	0.2365	36	49	803.0	0.0585
13	68	1025.0	0.3672	37	67	1453.0	0.0498
14	66	1421.0	0.0439	38	54	817.0	0.5238
15	59	746.0	0.2958	39	48	266.0	0.0046
16	68	1018.0	0.3448	40	48	475.5	0.2503
17	67	1141.0	0.9925	41	48	199.0	0.0001
18	68	594.0	0.0004	42	68	502.5	0.0000
19	68	1099.0	0.6533	43	59	898.0	0.9248
20	68	1089.0	0.6099	44	67	800.0	0.0345
21	68	1074.0	0.5469	45	68	449.0	0.0000
22	68	853.0	0.0508	46	66	1183.0	0.6225
23	66	1122.0	0.9185	47	68	1604.0	0.0037
24	67	876.0	0.1008	48	48	234.0	0.0003

Note: No. = number of forecaster. Obs. = number of observations. Statistic = Test statistic of the Wilcoxon-Test. The forecast error is defined as $s_{t+k} - f_{t+k}$.

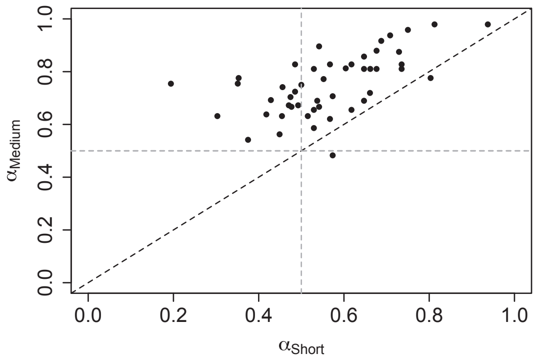
that forecasts are not consistent with the concept of forecast rationality. Such classic tests, however, implicitly assume that forecasters form their forecasts under a symmetric (that is, quadratic) loss function. If, in contrast, forecasters have an asymmetric loss function the bias in their forecasts may be consistent with forecast rationality.

Table 2 shows the numbers of observations along with the results of a Wilcoxon test under the null hypothesis that the distribution of forecast errors is symmetric around zero. The names of the forecasters and the institutions for which they work are not reported, but are available upon request. We report results for short-term forecasts. Confirming the results summarized in Table 1, we find evidence that a seizable number of forecasters seem to form forecasts under an asymmetric loss function. The results of the test are significant for 23 forecasters (at the 10% level of significance). For medium-term forecasts (results not reported), the Wilcoxon test yields significant results for 45 forecasters. Evidence of an asymmetric loss function, thus, is stronger for medium-term than for short-term forecasts. The results, however, are not significant for all forecasters, indicating again the presence of cross-sectional heterogeneity with regard to the shape of forecasters' loss function.

2. The Asymmetry Parameter and Forecast Rationality

To start our analysis of the asymmetry of forecasters' loss function, we consider a particularly simple version of the approach described in Section II. Equation (2) shows that the approach considerably simplifies in case of a lin-lin loss function if we assume that the only instrument being used is a constant. In this simple version of the approach, the estimate of the asymmetry parameter, $\hat{\alpha}$, can be computed as the proportion of negative forecast errors. We, thus, compute, under the assumption that the loss function is of the lin-lin type, the proportion of negative forecast errors for every forecaster in our dataset, and for both short-term and medium-term forecasts.

Figure 3 summarizes the results and shows the asymmetry parameter $\hat{\alpha}$ for short-term (medium-term) forecasts on the horizontal (vertical) axis. Three results stand out. First, there is a substantial heterogeneity across forecasters with respect to the estimated asymmetry parameter. It follows that cross-sectional heterogeneity with respect to the estimated asymmetry parameter accounts, at least in part, for the cross-sectional heterogeneity of forecasts shown in Figure 2. Second, for most forecasters, we find that the estimated asymmetry parameter assumes a value larger than 0.5, the value it would assume under a symmetric loss function. In the case of short-term forecasts, the forecasts made by some forecasters are consistent with an estimated asymmetry parameter smaller than 0.5. The majority of forecasters, however, form forecasts that are consistent with an estimated parameter larger than 0.5, implying that they seem to experience a higher loss when underpredicting the change in house prices rather than making an overprediction of the same size.



