

Herding Behavior of Business Cycle Forecasters in Times of Economic Crises

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Using a large international data set we analyze whether business cycle forecasters tend to herd or anti-herd. Applying different measures of economic crises, we distinguish between normal economic circumstances and times of crises. We find evidence for anti-herding behavior for most industrial economies, i.e. forecasters deliberately stick out their neck with extreme forecasts for strategic reasons. For a set of emerging market economies, by contrast, we find evidence for herding behavior. We relate this finding to the high incidence of economic and financial crises in these countries. A test for herding behavior during economic crises confirms that forecasters tend to herd in times of high forecast uncertainty.

JEL classification: E32; E37; E66

Keywords: Business Cycle; Forecasting; Economic Crises; (Anti-)Herding

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1 Introduction

Business cycle and growth expectations play a major role in understanding macroeconomic relationships. They also determine to what extent economic policy agents, including central banks, can influence macroeconomic outcomes. Researchers have analyzed whether business cycle forecasts are unbiased and rational (Döpke et al. 2010), and whether they are accurate and consistent with macroeconomic building blocks (Frenkel et al. 2011, Pierdzioch et al. 2010).

One way to deal with forecast uncertainty is to pool expectations of professional forecasters (Blix et al. 2001, Zarnowitz 1984) in order to hedge against errors of individual forecasters and thus to improve overall forecast quality. The idea is that although individual forecasters may outperform the average of a group of forecasters in certain cases, an individual forecaster rarely outperforms systematically. Zarnowitz and Lambros (1987) find that forecast errors of consensus forecasts fall short of most individual forecasters. Batchelor (2001) shows that consensus forecasts are more accurate than projections published by the OECD or the IMF.

Surveys of professional forecasters are provided by either central banks or by private companies. Examples of such pool or consensus forecasts for the U.S. are the Survey of Professional Forecasters (SPF) of the Federal Reserve Bank of Philadelphia (Croushore 1993) and the NABE Outlook or the Blue Chip Survey. The ECB publishes the SPF for euro area data (Garcia 2003, ECB 2007). But also private-sector firms, i.e. Consensus Economics and Focus Economics, provide pooled estimates of professional forecasters' predictions on a range of variables and for a broad set of countries worldwide. Survey participants typically work for banks, economic consulting firms or university research centers.

A strand in the related literature discusses whether the participation in these consensus surveys itself influences forecast behavior, i.e. forecasters may behave strategically. More specifically they may show herding or anti-herding tendencies. Forecaster herding arises if forecasters ignore their private information and instead follow the forecasts of others (Scharfstein and Stein 1990, Froot et al. 1992). Bewley and Fiebig (2002) for example show that interest rate forecasters tend to indicate values in the safe consensus range so as not to stick their neck out with "extreme" forecasts. The reason is that a poor forecast may not damage reputation if other forecasters also delivered poor forecasts. Herding behavior thus biases the

distribution towards the mean.

Forecaster anti-herding by contrast may arise if forecasters, for strategic or other reasons, deliberately scatter their forecasts away from the forecasts of others. Laster et al. (1999) show how such an incentive to publish extreme forecasts may arise when forecasters' income (or reputation) does not only depend on the accuracy of their forecasts, but also on the relative performance. In their model, two groups of customers buy forecasts. The first group buys forecasts regularly and chooses those forecasters who delivered the most accurate predictions over a longer time period. The second group of customers buys forecasts occasionally and picks those forecasters with the best performance in the last period. If the second group of customers dominates, forecasters have a strong incentive to differentiate their forecasts from those of others: Even though an "extreme" forecast may have a small probability of being accurate, the expected payoff can be high because, in the case of such a stroke of luck, a forecaster does not have to share with others revenues from the second group of customers.

(Anti-)herding behavior may also depend on the specific design of the forecast survey. If, for instance, survey terms require a certain continuity of participation, forecasters may have an incentive to provide updated results even if they are currently not running a fully-fledged forecast exercise.¹ In such a case a forecast close to the last consensus forecast may be on the safe side, providing incentives for herding behavior. This effect can be assumed to increase with the frequency of the survey (quarterly/monthly).

