# Housing Starts, Forecaster Herding, and the Livingston Survey

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#### Abstract

Recent research shows that forecasts of housing starts provide evidence of forecaster anti-herding. Because this result is in contrast to the widespread belief that forecasters herd, we reexamined the question of forecaster anti-herding using data from the Livingston Survey. Using a novel empirical test developed by Bernhardt et al. (2006, *Journal of Financial Economics*, 80, 657-67), we found strong evidence that forecasters of U.S. housing starts anti-herd.

Keywords: housing starts, forecasting, (anti-)herding

#### 1. Heading

Results of recent research indicate that forecasters of housing starts anti-herd (Pierdzioch, Rülke, &Stadtmann, *in press*). While evidence of forecaster anti-herding in the case of housing starts is in line with mounting evidence of forecaster anti-herding in other areas of economics (Bernhardt, Campello, &Kutsoati, 2006; Naujoks, Aretz, Kerl, & Walter, 2009), this evidence is at odds with the widespread belief that forecasters herd. Forecaster herding arises if forecasters follow the forecasts of others (Scharfstein& Stein 1990; Froot, Scharfstein, & Stein, 1992). Forecaster anti-herding, in contrast, arises if forecasters scatter their forecasts away from the forecasts of others (Laster, Bennett, &Geoum, 1999).

We reexamined forecaster (anti-)herding using data from the Livingston Survey. The Livingston Survey has a considerably long track record. It contains forecasts of housing starts for the United States that date back to December 1968. In addition, the Livingston Survey provides information on more than 14 000 forecasts published by 250 forecasters, for five different forecast horizons. Forecasts of housing starts are also available for various groups of forecasters (for example, academics, Federal reserve economists, forecasters working in the banking industry). In sum, the Livingston Survey is a particularly rich data set to study the issue of forecaster (anti-)herding.

We tested for forecaster (anti-)herding using a novel empirical test recently developed by Bernhardt et al. (2006), which also has been used in recent research (Pierdzioch, Rülke, &Stadtmann,*in press*). Our findings, thus, are directly comparable to results reported in recent literature. Upon applying the test to data from the Livingston Survey, we found strong evidence of forecaster anti-herding, corroborating the results of recent research. In order to assess the robustness of our findings, we also studied alternative specifications of the empirical test. For example, we tested for forecaster anti-herding among optimists and pessimists. Finally, we found that forecaster anti-herding is inversely correlated with forecast accuracy. Forecasters' loss function, therefore, seems to contain other arguments in addition to forecast accuracy as, for example, in the model developed by Laster et al. (1999).

## 2. A Simple Test

The test of forecaster anti-herding developed by Bernhardt et al. (2006) is easy to implement, and it has a straightforward economic interpretation. The intuition motivating the test can be illustrated by assuming that a forecaster, given some subjective distribution of future housing starts, forms an "efficient" private forecast. The efficient private forecast is unbiased because it is not influenced by the consensus forecast (that is, the average forecast made by others). The probability that an unbiased forecast overshoots or undershoots future housing starts should be 0.5.

Herding implies that a forecaster publishes a forecast that is tilted towards the consensus forecast. If the private forecast exceeds the consensus forecast, the eventually published forecast is closer to the consensus forecast than the private forecast. The probability of undershooting, thus, is smaller than 0.5. If the private forecast is smaller than the

consensus forecast, in turn, the published forecast exceeds the private forecast and the probability of overshooting is also smaller than 0.5.

Anti-herding implies that a forecaster publishes forecasts that deliberately scatter around the consensus forecast. A published forecast, thus, is farther away from the consensus forecast than the private forecast. If the private forecast exceeds the consensus forecast, the published forecast is larger than the private forecast, implying that the probability of undershooting is larger than 0.5. Similarly, if the private forecast is smaller than the consensus forecast, the probability of overshooting is also larger than 0.5.

Based on this intuition, under the null hypothesis that forecasters do not herd, the probability that an unbiased forecast (conditional on being above or below the consensus forecast) overshoots or undershoots the future realization of housing starts should be 0.5, regardless of the consensus forecast. Their test statistic, S, is simply the average of the two probabilities. In the case of unbiased forecasts, we thus should observe S=0.5. In the case of forecaster (anti-)herding, in contrast, we should observe S<0.5 (S>0.5). The test statistic, S, has an asymptotically normal sampling distribution.