Notes: This figure presents the estimates of the asymmetry parameter based on short-term and medium-term forecasts for a model that features as the only instrument a constant. The loss function is of the lin-lin type. The light grey dotted lines denote the 0.5 benchmark value. The bold black dotted line is the 45 degree line. We computed this graph and the empirical results documented in this research using the free software R (R Development Core Team 2012).

Figure 3: Estimate of the Asymmetry Parameter

Third, the degree of asymmetry of the loss function appears to be stronger in the case of medium-term than in the case of short-term forecasts. For some forecasters, we find that the estimated asymmetry parameter is smaller than 0.5 in the case of short-term forecasts while, for the same forecasters, the estimated asymmetry parameter appears to be larger than 0.5 in the case of medium-term forecasts (upper left cell of Figure 3).

Table 3

Estimation Results (Short-Term Forecasts, Lin-Lin Loss Function)

No.	Obs.	$\hat{\alpha}$	se	z-value	$J(0.5)$	p value	$J(\hat{\alpha})$	p value
1	68	0.5318	0.0605	0.5996	2.8822	0.2367	2.5243	0.1121
2	61	0.8082	0.0504	0.0000	22.853	0.0000	0.4857	0.4858
3	67	0.4919	0.0611	0.8941	2.7305	0.2553	2.7584	0.0967
4	68	0.7007	0.0555	0.0003	12.049	0.0024	4.1064	0.0427
5	68	0.6225	0.0588	0.0372	5.3572	0.0687	1.3359	0.2478
6	48	0.9450	0.0102	0.0000	39.357	0.0000	2.7866	0.0951
7	67	0.5700	0.0605	0.2468	2.6037	0.2720	1.3764	0.2407

(continued on the next page)

(Table 3: continued)

No.	Obs.	$\hat{\alpha}$	se	z-value	$J(0.5)$	p value	$J(\hat{\alpha})$	p value
8	65	0.4751	0.0619	0.6875	2.4416	0.2950	2.3968	0.1216
9	48	0.7812	0.0597	0.0000	15.506	0.0004	2.6661	0.1025
10	57	0.3066	0.0611	0.0015	9.0235	0.0110	6.5196	0.0107
11	68	0.6804	0.0566	0.0014	12.134	0.0023	6.2798	0.0122
12	68	0.4555	0.0604	0.4610	0.8165	0.6648	0.3086	0.5786
13	68	0.5312	0.0605	0.6060	2.2807	0.3197	1.9634	0.1611
14	66	0.2900	0.0559	0.0002	11.173	0.0037	2.0488	0.1523
15	59	0.6721	0.0611	0.0049	8.4279	0.0148	1.9075	0.1672
16	68	0.5796	0.0599	0.1838	4.3830	0.1118	2.5791	0.1083
17	67	0.5672	0.0605	0.2667	1.2456	0.5364	0.0323	0.8574
18	68	0.6646	0.0573	0.0040	7.7190	0.0211	0.5789	0.4468
19	68	0.5300	0.0605	0.6201	0.9046	0.6362	0.6728	0.4121
20	68	0.4836	0.0606	0.7861	3.5810	0.1669	3.6003	0.0578
21	68	0.4827	0.0606	0.7756	5.0471	0.0802	5.0527	0.0246
22	68	0.7416	0.0531	0.0000	15.913	0.0004	13.304	0.0003
23	66	0.4528	0.0613	0.4412	1.6608	0.4359	1.2159	0.2702
24	67	0.5587	0.0607	0.3330	4.9333	0.0849	3.6985	0.0545
25	48	0.5658	0.0715	0.3576	8.8873	0.0118	8.8054	0.0030
26	48	0.7296	0.0641	0.0003	10.143	0.0063	0.0411	0.8394
27	68	0.7365	0.0534	0.0000	15.263	0.0005	0.1733	0.6772
28	48	0.3479	0.0688	0.0270	5.4703	0.0649	4.2697	0.0388
29	48	0.6114	0.0704	0.1133	4.1385	0.1263	1.5610	0.2115
30	68	0.7463	0.0528	0.0000	16.595	0.0002	1.5161	0.2182
31	68	0.6260	0.0587	0.0318	6.2860	0.0432	2.2479	0.1338
32	67	0.1934	0.0483	0.0000	25.130	0.0000	0.0694	0.7923
33	68	0.4700	0.0605	0.6202	0.8740	0.6460	0.6576	0.4174
34	68	0.5867	0.0597	0.1467	6.7071	0.0350	5.1564	0.0232
35	56	0.4282	0.0661	0.2778	1.2556	0.5338	0.1286	0.7199
36	49	0.4484	0.0710	0.4680	0.7399	0.6908	0.2549	0.6137

