A Note on Forecasting Emerging Market Exchange Rates - Evidence of Anti-Herding

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Abstract

Using survey forecasts of a large number of Asian, European, and South American emerging market exchange rates, we studied empirically whether evidence of herding or anti-herding behavior of exchange-rate forecasters can be detected in the cross-section of forecasts. Emerging market exchange-rate forecasts are consistent with herding (anti-herding) if forecasts are biased towards (away from) the consensus forecast. Our empirical findings provide strong evidence of anti-herding of emerging market exchange-rate forecasters.

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JEL classification: F31, D84, C33

1 Introduction

Historical experience suggests that exchange rates are subject to recurrent large swings that do not necessarily reflect changes in fundamental macroeconomic conditions. The resulting misalignments seem to have a stronger effect on economic growth in emerging market countries than in developed countries (MacDonald and Vieira, 2010). It is, therefore, not surprising that many researchers have studied whether swings in exchange rates and exchange rate volatility reflect investor exuberance, market frenzies, and herding of market participants (Carlson and Osler, 1998; De Grauwe and Grimaldi, 2005). An interesting and important question is whether such herding, to the extent that it occurred, is reflected in forecasts of emerging-market exchange rates of professional exchange-rate forecasters.

Survey data of exchange-rate forecasts provide empirical researchers with a rich and reliable data source to study forecast formation and potential herding behavior of forecasters. A key advantage of survey data of exchange-rate forecasts is their panel-data structure, that is, the data have a time-series and a cross-sectional dimension. The time-series dimension of survey data summarizes the results of recurrent questionnaire surveys of professional exchange-rate forecasters, and the cross-sectional dimension of the data reflects that in general many forecasters regularly participate in questionnaire surveys.

Empirical studies of survey data have yielded strong evidence of forecaster heterogeneity (MacDonald and Marsh, 1996; Bénassy-Quéré et al., 2003; Dreger and Stadtmann 2008). The contribution of our empirical study is that we provide empirical evidence on one potentially important source of forecaster heterogeneity. Based on a new empirical test developed by Bernhardt et al. (2006), we analyzed whether the cross-sectional dimension of survey data of forecasts of emerging market exchange rates is consistent with herding or with anti-herding of forecasters. Exchange-rate forecasts are consistent with herding (anti-herding) of forecasters if forecasts are biased towards (away from) the consensus forecast. While herding of forecasters should reduce forecaster heterogeneity, anti-herding should inflate the cross-sectional heterogeneity of forecasts.

We report strong evidence of anti-herding of forecasters of eighteen Asian, European, and South-American emerging market exchange rates. Our empirical findings, thus, indicate that anti-herding rather than herding seems to characterize the cross-sectional dimension of forecasts of emerging market exchange rates. Our evidence of anti-herding of exchange-rate forecasters is consistent with recent empirical evidence of anti-herding among stock market analysts reported by Berhardt et al. (2006) and Naujoks et al. (2008). Earlier empirical evidence of anti-herding among macroeconomic forecasters has been reported by Batchelor and Dua (1990). Our empirical findings, thus, contribute to an emerging pattern of results that suggests that anti-herding seems to prevail among diverse groups of forecasters.

In Section 2, we describe the empirical test that we used to test for forecaster (anti-)herding. In Section 3, we describe the survey data used in our empirical analysis, and we report our empirical findings. In Section 4, we provide some concluding remarks.

2 Testing for (Anti-) Herding

We used a test that recently has been proposed by Bernhardt et al. (2006) to analyze whether forecasters (anti-)herd. Their test is easy to implement and the economic interpretation of the test results is straightforward. In order to illustrate how their test works, it is useful to consider a forecaster who forms an "efficient" private forecast of the exchange rate. The forecaster derives her private forecast by applying her "optimal" forecasting model, and by using all information available to her at the time the forecast is to be made. Her private forecast, thus, will be unbiased and the probability that her unbiased private forecast of the exchange rate overshoots (undershoots) the exchange rate should be 0.5.

Her eventually published forecast will differ from her private forecast if the published forecast is influenced by the s *'consensus'* forecast, which can be defined as the cross-sectional mean of forecasts delivered by all forecasters who participate in a forecasting cycle. In the case of forecaster herding, 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, implying that the probability of undershooting is smaller than 0.5. In a similar vein, if the private forecast is smaller than the consensus forecast, the probability of overshooting is also smaller than 0.5. In contrast, if a forecaster anti-herds, the published forecast will be farther away from the consensus than the private forecast. The result is that the probabilities of undershooting and overshooting will be larger than 0.5.