A second factor that may matter for (anti-)herding behavior is whether the names of forecaster are disclosed. If forecaster names are published, incentives to publish extreme forecasts to gain reputation can be expected to be larger. Similarly the tendency to hide in the crowd when the own updated forecasts are just quick shots may be more pronounced if names are disclosed. In both cases the revealed forecast may deviate from their best forecast.² This is why some of the consensus surveys, such as the SPF of the Federal Reserve Bank of Philadelphia or the ECB, opt for the anonymity of the forecasters.

¹A survey among SPF participants (ECB 2009) reveals that about 60% of involved forecasters update their real growth forecasts on a quarterly basis or even less frequently.

²The above mentioned effects may be further reinforced if – as Kenny (2010) proposes – forecasts with a better track record and/or forecasts which are less correlated with other forecasts receive a higher weight in pooled forecasts.

Finally, the stage within the business cycle and therefore the level of economic uncertainty may matter for incentives of researchers to hide in the comfortable consensus middle or to go out on a limb with extreme forecasts. This effect is so far not investigated in the literature but is explicitly taken into account in our study. More specifically we investigate (anti-)herding tendencies during times of economic crises.

It is important to emphasize that forecast clustering need not imply herding behavior. After all forecasters have access to the same set of economic data and similar forecast techniques. It is thus not surprising to observe similar forecasts. But herding behavior implies that forecasters deliberately deviate from their best private forecast for strategic reasons. It should be emphasized that herding does not necessarily imply non-optimal forecasts since forecasters can herd towards an optimal forecast. This implies that herding acts an informational means by which valuable information spreads among the forecasters. Morris and Shin (2002) develop a theoretical framework based on the beauty contest and show how the flow of information can improve the expectation formation process. In such a beauty contest professional forecasters herd since forecasters are trend followers. If the business cycle exhibits large swings, a forecaster who follows a trend might rely to a higher extent on forecasts of his colleagues. Hence, a forecaster who expects his colleagues to predict a higher growth rate might submit a similar forecast which in turn improves his forecast accuracy. This argument might explain why empirical studies suggest that the Consensus forecasts tend to be unbiased and rational (Dovern and Weisser 2011).

From a monetary and economic policy perspective, knowledge about the reliability of forecasts is of utmost importance. To hide in the safe consensus range a forecaster might submit a forecast that is closer to the consensus forecast than his private efficient estimate. This does not only imply a smaller level of forecast heterogeneity but also forecast inertia, so that the adjustment of the consensus forecast to newly available economic data is delayed. It is therefore essential to understand whether pooled forecasts are subject to (anti-)herding biases and whether reliability depends on the level of economic uncertainty (Morris and Shin 2002). After all, forecasts may themselves influence economic reality through self-fulfilling prophecy effects (Grisse 2009). Especially financial market participants are extremely sensitive to forecasts.

But forecast clustering - either because forecasters use the same economic information and techniques or because of herding behavior - may also matter

from a statistical point of view. If "clumped" forecasts are a quite common phenomenon it may be important to account for this correlation when combining forecasts. Graham (1996) suggests methods to model explicitly the associated positive correlation.

In this study we analyze the herding behavior of business cycle forecasters participating in the Consensus Economics forecast poll. Since 1989 Consensus Economics publishes average forecasts on a broad set of countries. Today the monthly survey covers more than 700 economists worldwide, over 85 countries and various variables (real growth rate, inflation rate, the current account balance, interest rates) and also provides surveys on long-term forecasts. For about half of the covered countries the survey provides disaggregated forecast data, i.e. the forecasts of the single survey participants are disclosed. Participation in each period is voluntary. In July 2012 for example only 24 out of 68 of the participating forecasters in the United Kingdom actually submitted updated figures. Nevertheless it can be assumed that a minimum level of continuity is required from survey participants.

We study forecaster herding using a novel empirical test developed by Bernhardt et al. (2006). We find evidence for anti-herding behavior for most industrial economies but signs of forecaster herding for emerging economies. We relate this finding to the high incidence of economic and financial crises in these countries. A test for herding behavior during economic crises confirms that forecasters tend to herd in times of high forecast uncertainty while we do not find any evidence for a statistically significant relationship between economic development and growth forecasts.

We organize the remainder of this paper as follows. We sketch the essential elements of the herding test in Section 2. We present our data in Section 3 and our empirical findings in Section 4. We will analyze the impact of economic uncertainty on forecasting behavior in Section 5 and offer some concluding remarks in Section 6.