(continued on the next page)

(Table 3: continued)

No.	Obs.	$\hat{\alpha}$	se	z-value	$J(0.5)$	p value	$J(\hat{\alpha})$	p value
37	67	0.3978	0.0598	0.0873	6.5791	0.0373	6.599	0.0102
38	54	0.5000	0.0680	1.0000	3.7355	0.1545	3.7355	0.0533
39	48	0.7322	0.0639	0.0003	11.601	0.0030	2.4635	0.1165
40	48	0.5564	0.0717	0.4319	7.3863	0.0249	6.257	0.0124
41	48	0.8138	0.0562	0.0000	18.891	0.0001	0.0974	0.7550
42	68	0.6478	0.0579	0.0107	6.0494	0.0486	0.1619	0.6874
43	59	0.4746	0.0650	0.6955	0.1728	0.9172	0.0218	0.8827
44	67	0.5392	0.0609	0.5196	2.1316	0.3444	1.6226	0.2027
45	68	0.6993	0.0556	0.0003	13.092	0.0014	3.8902	0.0486
46	66	0.5155	0.0615	0.8005	0.9380	0.6256	0.8433	0.3585
47	68	0.3518	0.0579	0.0105	6.0423	0.0487	0.2523	0.6154
48	48	0.7447	0.0629	0.0001	15.426	0.0004	5.6117	0.0178

Note: No. = number of forecaster. Obs. = number of observations. se = standard error. Instruments = constant, lagged change in house prices. z value = p value of the z-test.

Table 4

Estimation Results (Short-Term Forecasts, Quad-Quad Loss Function)

No.	Obs.	$\hat{\alpha}$	se	z-value	$J(0.5)$	p value	$J(\hat{\alpha})$	p value
1	68	0.5544	0.0724	0.2276	0.5408	0.7631	0.0042	0.9486
2	61	0.9038	0.0328	0.0000	22.916	0.0000	1.7178	0.1900
3	67	0.5227	0.0711	0.3753	11.013	0.0041	10.646	0.0011
4	68	0.9484	0.0166	0.0000	28.029	0.0000	5.0037	0.0253
5	68	0.6057	0.0690	0.0652	2.4533	0.2933	0.1339	0.7145
6	48	0.9235	0.0035	0.0000	32.217	0.0000	2.7951	0.0946
7	67	0.7394	0.0544	0.0000	9.9990	0.0067	0.0128	0.9098
8	65	0.6353	0.0711	0.0309	7.6023	0.0223	4.3787	0.0364
9	48	0.9030	0.0403	0.0000	22.077	0.0000	1.6263	0.2022
10	57	0.1931	0.0559	0.0000	11.476	0.0032	4.7846	0.0287
11	68	0.8614	0.0440	0.0000	22.751	0.0000	4.9611	0.0259

(continued on the next page)

(Table 4: continued)