The probabilities of undershooting and overshooting can be used to setup a test of forecaster (anti-)herding. The null hypothesis of the test is that published forecasts are unbiased (no herding or anti-herding). The probability, P, that an unbiased forecast of the exchange rate, $E_{i,t}[s_{t+1}]$, made by forecaster i overshoots (undershoots) the exchange rate, s_{t+1}, should be 0.5, regardless of the consensus forecast, $\bar{E}_t[s_{t+1}]$. It follows that the conditional probability of undershooting (overshooting) in case a forecast exceeds (is smaller than) the consensus forecast should be

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

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

In contrast, in case a forecaster herds, the published forecast will be closer to the consensus than in the case of an unbiased forecast. As a result, the conditional probabilities should be smaller than 0.5. In the opposite case of anti-herding, the published forecast will be farther away from the consensus than in the case of an unbiased forecast, and the conditional probabilities should be larger than 0.5.

The test statistic, S, is defined as the average of the sample estimates of the two conditional probabilities. Unbiased forecasts imply $S = 0.5$, herding implies $S < 0.5$, and anti-herding implies $S > 0.5$. Bernhardt et al. (2006) show that the test statistic, S, asymptotically has a normal sampling distribution. They also demonstrate that the test statistic, S, is robust to phenomena like, for example, correlated forecast errors and market-wide shocks. Such phenomena make it harder to reject the null hypothesis of unbiased forecasts. It should also be noted that the test statistic, S, is robust to outliers in the data, data entry errors, or "unusual" events as, for example, the Asian economic and financial crisis of 1997.

3 Empirical Analysis

Our data on emerging market exchange-rate forecasts are taken from the Consensus Economics Inc. questionnaire survey database. This database contains information on individual exchange-rate forecasts made by a large number of professional forecasters working at, for example, investment banks, research institutes, and universities. The database contains informations on questionnaire studies that have been conducted for many years, albeit at irregular time intervals. While the database covers more than twenty exchange rates of emerging economies, we extracted those exchange rates for which forecasts have been published on a regular basis.[1]

Specifically, we used one-month-ahead exchange-rate forecasts vis-a-vis the US dollar for the following eighteen emerging market economies:

- *Asian economies*: India, Indonesia, Philippines, Singapore, South Korea, Thailand.
- *European economies*: Czech Republic[2], Hungary[3], Poland[4], Russia, Slovak Republic[5], Turkey.
- *South-American economies*: Argentina, Brazil, Chile, Columbia, Mexico, Peru.

Table 1 reports summary statistics of the data. For every exchange rate, the table reports the sample period for which data are available, the number of forecasters (institutions) participating in the questionnaire studies, and the total number of questionnaire studies available.