2 Testing for Forecaster Herding

The intuition motivating the test for forecaster (anti-)herding developed by Bernhardt et al. (2006) can best be elucidated by considering, as a benchmark scenario, a forecaster who forms an "efficient" private forecast of the future real growth rate. The efficient private forecast should be unbiased

and the probability that it overshoots or undershoots the growth rate should be 0.5, independently of the forecasts of the others. If, in contrast, forecasts are biased because forecasters (anti-)herd, the published forecasts will differ from the efficient private forecast.³ As a result, the probability that it overshoots or undershoots the growth rate should be larger or smaller than 0.5.

In the case of forecaster herding, the published forecast deviates from the (unobservable) efficient private forecast because a forecaster follows the forecasts of others. The forecasts of others, in turn, can be measured in terms of the consensus forecast $\tilde{s}_{i,t-1,t+k}$ (the average forecast made by other forecasters).⁴ The published forecast, thus, is closer to the consensus forecast than the efficient private forecast. A published forecast exceeding the consensus forecast is smaller than the efficient private forecast, leaving less room for forecast overshooting. Similarly, a published forecast smaller than the consensus forecast is larger than the efficient private forecast, leaving less room for forecast undershooting. Conversely, in the case of forecaster anti-herding, a published forecast larger (smaller) than the consensus forecast is also larger (smaller) than the efficient private forecast, inflating the probability of overshooting (undershooting).

More formally, published forecasts, under the null hypothesis of unbiasedness (no herding or anti-herding), should imply that the conditional probability of overshooting (undershooting), P_o (P_u), should be 0.5, regardless of the consensus forecast. We then have:

$$P_o = P(s_{t+k} < s_{i,t,t+k} \mid s_{i,t,t+k} > \tilde{s}_{i,t-1,t+k}, s_{t+k} \neq s_{i,t,t+k}) = 0.5, \quad (1)$$

$$P_u = P(s_{t+k} > s_{i,t,t+k} \mid s_{i,t,t+k} < \tilde{s}_{i,t-1,t+k}, s_{t+k} \neq s_{i,t,t+k}) = 0.5, \quad (2)$$

where $s_{i,t,t+k}$ reflects the forecast made by forecaster i in period t for the real growth rate s_{t+k} in period $t+k$ (with $k = 12, 11, \dots, 1$ for the current-year forecasts, and $k = 24, 23, \dots, 13$ for the next-year forecasts), and $\tilde{s}_{i,t-1,t+k}$

³Our analysis concerns the cross-sectional (anti-)herding of forecasters. In the empirical literature, researchers use the term “herding” to characterize the time-series properties of forecasts (Gregory and Yetman 2004). Our usage of the term herding, thus, should not be confused with the terminology used by other researchers who utilize the term herding to describe, for example, destabilizing trend-extrapolative forecasts in a time series context.

⁴We used the consensus forecast of the previous survey to make sure that the information set of a forecaster includes consensus forecast. Additionally, we excluded the forecaster’s own projection published in the previous survey to compute a forecaster-specific consensus forecast.

refers to the last consensus forecast that is observable. Forecaster herding then implies:

$$P_o = P(s_{t+k} < s_{i,t,t+k} \mid s_{i,t,t+k} > \tilde{s}_{i,t-1,t+k}, s_{t+k} \neq s_{i,t,t+k}) < 0.5, \quad (3)$$

$$P_u = P(s_{t+k} > s_{i,t,t+k} \mid s_{i,t,t+k} < \tilde{s}_{i,t-1,t+k}, s_{t+k} \neq s_{i,t,t+k}) < 0.5. \quad (4)$$

Finally, forecaster anti-herding implies

$$P_o = P(s_{t+k} < s_{i,t,t+k} \mid s_{i,t,t+k} > \tilde{s}_{i,t-1,t+k}, s_{t+k} \neq s_{i,t,t+k}) > 0.5, \quad (5)$$

$$P_u = P(s_{t+k} > s_{i,t,t+k} \mid s_{i,t,t+k} < \tilde{s}_{i,t-1,t+k}, s_{t+k} \neq s_{i,t,t+k}) > 0.5. \quad (6)$$

Bernhardt et al. (2006) suggest to test for forecaster (anti-)herding using the average of the two conditional probabilities. Their test statistic is defined as $S = (P_o + P_u)/2$, and has an asymptotically normal sampling distribution. Unbiased forecasts imply $S = 0.5$, herding implies $S < 0.5$, and anti-herding implies $S > 0.5$. The averaging of the two conditional probabilities implies that a positive market-wide shock that, for example, increases s_{t+k} leaves the test statistic S , unaffected. The reason is that such a shock increases P_u and, at the same time, decreases P_o . The appealing feature of the S statistic is that it is robust to correlated information among forecasters, to unexpected shocks and to new information arrivals. It does, thus, not depend on how forecasts are formed and does not require assumptions about the distribution of the individual priors.