No.	Obs.	$\hat{\alpha}$	se	z-value	$J(0.5)$	p value	$J(\hat{\alpha})$	p value
12	68	0.4267	0.0724	0.1576	3.2898	0.1930	3.1830	0.0744
13	68	0.5698	0.0754	0.1789	3.2623	0.1957	2.2893	0.1303
14	66	0.3377	0.0672	0.0093	5.3001	0.0707	1.1801	0.2773
15	59	0.5925	0.0767	0.1163	3.2977	0.1923	1.5019	0.2204
16	68	0.6594	0.0684	0.0114	9.1314	0.0104	4.7955	0.0285
17	67	0.4854	0.0751	0.4232	0.0465	0.9770	0.0095	0.9222
18	68	0.8140	0.0480	0.0000	18.476	0.0001	1.7035	0.1918
19	68	0.5233	0.0731	0.3754	0.1327	0.9358	0.0297	0.8633
20	68	0.5719	0.0676	0.1459	8.4517	0.0146	6.8939	0.0086
21	68	0.5716	0.0673	0.1457	3.1703	0.2049	1.9941	0.1579
22	68	0.7473	0.0596	0.0000	16.022	0.0003	9.8348	0.0017
23	66	0.5193	0.0743	0.3979	0.5735	0.7507	0.4790	0.4889
24	67	0.6831	0.0618	0.0021	10.415	0.0055	3.5596	0.0592
25	48	0.6321	0.0821	0.0572	7.0977	0.0288	5.9797	0.0145
26	48	0.8029	0.0585	0.0000	12.719	0.0017	0.1217	0.7272
27	68	0.8868	0.0337	0.0000	25.540	0.0000	2.6301	0.1049
28	48	0.3378	0.0812	0.0258	4.9767	0.0831	6.4762	0.0109
29	48	0.4282	0.0804	0.1883	1.0779	0.5834	0.5241	0.4691
30	68	0.8126	0.0495	0.0000	18.852	0.0001	3.6188	0.0571
31	68	0.6799	0.0646	0.0035	10.608	0.0050	4.0903	0.0431
32	67	0.1243	0.0439	0.0000	23.945	0.0000	0.4486	0.5030
33	68	0.4511	0.0734	0.2539	2.5737	0.2761	2.6317	0.1047
34	68	0.5822	0.0698	0.1216	2.0529	0.3583	0.7070	0.4004
35	56	0.5251	0.0803	0.3779	7.6481	0.0218	7.1226	0.0076
36	49	0.3375	0.0750	0.0177	3.8671	0.1446	0.0036	0.9520
37	67	0.3178	0.0635	0.0028	6.2734	0.0434	0.2171	0.6413
38	54	0.5108	0.0817	0.4477	5.9531	0.0510	5.7621	0.0164
39	48	0.8268	0.0641	0.0000	12.242	0.0022	2.3409	0.1260
40	48	0.6165	0.0875	0.0948	2.9727	0.2262	1.0496	0.3056
41	48	0.8460	0.0526	0.0000	17.150	0.0002	0.0265	0.8707
42	68	0.8257	0.0435	0.0000	18.457	0.0001	1.9582	0.1617
43	59	0.5127	0.0773	0.4350	0.4450	0.8005	0.4064	0.5238

(continued on the next page)

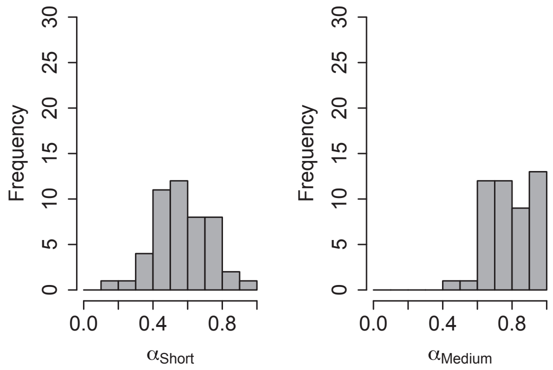
(Table 4: continued)

No.	Obs.	$\hat{\alpha}$	se	z-value	$J(0.5)$	p value	$J(\hat{\alpha})$	p value
44	67	0.7584	0.0630	0.0001	14.851	0.0006	6.2470	0.0124
45	68	0.9055	0.0290	0.0000	24.177	0.0000	3.4098	0.0648
46	66	0.4388	0.0750	0.2088	1.5021	0.4719	1.1911	0.2751
47	68	0.2591	0.0663	0.0003	8.5174	0.0141	0.1409	0.7073
48	48	0.9203	0.0337	0.0000	22.079	0.0000	2.6301	0.1049

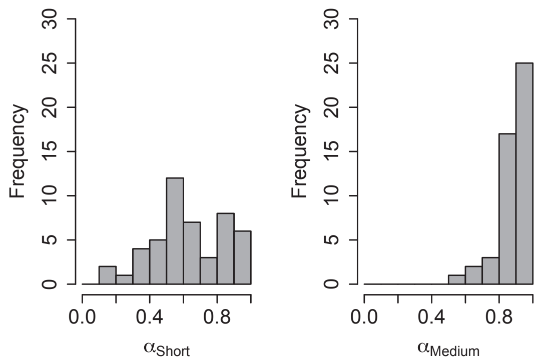
Note: No. = number of forecaster. Obs. = number of observations. se = standard error. Instruments = constant, lagged change in house prices. value = p value of the z-test.