Table 1: Descriptive Statistics

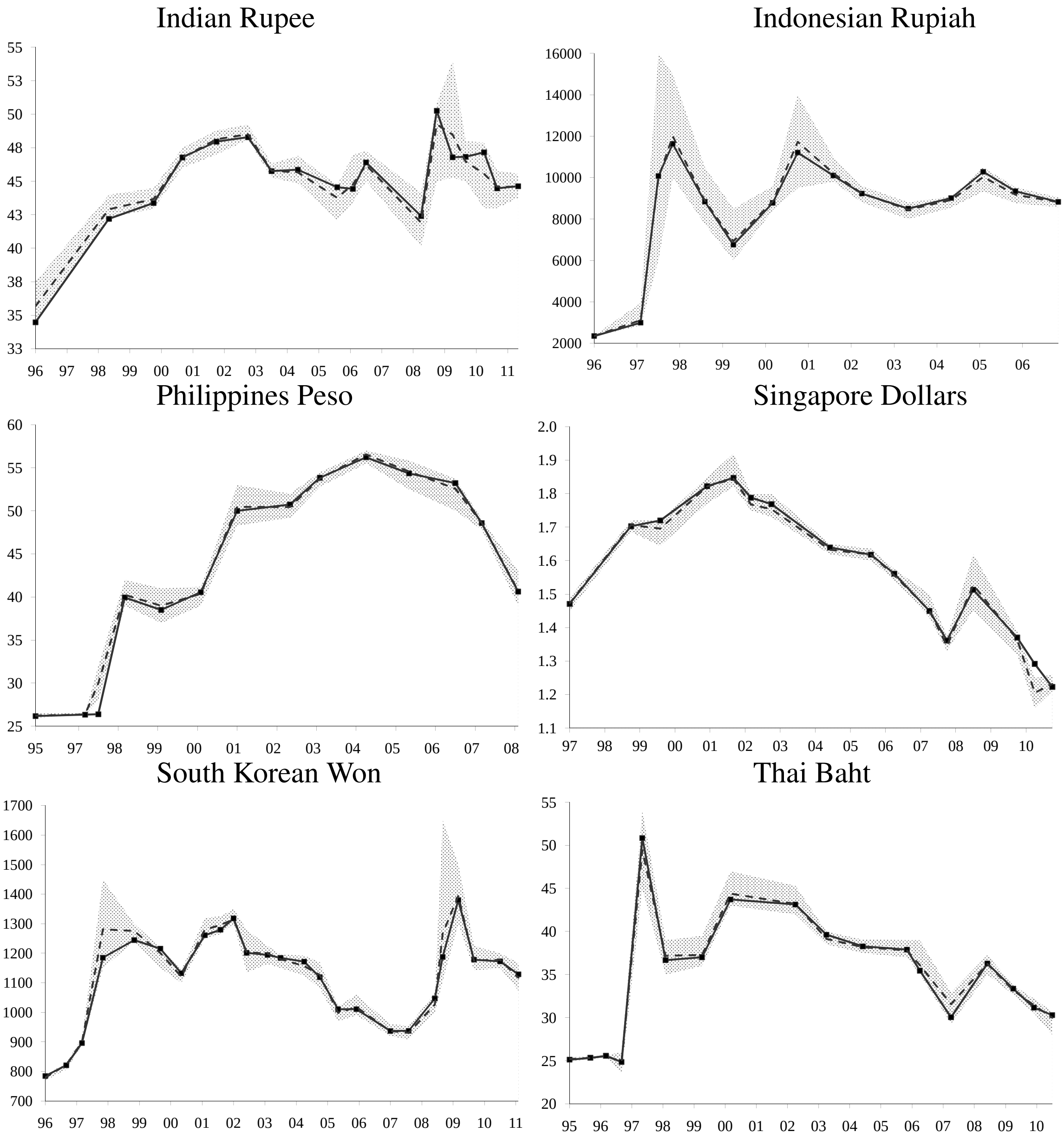
	Time	Institutions	Surveys
Asia			
India	Mar 06 – Jul 11	23	18
Indonesia	Aug 96 – Jun 07	28	15
Phillipine	Dec 95 – Feb 08	26	14
Singapore	Aug 97 – May 11	22	16
South Korea	Feb 96 – Mar 11	26	25
Thailand	Oct 95 – Apr 11	27	18
Eastern Europe			
Czech Rep.	Apr 96 – Apr 11	25	30
Hungary	Feb 96 – May 11	27	29
Poland	Jan 96 – Jun 11	26	29
Russia	Oct 95 – Mar 11	24	34
Slovak Rep.	Aug 97 – Jul 08	24	16
Turkey	Jun 99 – Jul 11	29	22
South America			
Argentina	Aug 96 – Jul 11	25	23
Brazil	Feb 96 – Jul 11	31	32
Chile	Jun 96 – Jun 11	31	27
Columbia	Feb 97 – Feb 11	26	25
Mexico	Nov 95 – Apr 11	30	33
Peru	Dec 96 – Mar 11	26	20

Note:
Institutions denotes the number of different forecasters who participated in the survey studies. Surveys denotes the number of forecasting cycles for which data are available.

Figures 1−3 plot the exchange rates (solid lines with rectangles), the consensus forecast (dotted lines), and the dispersion of individual forecasts around the consensus forecast (maximum forecast minus minimum forecast, shaded areas). Most of the time, the consensus forecast is close to the actual exchange rate. The dispersion of individual forecasts around the consensus, in contrast, fluctuates substantially over time. For example, in the case of the Asian emerging market economies, the dispersion of individual forecasts was relatively small before the Asian economic and financial crisis gathered steam. In the aftermath of the crisis, however, dispersion substantially grew, which is likely to reflect increased uncertainty triggered by the financial market jitters of that time. It is also evident from Figures 1−3 that the dispersion of individual forecasts tended to increase after trend reversals, that is, when a depreciation trend changed into an appreciation trend, et vice versa.