Of course the crucial assumption that forecasts are unbiased in the absence of herding or anti-herding behavior can be challenged. One could argue that real growth forecasters may have a positive forecast bias. This may arise for example because forecasters take positive external effects of positive forecasts on financial products into account. Bernhardt et al. (2006) themselves raise the example that financial analysts may issue optimistic forecasts early in the forecasting cycle and pessimistic forecasts later in the cycle, which is unrelated to herding. One could also argue that forecasting behavior changes over the forecast cycle as uncertainty declines the shorter the forecast horizon gets. Because of the specific design of the S statistic that nets out opposing effects the test statistic is unaffected by this type of biases.

3 Data

In our empirical analysis we use monthly survey data on business cycle forecasts compiled by Consensus Economics for all 45 countries for which the

disaggregated forecasts are available. While some industrialized countries have been included in the survey since October 1989, the majority of countries has been covered since the mid 1990s. Hence, the number of forecasters and forecasts varies across countries. While we have about 800 forecasts submitted by a group of 18 forecasters for the Philippines at our disposal, we can study data for 68 forecasters who published more than 14,000 business cycle forecasts for the United Kingdom. Our sample period ends in December 2011, and it covers a total of 226,851 business cycle forecasts published by 1,604 forecasters. Consensus Economics publishes forecasts for two different time horizons, namely for the end of the current year and the end of the next year. Since the survey is collected monthly there are thus 24 consecutive consensus forecasts for a given calendar year.

There are at least three reasons why our data set is particularly suited to study the herding instinct of business cycle forecasters. First, because the poll is conducted each month during the first week, and is released within the second week, it is a timely and frequent mean for central banks to get to know how business cycle expectations develop. In fact, at least some central banks include these forecasts in their inflation report to justify their monetary policy decisions (Banco de Brazil 2001, p.122). Second, the data set allows its large cross-sectional dimension and its extensive time-series dimension of more than twenty years to be analyzed. Third, individual forecasts are published along with the name and affiliation of a forecaster.⁵ Finally participation in each survey is voluntary, so that the composition of the survey participants changes each time. This has the advantage that forecasters are not forced to come up with new numbers even if they had not run a new forecast round recently.

Given this rich set of information, we are thus able to evaluate the performance of an individual forecaster. As mentioned previously, performance can be expected to have an effect on the reputation of a forecaster. On the one hand, the link between performance and reputation may strengthen the incentive to herd. The reason is that a poor forecast may not damage reputation if other forecasters also delivered poor forecasts. On the other hand, the effect of performance on reputation may foster scattering of forecasts if an occasional excellent forecast gives rise to a "superstar" effect.

⁵Forecasters work with the private sector in the respective country. The survey participants are professional economists working for universities and financial institutions such as international economic research institutes, investment and commercial banks. Further information concerning the survey can be found on the website: www.consensuseconomics.com.

These reputation effects may change with the stage in the business cycle or generally with the level of economic uncertainty.

In order to examine the time-series dimension and the cross-sectional dimension of the survey data, Figure 1 plots the time series of (i) the cross-sectional mean values of the current-year growth forecasts (dashed lines), (ii) the actual annual growth rates taken from the IMF database (solid lines), and, (iii) the cross-sectional heterogeneity of forecasts as measured by the cross-sectional range of forecasts (shaded areas) for a selection of countries exemplarily. We depict these results for a number of countries at different stages of development ranging from the United Kingdom and the United States to a selection of emerging countries that were subject to severe economic crises in the past such as Argentina, Russia, or Turkey. In all cases the recent recession in the course of the global financial crisis is clearly visible. The vertical distance between the dashed line and the solid line can be interpreted as the cross-sectional forecast error.

Insert Figure 1 about here.