Tables 3 (lin-lin loss function) and 4 (quad-quad loss function) summarize the estimation results for an extended model that features, in addition to a constant, the lagged change in house prices as an additional instrument. The estimation results corroborate the results that forecasters are heterogeneous with regard to the shape of their loss function. The results of the z-test are significant for 24 (31) forecasters under a lin-lin (quad-quad) loss function. For those forecasters for whom we find a significant z-test, the estimated asymmetry parameter exceeds its benchmark value of 0.5 for 18 (23) forecasters. These forecasters, therefore, appear to experience a larger loss when overestimating changes in house prices as compared to an underestimation of the same size, corroborating the results shown in Figure 3. There are several possible explanations such as reputation, financial incentives or other penalties for why forecasters prefer to overpredict house price changes. *Lamont* (2002) shows that forecasters may use their forecasts in order to manipulate beliefs about their ability. Using a model of reputation he finds that as forecasters become more established they produce more radical forecasts which are less accurate. *Laster* et al. (1999) develop a theoretical model to illustrate that optimistic forecasts arise in a game-theoretic model of forecaster interaction. Because the WSJ forecasters work in the financial industry they might have an incentive to publish optimistic forecasts because of monetary compensation. Hence, forecasters may find it rational to overestimate housing prices to provide an optimistic outlook of the real estate market. Compared to this, it might be rational to underestimate housing starts to signal a future contraction on the supply side of the real estate market indicating future returns in the housing market.

Panel A: Lin-lin loss function



Panel B: Quad-quad loss function



Notes: This figure presents the estimates of the asymmetry parameter based on short-term and medium-term forecasts for a model that features as instruments a constant and the lagged change in house prices.

Figure 4: Estimate of the Asymmetry Parameter

The rationality tests reported in Tables 3 and 4 imply that the $J(0.5)$ is significant for 29 (32) forecasters under a symmetric lin-lin (symmetric quad-quad) loss function. The $J(\hat{\alpha})$ test is significant only for 16 (17) forecasters under a lin-lin (quad-quad) loss function (at the 10% level of significance). Corroborating results reported by *Pierdzioch* et al. (2013) for housing starts, assuming an asymmetric loss function, thus, helps to reconcile forecasts with the concept of forecast rationality in many, but not in all cases.

Figure 4 summarizes the estimated asymmetry parameters for both a lin-lin (Panel A) and a quad-quad loss function (Panel B), and for both forecast horizons. The cross-sectional heterogeneity of the estimated asymmetry parameter is larger for short-term than for medium-term forecasts. In the case of short-term forecasts, the cross-sectional heterogeneity is larger under a quad-quad than under a lin-lin loss function. The estimated asymmetry parameter tends to be larger for medium-term forecasts than for short-term forecasts, corroborating the results shown in Figure 3.

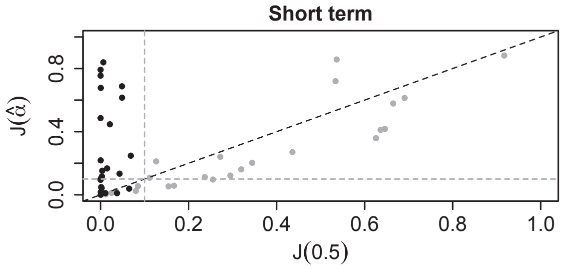
Figure 5 summarizes the results of the J-tests for rational forecasts. The figure compares the p values of the $J(0.5)$ tests with the p values of the $J(\hat{\alpha})$ test. The black (grey) dots represent results for those forecasters for which the z-test yields evidence of an asymmetric (a symmetric) loss function. Two results stand out. First, evidence against forecast rationality is weaker in the case of short-term than in the case of medium-term forecasts. Second, assuming an asymmetric loss function in many cases (but not always) makes forecast look rational, especially when the z-test yields significant evidence of an asymmetric loss function.