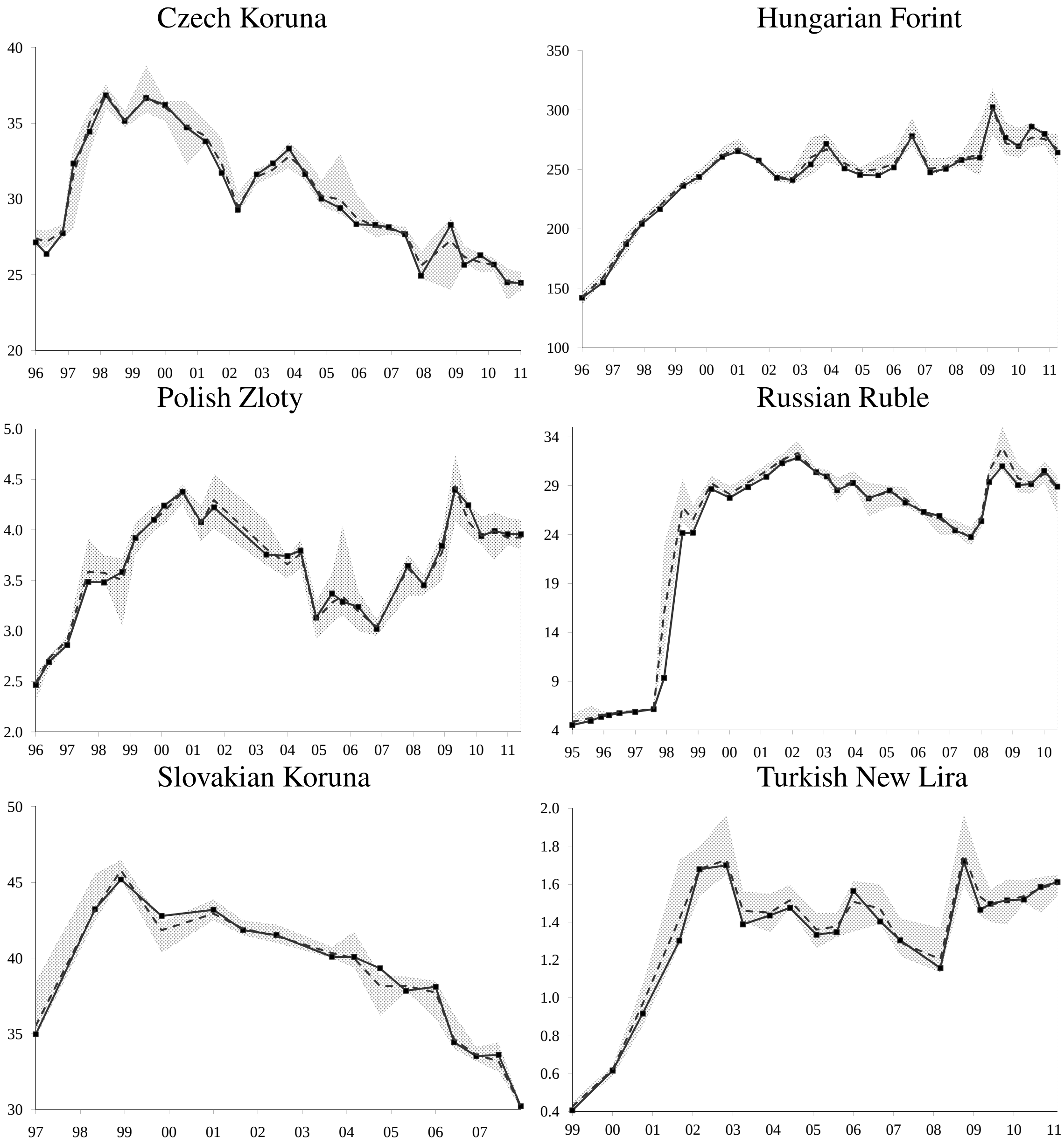
Table 2 summarizes our empirical findings. The table reports, for every emerging market economy, the number of forecasts available, the conditional probabilities defined in Eqs. (1)−(2) (denoted as Prob1 and Prob2), the S statistic, and the boundaries of the 95% confidence interval. The table also summarizes the empirical findings that we obtained when we pooled, for all three continents separately and across all three continents, forecasts across exchange rates.