These cross-sectional mean values move in tandem with the respective actual values, at least as far as the end-of-year values are concerned. This result is intuitive because the forecast accuracy should increase as the forecast horizon shrinks. Another important piece of information is that the cross-sectional heterogeneity of forecasts is substantial. For instance, in January 1999 the forecast range of the real growth rate in Russia was between -3.0 and -11.0 percent. In February 2009 the forecasts of the real growth rate in the United States (United Kingdom) ranged between -3.1 and 2.1 (-3.5 and 2.5) percent indicating a substantial degree of disagreement among the forecasters. In such periods, growth forecasts resemble forecasts of considerably more volatile variables such as, for example, exchange rates (Benassy-Quere et al. 2003).

To the best of our knowledge, the cross-sectional heterogeneity of forecasts of the real growth rate for such a large sample of countries has not yet been documented in the literature. Given this substantial heterogeneity an analysis of the formation of growth forecasts by individual professional forecasters seems appealing. This follows in the next section. As we will see, anti-herding behavior of growth forecasters is one source of the substantial heterogeneity of growth forecasts in most industrial countries.

4 Empirical Analysis

Table 1 presents our main results and reports the S statistic, its standard error, and the boundaries of a confidence band for all countries. It also contains information on the sample period, the number of forecasters available for every country in our sample, and the total number of observations. Three things stand out. First, the test statistic concerning the current-year (next-year) forecasts significantly exceeds the value of 0.5 in 20 (31) out of 45 cases indicating that in the majority of countries business cycle forecasters exhibit anti-herding behavior for the majority of economies. Hence, business cycle forecasters deliberately scatter their forecasts farther away from the consensus. Second, for 9 (5) countries, the test statistic for the current-year (next-year) is significantly lower than 0.5 implying that in some countries business cycle forecasters place their forecast towards the consensus. Such a herding behavior can be found for Argentina, Colombia, Estonia, Latvia, Lithuania, Mexico, Peru, Poland, and Turkey. These are mostly developing or transition countries. Third, for some countries like Brazil, Italy, Sweden and the Ukraine, the S statistic is not significantly different from 0.5 indicating no (anti-)herding.

Insert Table 1 about here.

In sum, Table 1 gives the impression that forecaster herding is a typical phenomenon in emerging market economies countries. To investigate this hypothesis Figure 2 plots the S statistic and GDP per capita as of 2011 for all 45 countries. Although the slope of the regression line is positive indicating that in less developed countries forecasters have a higher tendency to herding behavior, this relationship is not statistically significant.

Insert Figure 2 about here.

Hence, other factors than the economic situation seem to be related to the herding behavior. Since less developed countries are also more prone to economic and financial crises, one may therefore hypothesize that it is not the level of economic development but rather the incidence of economic crisis that explains the differences in herding and anti-herding behavior.

In order to shed more light on this hypothesis Figure 3 plots the S statistic for current-year forecasts of each country against the average Reinhart-Rogoff (RR) index over the sample period of the country (Reinhard and Rogoff 2011). This index reflects a comprehensive crisis definition, as it encompasses financial, currency and economics crises. A composite indicator

is constructed by adding up the incidence of a crises in one year in each of six different domains (banking crisis, currency crash, domestic default (or restructuring), external default (or restructuring), inflation crisis, and stock market crash. The resulting crisis tally ranges from 0 (no crisis) to 6 (severe crisis).

Figure 3 shows that in countries with a higher average crisis index and, hence, more frequent and severe crisis experience, forecasters show a stronger tendency to herd. Compared to that, countries located on the left of the figure experienced on average fewer crises and simultaneously business cycle forecasters in these countries tend to anti-herd. The slope coefficient of the regression line (solid line) shows a significantly negative relationship between both variables. One might also interpret this finding in the way that in countries which are more prone to economic crises forecasters tend to show herding behavior - a hypothesis that we investigate in the next section.

Insert Figure 3 about here.

Given the large swings and sharp reversals in the growth rate during our sample period, we also analyzed the variation in the S statistic over time. Fluctuations in the S statistic should signal changes in the prevalence of forecaster (anti-)herding. We use a rolling-window estimation approach where every window represents one year of data.