3. Subsample Analysis

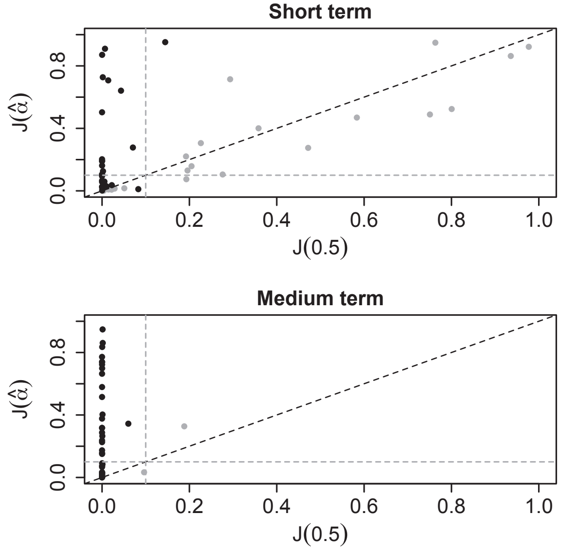
Figure 2 and Table 1 provide informal evidence that the degree of asymmetry in forecasters' loss function may have changed to some extent during the recent financial and economic crisis. We, therefore, split our sample period according to the NBER classification into a "no crisis" period and a "crisis" period. We then estimate forecasters' loss function for both subsample periods. Finally, we compute the average of the estimated asymmetry parameter, insert the results into Equation (1), and draw the loss functions shown in Figure 6. We plot both the loss functions for short-term forecasts and the loss functions for medium-term forecasts, where the dark line (grey line) represents the loss function in times of no crisis (times of crisis).

As for the short-term forecasts, the figure shows that in times of no crisis an underprediction of the change in housing prices of two points (Point A) yields the same loss compared to an overprediction of two points (Point B). Compared to this, in times of crisis, an underprediction of the change in house prices of two points (Point C) yields the same loss compared to a four-percentage point overprediction (Point D) in times of crisis. The underprediction in Point D is twice as large as the overprediction in Point A and yields the same loss. Evidently, this asymmetry is stronger for medium-term forecasts than for short-term forecasts. The

Panel A: Lin-lin loss function

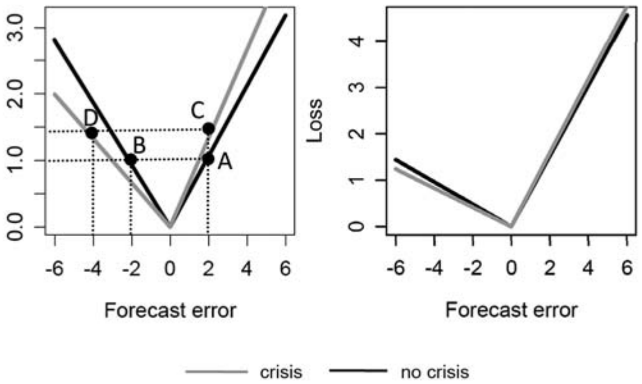


Panel B: Quad-quad loss function



Notes: This figure presents the p values of the J-tests for a model that features as instruments a constant and the lagged change in house prices. The black (grey) dots represent results for those forecasters for which the z-test yields evidence of an asymmetric (a symmetric) loss function. The light grey dotted lines are the boundaries of the 10% significance interval. The bold black dotted line is the 45 degree line.

Figure 5: Rationality Tests



Note: This figure plots the lin-lin loss function depending on the forecast error defined as $s_{t+1} - f_{t+1}$. The results are based on the cross-sectional average of the asymmetry parameter (a) for the period of "crisis" (grey line) and "no crisis" (black line). The crisis period is defined using the NBER dating of the recession as the period of time between December 2007 and June 2009 (see http://www.nber.org/cycles.html). Left-hand panel: short-term forecasts. Right-hand panel: medium term forecasts