Figure 1: Asian Emerging Market Economics



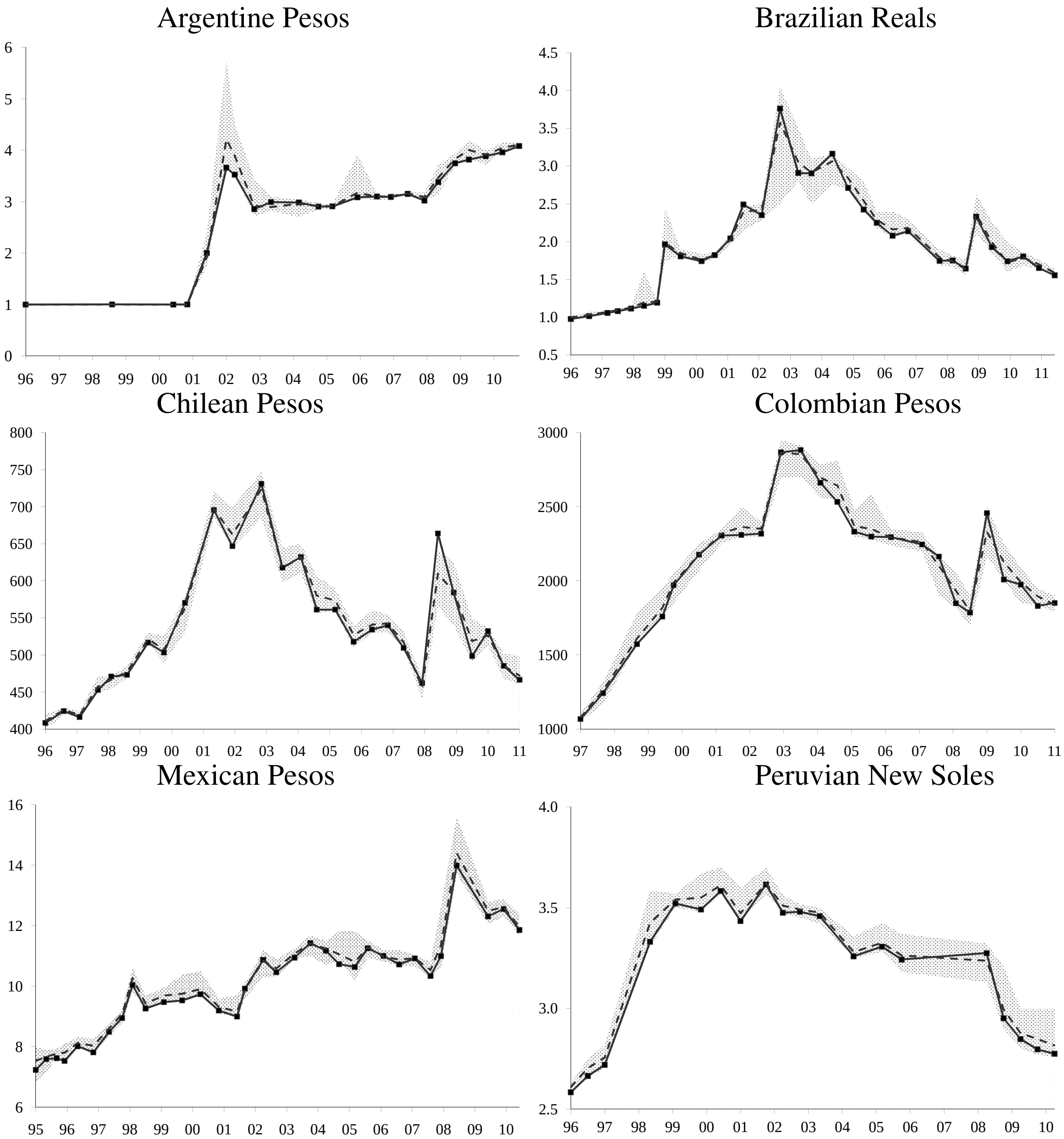
Note: The line with the rectangles denotes the exchange rate, s_t. The dotted line denotes the average of exchange rate expectations, $\bar{E}_t[s_{t+1}]$. The shaded area indicates the range of individual exchange rate forecasts.

Figure 2: Eastern European Emerging Market Economics



Note: The line with the rectangles denotes the exchange rate, s_t. The dotted line denotes the average of exchange rate expectations, $\bar{E}_t[s_{t+1}]$. The shaded area indicates the range of individual exchange rate forecasts.

Figure 3: South American Emerging Market Economics



Note: The line with the rectangles denotes the exchange rate, s_t. The dotted line denotes the average of exchange rate expectations, $\bar{E}_t[s_{t+1}]$. The shaded area indicates the range of individual exchange rate forecasts.

Table 2: Empirical Results

Asia	Obs.	Prob1	Prob2	S-Stat	Lower 95 %	Upper 95%
India	167	0.714	0.807	0.761	0.685	0.837
Indonesia	181	0.762	0.697	0.730	0.656	0.803
Philippines	160	0.617	0.848	0.733	0.655	0.810
Singapore	203	0.757	0.511	0.634	0.565	0.703
South Korea	287	0.655	0.691	0.673	0.615	0.731
Thailand	211	0.568	0.817	0.693	0.625	0.760
Sum	1209	0.677	0.722	0.700	0.671	0.728
Eastern Europe	Obs.	Prob1	Prob2	S-Stat	Lower 95 %	Upper 95%
Czech Rep.	319	0.612	0.669	0.640	0.586	0.695
Hungary	302	0.637	0.836	0.736	0.680	0.793
Poland	320	0.694	0.694	0.694	0.639	0.749
Russia	324	0.539	0.795	0.667	0.612	0.722
Slovak Rep.	147	0.793	0.585	0.689	0.607	0.770
Turkey	311	0.487	0.787	0.637	0.582	0.693
Sum	1723	0.612	0.740	0.676	0.652	0.699
South America	Obs.	Prob1	Prob2	S-Stat	Lower 95 %	Upper 95%
Argentina	261	0.531	0.797	0.664	0.603	0.725
Brazil	375	0.533	0.809	0.671	0.620	0.722
Chile	317	0.481	0.712	0.596	0.541	0.651
Columbia	263	0.669	0.684	0.677	0.616	0.737
Mexico	419	0.467	0.824	0.646	0.598	0.694
Peru	198	0.543	0.939	0.741	0.670	0.812
Sum	1833	0.529	0.786	0.657	0.635	0.680
Sum Total	4765	0.598	0.754	0.676	0.661	0.690