#### 3. Empirical Analysis

The Federal Reserve Bank of Philadelphia (2012) maintains the Livingston Survey. The survey data contain information on forecasts of various macroeconomic and financial data, including housing starts. The survey data of housing starts are available at a semiannual frequency for the sample period from December 1968 (depending on the forecast horizon) to December 2011. Forecasts are compiled during the first week of June and December and are available at five different forecast horizons: one month (1M), six months (6M), twelve months (12M), 18 months (18M), and 24 months (24M). Forecasts of housing starts are available for various groups of forecasters. In total, more than 14 000 forecasts are available.



This figure shows the consensus forecast (dashed line), the range of the forecasts (shaded area), and the actual value (solid lines) for the housing starts in the United States (in mn. units per year).

Figure 1 shows the actual housing starts (solid lines), the consensus forecast (dashed line), and the range of forecasts (shaded area) of housing starts in the United States (in mn. units per year). While the general trend in the consensus forecast tracks the one of the actual value, the cross-sectional range of forecasts visualizes the cross-forecaster heterogeneity of forecasts. Forecaster anti-herding may be an important determinant of this heterogeneity of forecasts because such anti-herding behavior results in a scattering of forecasts around the consensus forecast.

Table 1 summarizes our empirical findings. The table shows the test statistic, S, its standard deviation, and the number of forecasts available for every forecast horizon and every group of forecasters. In the majority of cases, we find S>0.5, where we cannot reject the null hypothesis of no forecaster (anti-)herding only for the categories "Consulting" and "Industry". For the category "Industry", however, the number of observations is relatively small as compared to the numbers of observations available for the study of the other groups of forecasters. Corroborating results of recent research (Pierdzioch, Rülke, &Stadtmann, *in press*), our empirical findings, thus, provide evidence of forecaster anti-herding.

Category	Horizon	1M	6M	12M	18M	24M
	S-statistic	0.69*	0.69*	0.65*	0.65*	0.59*
Academia	Stand. Dev.	0.03	0.02	0.02	0.02	0.03
	Obs.	214	727	720	708	306
	S-statistic	0.65*	0.71*	0.68*	0.63*	0.64*
Commercial banking	Stand. Dev.	0.03	0.02	0.02	0.02	0.03
	Obs.	245	962	953	891	320
	S-statistic	0.59	0.59	0.55	0.58	0.43
Consulting	Stand. Dev.	0.05	0.04	0.04	0.05	0.06
	Obs.	119	119	129	123	60
	S-statistic	0.67*	0.67*	0.71*	0.63*	0.56
Investment banking	Stand. Dev.	0.03	0.02	0.02	0.02	0.04
	Obs.	357	602	579	581	183
	S-statistic	0.57	0.71*	0.58*	0.52	0.48
Industry	Stand. Dev.	0.06	0.05	0.06	0.05	0.08
	Obs.	82	85	82	91	35
	S-statistic	0.70*	0.72*	0.70*	0.65*	0.62*
Non-financial	Stand. Dev.	0.03	0.02	0.02	0.02	0.02
	Obs.	314	1 018	1 013	962	411
	S-statistic	0.67*	0.69*	0.69*	0.69*	0.70*
Federal Reserve	Stand. Dev.	0.06	0.04	0.04	0.04	0.06
	Obs.	84	157	156	145	63
Labor	S-statistic	0.72*	0.75*	0.65	0.67*	0.64
	Stand. Dev.	0.04	0.04	0.04	0.04	0.07
	Obs.	119	148	147	126	49
	S-statistic	0.68*	0.70*	0.68*	0.64*	0.60*
Total	Stand. Dev.	0.01	0.01	0.01	0.01	0.01
	Obs.	1 534	3 836	3 779	3 627	1 427

Table 1. Empirical results

This table shows the herding statistic, S, and its standard deviation. \* indicates whether the S-statistic is significantly different from 0.5 at a one percent level.