Figure 6: Lin-Lin Loss Function

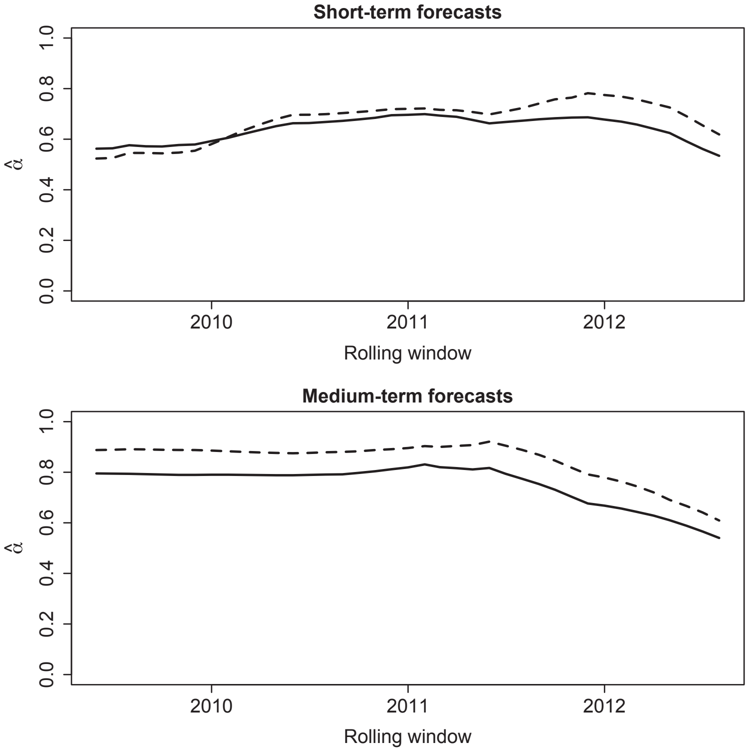
figure also illustrates that the crisis had a stronger impact on forecasters' loss function in the case of short-term forecasts than in the case of medium-term forecasts.

In economic terms result indicates that in times of no crisis, house price forecasters appear to target the actual house price development (in the case of short-term forecasts) and perceive an equal loss when over- or underpredicting the house price. Compared to that, in times of crisis an underprediction is more costly which reflects that house price forecasters on average publish too optimistic forecasts. In terms of a suggested policy implication our results show that the policy makers should be aware that house price forecasters behave differently in times of crisis. Central banks which respond to developments in real-estate markets (*Goodhart/Hofmann* (2008)) should be aware of the shift the forecasting behavior of house price forecasters. Also financial market participants should make their savings and investments decisions in the real estate market with caution when relying on house price forecasts in times of crises. The shift in forecasts is less pronounced for the medium-term horizon compared to the short-term horizon.

It is interesting to compare the loss functions shown in Figure 2 with the loss functions that *Pierdzioch* et al. (2013) estimate on forecasts of housing starts. They observe a general tendency towards a higher loss of overpredictions relative to underpredictions. Figure 2, in contrast, shows that forecasters of changes in house prices tended to experience a higher loss in case of underpredictions than in the case of overpredictions. The shape of the loss function, in other words, is reversed in the case of forecasts of changes in house prices as compared to forecasts of housing starts.[1] A natural question is whether the reversed shape of the loss function traces back to a fundamental economic difference between forecasts of changes in house prices and forecasts of housing starts. In order to answer this question, it is useful to consider a simple demand-supply model of the housing market. Consider the case that a forecaster assumes that changes in housing-market equilibrium were mainly triggered by demand shocks. Given a sequence of demand shocks, equilibrium in the housing market can be restored by a mixture of responses of quantities (that is, housing starts) and house prices. The flatter is the slope of the supply schedule that a forecaster uses to form a forecast (that is, the larger is the expected responsiveness of housing supply to changes in house prices), the larger (smaller) is the expected response of the quantity of houses (changes in house prices) required to restore market equilibrium. Thus, if a forecaster misperceives the slope of the supply schedule in the wake of a demand shock, a high loss when a forecaster overestimates movements in housing starts should correspond to a high loss in case of an underestimation of changes in house prices. Conversely, in case mainly supply shocks hit the housing market, overestimation (underestimation) of the responsiveness of quantities (prices) should result if a forecaster uses a demand schedule that is flatter than the actual demand schedule to form forecasts. Again, overestimation of quantities should correspond to underestimation of movements in house prices. As a result, if forecast errors mainly stem from a misperception of the slope of the demand curve, the result should be a high loss in case of overestimations (underestimation) of housing starts (movements in house prices).

In order to study further potential variation of the asymmetry parameter across time, we estimate the asymmetry parameter based on a rolling 30-survey-estimation window. Figure 7 summarizes the results for a model that features a constant as the sole instrument. Results for a mod-

[1] Still, the results shown in Figure 6 confirm results reported by *Pierdzioch* et al. (2013b) insofar as they find, based on data on U.S. housing starts covering the sample period 1989–2010, that the asymmetry parameter tended to increase towards the end of their sample period.