Note:
Prob1 = $P(s_{t+1} > E_{i,t}[s_{t+1}] \,|\, E_{i,t}[s_{t+1}] < \bar{E}_t[s_{t+1}], s_{t+1} \neq E_{i,t}[s_{t+1}])$
Prob2 =$P(s_{t+1} < E_{i,t}[s_{t+1}] \,|\, E_{i,t}[s_{t+1}] > \bar{E}_t[s_{t+1}], s_{t+1} \neq E_{i,t}[s_{t+1}])$

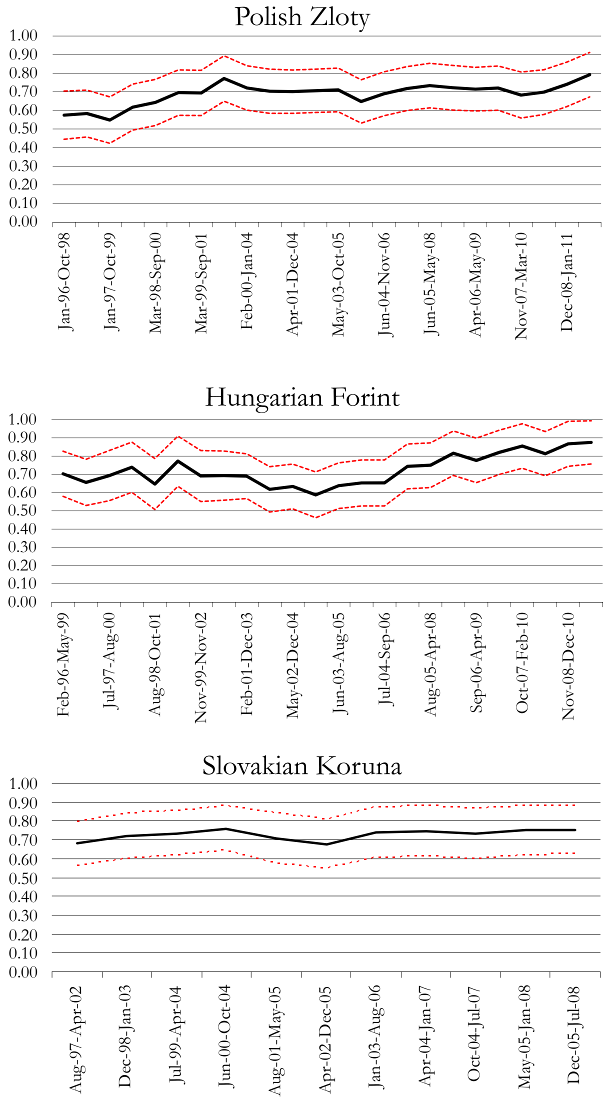
The results summarized in the table can be interpreted as follows. For example, in the case of India, we could use 167 forecasts. The forecasts implied that the conditional probability of overshooting (given that a forecast fell short of the consensus forecast) was 0.714. In other words, in terms of relative frequencies, in 71.4% of all cases where forecasts exceeded the consensus forecast, we observed an overshooting of the exchange rate relative to the forecasts. Similarly, we estimated a conditional probability of undershooting (given that a forecast exceeded the consensus forecast) of 0.807. Thus, in terms of relative frequencies, in 80.7% of all cases where forecasts exceeded the consensus forecast, we observed an undershooting of the exchange rate relative to the forecasts. The test statistic, S, is the average of the two conditional probabilities and is, thus, given by $S = 0.761$. The boundaries of the 95% confidence interval are 0.685 and 0.837, implying that the test statistic, S, significantly exceeds 0.5, the value it would assume under the null hypothesis of unbiased forecasts.