Table 2 reports the results of some robustness tests. First, we defined the consensus forecast in terms of the lagged longer-term forecast. For example, the lagged 12M forecasts have the same forecast horizon as the current 6M forecasts, and they are known at the time a forecast is being made. Upon defining the consensus forecast in this way, we accounted for the fact that forecasters may not know the contemporaneous consensus forecast when submitting their forecasts. Second, we examined whether optimism and pessimism among forecasters affects our empirical findings. To this end, we identified optimistic (pessimistic) forecasters who predict a higher (lower) real growth rate of output for the next six months than the average forecaster. Findings of both robustness tests provide evidence of forecaster anti-herding.

Model	Horizon	S-statistic	Stand. Dev.	Obs.
	1M	0.60*	0.01	1 457
Lagged	6M	0.59*	0.01	3 678
consensus	12M	0.56*	0.01	3 937
	18M	0.51	0.01	3 626
	1M	0.68*	0.02	761
	6M	0.71*	0.01	1 883
Optimists	12M	0.68*	0.01	1 847
	18M	0.65*	0.01	1 935
	24M	0.61*	0.02	778
	1M	0.69*	0.02	694
	6M	0.69*	0.01	1 953
Pessimists	12M	0.67*	0.01	1 932
	18M	0.63*	0.01	1 692
	24M	0.59*	0.02	649

## Table 2. Robustness tests

This table shows the herding statistic, S, and its standard deviation. \* indicates significance at the one percent level.

We further analyzed whether forecast accuracy correlates with forecaster anti-herding. To this end, we computed, for every forecaster i (i = 1,..., 250) a forecaster-specific  $S_i$ -statistic and a forecaster-specific root-mean-squared error, RMSE<sub>i</sub>. In order to empirically assess the significance of the correlation, we estimated the following regression model: RMSE<sub>i</sub> = a + b  $S_i$  +  $e_i$ , where  $e_i$  denotes a forecaster-specific disturbance term. Table 3 reports the estimation results. For three out of five forecast horizons, there is a clear-cut and statistically significant positive correlation between anti-herding and the root-mean-squared error implying that forecast accuracy is significantly negatively correlated with forecaster anti-herding. Forecast accuracy, thus, likely is not the only argument in the loss function of anti-herding forecasters. The correlation remains positive, but becomes insignificant at longer-term forecast horizons.

Horizon	1M	6M	12M	18M	24M
a	0.41* (0.01)	0.78* (0.14)	0.17* (0.03)	0.44* (0.05)	0.33* (0.04)
b	0.08* (0.02)	0.11* (0.02)	0.14* (0.04)	<0.00 (0.08)	0.09 (0.06)
Obs.	112	248	250	236	147
R <sup>2</sup>	0.13	0.11	0.06	< 0.00	0.02

Table 3. Forecast accuracy and individual herding

This table shows estimation results for the regression model  $RMSE_i = a + b S_i + e_i$ . Robust Newey-West standard errors are given in parentheses. \* indicates significance at the one percent level.

To sum up, we found, based on data from the Livingston Survey, strong evidence of forecaster anti-herding. We could reject the null hypothesis of the S-statistic (unbiased forecasts) in favor of the alternative hypothesis of anti-herding using forecasts for different forecasting horizons (from one month to twentyfour months). Moreover, we found that our results are robust to several alternative specifications of the empirical test (lagged consensus, optimism and pessimism among forecasters). Finally, we found that the accuracy of forecasts and forecaster anti-herding are negatively correlated.

# 4. Concluding Remarks

Using an empirical test that has been applied in recent research to study forecaster ant-herding (Bernhardt, Campello, &Kutsoati, 2006; Pierdzioch, Rülke, &Stadtmann, *in press*), we found that forecasters who participate in the Livingston survey seem to anti-herd when it comes to forecasting housing starts. Anti-herding forecasters scatter their forecasts around a consensus forecast. Scattering of forecasts may reflect a "superstar effect" (Scharfstein& Stein, 1990, p. 476) and compensation effects (Laster, Bennett, &Geoum, 1999) that strengthen incentives to differentiate forecasts from the forecasts of others. Together with results of recent research, our findings imply that when researchers analyze forecasters' loss function it is interesting not only to account for forecasts from the forecasts of others.

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