Note: This figure shows the asymmetry parameter estimated on data for a rolling estimation window.estimated asymmetry parameter. The solid (dashed) line represents the results for a lin-lin (quad-quad) loss function. Estimates are for Model 1.

Figure 7: Recursive-Estimation Window

el that features the lagged change in house prices as an additional instrument are similar (not reported, but available upon request). Two results emerge from the figure. First, the estimated asymmetry parameter was relatively stable over time, except at the end of the sample period. Second, the estimated asymmetry parameter tends to be somewhat larger for the quad-quad loss function than for the lin-lin loss function, especially in the case of medium-term forecasts.

The stability of the estimated asymmetry parameter is important in another respect. Our sample period covers the U.S. subprime mortgage crisis. One could imagine a scenario in which this severe crisis triggered changes in elasticities in popular forecasting models like ARIMA models and VAR models since 2006. If forecasters use such models to form their forecasts based on historical data, they will incorporate the information on changing elasticities into their forecasts only with a lag as they start learning about the changes that have taken place. This gradual learning process easily can lead for some time to the type of overprediction that we found in the data. If so, forecasters' loss function may be symmetric while the data-driven empirical technique advanced by *Elliott* et al. (2005) detects asymmetries. However, if the detected asymmetry of forecasters' loss function is spurious due to the effect of forecaster learning, one would expect that the estimated asymmetry parameter gradually converges to its "true" value of 0.5 as forecasters update their forecasting models. Figure 7 witnesses that such a convergence can only be detected at the very end of the sample period, implying that one would have to assume a rather slow learning process to explain our empirical results in terms of forecaster learning.

IV. Concluding Remarks

Based on the large WSJ questionnaire survey of forecasts of changes in house prices, we have analyzed the heterogeneity of forecasts, the shape of forecasters' loss function, the rationality of forecasts, and the temporal variation in forecasts at the aggregate level. Our results show that the heterogeneity of forecasts of housing starts is substantial, and differences in the shape of forecasters loss functions may account at least in part for this heterogeneity. Moreover, accounting for an asymmetric loss function has the potential to make forecasts look rational in some, but not in all cases. We also have studied variation over time in the asymmetry of forecasters' loss function. Results show that the asymmetry parameter tended to increase during the recent recession. Finally, we have compared our results with results reported by *Pierdzioch* et al. (2013b) for U.S. housing starts. This comparison has shown that, in order to draw a comprehensive picture of developments in housing markets it is interesting to analyze the properties of forecasts of both housing quantities *and* housing prices.

Our results imply that traditional tests of forecast rationality (unbiasedness regressions, orthogonality regressions) need some adjustment when researchers use such tests to study forecast rationality of forecasts of changes in house prices. Such adjustments have been proposed by *Batchelor/Peel* (1998) and *Elliott* et al. (2008). *Batchelor/Peel* (1998) suggest that extending traditional unbiasedness regressions to incorporate an ARCH-in-mean effect captures the effect of an asymmetric loss function on rationality tests in case forecasters have a lin-lin loss function. *Elliott* et al. (2008), in turn, show that, for a quad-quad loss function, asymmetry of forecasters' loss function requires adjusting classic orthogonality regressions by a factor that depends on the asymmetry parameter multiplied by the absolute forecast error. The estimates of the asymmetry parameter that we have reported in this research may be useful when researchers seek to implement such adjusted orthogonality regressions in future research.

Studying forecasts of changes in house prices is also important for another reason. The quantity-based forecasts of housing starts and housing approvals have undergone relatively large swings in recent years in the aftermath of the U.S. subprime mortgage crisis. In fact, the subprime mortgage crisis and the economic turbulences it triggered may have caused even a structural break in the time series of housing starts and housing approvals. If such structural breaks have went unnoticed by forecasters, the resulting forecast errors analyzed in earlier research could be biased and, hence, the assumptions underlying tests for rationality would be violated. Changes in house prices, in contrast, are more likely to have a stationary distribution. It is, thus, reassuring that the results of this research corroborate a major result reported in earlier literature based on housing starts and housing approvals insofar as assuming an asymmetric loss function tends to mitigate the case for deviations from rationality in many (but not in all) cases.

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