The central message to take home, thus, is that the S statistic significantly exceeds 0.5, indicating forecaster anti-herding. The S statistic yields evidence of forecaster anti-herding for individual emerging market economies and for pooled data. It follows that, although the number of forecasters participating in the questionnaire studies, the total number of questionnaire studies available, and the sample periods differ to some extent across the emerging market countries, we found robust evidence of forecaster anti-herding. Because the emerging market economies in our sample differ regarding their de facto exchange-rate regimes (Levy-Yeyati and Sturzenegger, 2005; Frömmel and Schobert, 2006), our empirical findings imply that forecaster anti-herding is not bound to specific exchange-rate regimes.

To overcome the potential drawback that the forecasters do not know the consensus when the survey is conducted, we used information that is available to the forecasters at the time they submit their forecasts. To this end and as a robustness test we used the forward rate and the current spot rate to measure the consensus forecast. The forward rate is publicly known and, thus, may instrument the information set of forecasters better than the cross-sectional mean of forecasts. We used the forward rate that matches the forecast horizon and is known to forecasters before they publish their forecasts. Similarly, if exchange rates are random walks, the current spot rate is the best forecast of the future spot rate and may, thus, be a good proxy of the consensus forecast. The findings (not reported, but available upon request) turned out very similar to the empirical findings reported in Table 2.

We also analyzed whether forecaster anti-herding is bound to specific subsample periods or specific exchange-rate regimes. The Polish Zloty, the Hungarian Forint, and the Slovakian Koruna provide an interesting case study in this respect. According to Frömmel and Schobert (2006), the exchange-rate regime in the case of the Polish Zloty can be classified as a free float (since 2000), the Hungarian Forint fluctuates in an exchange-rate target zone vis-à-vis the euro, and the exchange-rate regime in the case of the Slovakian Koruna can be classified as a managed float. Figure 4 plots for these three exchange rates the results of a rolling-estimation window analysis. Every rolling-estimation window comprises data from six survey studies, which represent about two and a half years of data. When rolling the estimation window forward in time, we dropped the data for the first survey and added data for the next following survey. We continued this rolling-window estimation process until the end of our sample period. Figure 4 plots the S statistics and the corresponding 95% confidence bands. While there are fluctuations of the test statistic, S, across the rolling estimation windows, the test statistic is larger than 0.5 for almost all rolling estimation windows.[6]

Figure 4: Rolling Estimation Windows



Note:
The solid line denotes the S-statistic over time, while the dashed lines show the 95 % confidence band. Every estimation contains 6 different surveys. The date on the horizontal axis labels the date of the first and last survey included. The surveys are irregularly spaced in time.

4 Conclusions

Our empirical findings suggest that anti-herding is prevalent among forecasters of emerging market exchange rates. Our empirical findings, thereby, imply that forecaster anti-herding is a non-negligible source of the kind of cross-sectional heterogeneity of exchange-rate forecasts reported in earlier literature. While forecaster anti-herding certainly is not the only element useful for the modeling the heterogeneity of exchange-rate forecasts, our empirical findings illustrate that forecaster anti-herding is consistent with forecasts of emerging market exchange rates.

Anti-herding may reflect that forecasters who act in a competitive industry attempt to differentiate themselves from the free prediction of “no change” in order to sell their forecast. For example, Ottaviani and Sörensen (2006) argue that, in a forecasting contest, forecasters differentiate their predictions from forecasts of competitors because the benefits are large in case such a forecast turns out to be correct, since the number of forecasters that have delivered a similar forecast is small.[7] Similarly, Laster et al. (1999) argue that anti-herding can arise if two groups of customers buy forecasts. In their model, one group of customers buys forecasts regularly. This group, thus, buys from forecasters who have published accurate forecasts over a longer period of time. The second group of customers only buys forecasts occasionally. This group buys from the forecaster who published the most accurate forecast in the immediate past. Laster et al. (1999) show that the incentive to anti-herd becomes stronger as the proportion of the second group of customers gets larger. While the probability of making an accurate forecast is smaller in the case of anti-herding, the benefit in case an “extreme” forecast turns out to be correct ex post are large because only few competitors delivered a similar forecast.[8]

References

Batchelor, Roy A. and Pami Dua, ”Product Differentation in the Economic Forecasting Industry,” *International Journal of Forecasting* 6 (1990): 311 – 316.

Bénassy-Quéré, Agnès, Sophie Larribeau, and Ronald MacDonald, ”Models of Exchange Rate Expectations: How Much Heterogeneity?” *Journal of International Financial Markets, Institutions and Money* 13 (2003): 113 – 136.

Bernhardt, Dan, Murillo Campello, and Edward Kutsoati, ”Who Herds?” *Journal of Financial Economics* 80 (2006): 657 – 675.

Carlson, John A. and Carol L. Osler, ”Rational Speculations and Exchange Rate Volatility,” Working Paper, Federal Reserve Bank of New York, 1998.

De Grauwe, Paul and Marianna Grimaldi, ”The Exchange Rate and its Fundamentals in a Complex World,” *Review of International Economics* 13 (2005): 549 – 575.

Dreger, Christian and Georg Stadtmann, ”What Drives Heterogeneity in Foreign Exchange Rate Expectations: Insights from a New Survey,” *International Journal of Finance and Economics* 13 (2008): 360 – 367.

Frömmel, Michael and Franziska Schobert, ”Exchange rate Regimes in Central and East European Countries: Deeds vs. Words,” *Journal of Comparative Economics* 34 (2006): 467 – 483.

Lamont, Owen A., ”Macroeconomic Forecasts and Microeconomic Forecasters,” *Journal of Economic Behavior and Organization* 48(2002): 265 – 280.

Laster, David, Paul Bennett, and In Sun Geoum, ”Rational Bias in Macroeconomic Forecasts,” *Quarterly Journal of Economics* 114 (1999): 293 – 318.

Levy-Yeyati, Eduardo and Federico Sturzenegger, ”Classifying Exchange Rate Regimes: Deeds vs. Words,” *European Economic Review* 49 (2005): 1603 – 1635.

MacDonald, Ronald and Ian W. Marsh, ”Currency Forecasters Are Heterogeneous: Confirmation and Consequences,” *Journal of International Money and Finance* 15 (1996): 665 – 685.

MacDonald, Ronald and Flávio Vieira, ”A Panel Data Investigation of Real Exchange Rate Misalignment and Growth,” CESifo Working Paper No. 3061, 2010.

Naujoks, Marcel, Kevin Aretz, Alexander Gabriel Kerl, and Andreas Walter, ”Do German Security Analysts Herd?” *Financial Markets and Portfolio Management* 23 (2009): 3 – 29.

Ottaviani, Marco and Peter Norman Sørensen, ”The strategy of professional forecasting,” *Journal of Financial Economics* 81 (2006): 441 – 466.

Notes

1. The scope of the Consensus Economics survey database is limited insofar as the surveys for developing countries are performed irregularly and only about two times a year. This is a difference compared to the exchange rate forecasts of industrialized countries which are surveyed regularly on a monthly basis. A further limitation is that not all forecasters submit forecasts all the time, implying that we could analyze an unbalanced database. Nevertheless, the Consensus Economic survey database is, for the purpose of our analysis, much more useful than other survey databases like the Wall Street Journal Poll, which covers only two exchange rates (USD/Yen, EUR/USD) on a biannual basis. Also, the Survey of Professional Forecasters (SPF) of the European Central Bank only includes dollar/euro forecasts. Some surveys, such as the Livingston survey or the SPF of the Federal Reserve, do not include exchange rate forecasts at all. In order to deal to some extent with the problem of missing data, we computed the S statistic based on forecasts from those forecasters who participated at least in 75 % of all surveys. Results (available upon request) corroborated the results shown in Table 2.

2. Until June 1998 vis-à-vis the US dollar, in June 1998 vis-à-vis the German mark. Thereafter vis-à-vis the Euro.

3. Until November 1999 vis-a-vis the US dollar. Thereafter vis-à-vis the Euro.

4. Until November 1999 vis-à-vis the US dollar. Thereafter vis-à-vis the Euro.

5. Before December 1999 vis-à-vis the US dollar. In December 1999, vis-à-vis German mark. Thereafter, vis-à-vis the Euro.

6. As yet another robustness check, we computed the S statistic for individual forecasters. While we found some heterogeneity of forecasters with respect to their S statistic, the S statistic was

larger than 0.5 for the vast majority of forecasters. We also correlated the forecaster-specific *S* statistic with a forecaster-specific root mean squared forecast error to analyze whether anti-herding and forecast accuracy are correlated. Due to the small number of cross-sectional observations (see Table 1) the estimated correlations were significant in only 5 out of 18 emerging market countries. In 12 emerging market countries (including those for which the correlations were significant), however, the correlations were positive. Results are available upon request.

7. Ottaviani and Sörensen (2006) argue that such a forecasting contest seems to be likely to unfold when the name of the forecaster (or the name of the employing institution) is being published, as Consensus Economics does.

8. Similarly, Lamont (2002, p. 268) argues: *"If forecasters are paid according to relative ability, they might scatter, since it is hard to win when making a forecast similar to others."* Empirically, we found (see Footnote 6) that anti-herding and forecast accuracy are negatively correlated (a larger forecaster-specific *S* statistic is positively correlated with a larger forecaster-specific forecast error).