Figure 4 plots the S statistics and the resulting 99% confidence bands for some selected countries together with the RR index (dotted line) as a measure of economics crises. The results suggest that the S statistic varies over time and sometimes significantly exceeds the value of 0.5 (anti-herding) while in other periods it falls short of the value of 0.5 (herding). Overall anti-herding behavior is more prevalent than herding, especially during economically quiet times, indicating that forecasters differentiate their forecasts from those of their colleagues. Interestingly, the S statistic and the RR index seem to exhibit contrary movements. For instance, during the Russian Crisis in 1998/1999 the herding statistic is significantly lower than 0.5, indicating forecaster herding behavior. Similar evidence is found for Argentina in 2000-03, Mexico (1994-96 and 1999-00) or Turkey (1999-2001): Whenever the RR crisis index increases, forecasters tend to show herding behavior. To a lesser extent this is true for industrial countries in the course of the global financial crisis, e.g. in United Kingdom. Overall Figure 4 corroborates our hypothesis, that there is a link between herding behavior and times of economic crisis rather than a link between herding behavior and the level of economic de-

velopment. We will investigate this hypothesis more thoroughly in the next section.

Insert Figure 4 about here.

5 Forecasting Behavior in Times of Economic Uncertainty

In this section we analyze the link between business cycle forecasters (anti-)herding behavior and the incidence of difficult economic times. To this end, we do not restrict ourselves to crisis periods but investigate more broadly times of high economic uncertainty. To ensure the robustness of our results we define economic uncertainty from three completely different angles.

Our first measure is the RR index described above which explicitly defines financial, currency and economics crises. It is a discrete variable ranging between 0 and 6, with a higher value indicating a more severe crisis in the sense that it affects many dimensions of the economy.

Our second measure identifies recessions according to the conventional rule defined as two consecutive quarters of negative real growth. This measure of uncertainty thus refers to recessions rather than to economic crises. We construct a binary dummy for each year. If two consecutive quarters exhibit negative growth rates the dummy takes the value of one, and zero otherwise.⁶

As a third measure of economic uncertainty we use a proxy directly observed from the Consensus Economics survey. To measure the extent of macroeconomic uncertainty, we make use of the forecasting cycle within this survey which consists of 24 months for each year. Since the forecasters are required to predict the growth rate of the current and the next year, each year is forecasted in 24 consecutive surveys. Naturally, the closer the survey approaches the end of the forecasting cycle the more precise are the forecasts. This can be seen in Figure 1 which shows that the consensus forecast (dotted line) approaches the realized value (solid line) as far as end of year forecasts are concerned. The extent of the revisions for a specific year is then a natural measure for the level of forecast uncertainty. We proceeded by using the sequence of the 24 consecutive consensus forecasts within a forecasting cycle and calculated the standard deviation for each

⁶If negative real growth is recorded in the fourth quarter of a year and in the first quarter of the subsequent year, we date the recession to the subsequent year.

forecaster over time as a proxy for forecast revisions. Hence, we obtain for each year and country a measure of the forecast uncertainty. In total, we have more than 7,000 observations for each measure available. As compared to the other two measures this proxy interprets economic uncertainty symmetrically, i.e. high forecast revisions in boom periods are treated the same way as revisions during recessions. It is furthermore not a binary dummy but a continuous variable.

Table 2 reports the correlation between the S statistic and the three measures of economic uncertainty. The level of correlation between our three measures is significantly different from zero but quite low which is not surprising given that they are derived from totally different data sources and statistical approaches and also define economic uncertainty from different points of view. Nevertheless the correlation between the measures and the S statistic is negative in all three cases and significant in two of them, indicating that the S statistic declines with the level of economic uncertainty. This confirms our previous visual analysis.

Insert Table 2 about here.

To underpin our argument further, we subsequently link all three measures of forecast uncertainty to the time-varying (anti-)herding statistic $S_{i,t}$ for each country i at the time t (recall that the time-varying S_t is shown in Figure 4 for selected countries). To this end, we regress the $S_{i,t}$ statistic on each measure of forecast uncertainty by means of the following equation:

$$S_{i,t} = \alpha_i + \beta Crisis_{i,t} + \gamma GDPpc_{i,t} + \epsilon_{i,t} \quad (7)$$

where the α coefficient indicates the presence of (anti-)herding behavior and the β coefficient measures the extent to which forecaster deviate from this behavior in times of crisis. Table 3 reports the estimation results based on OLS with Newey-West (1987) robust standard errors to take autocorrelation and cross-section correlation into account as well as in a panel fixed-effect specification to allow for systematic difference among the countries. We generally observe anti-herding behavior in normal times as reflected by the constant term α of about 0.57 which is significantly higher than 0.5 indicating that business cycle forecasters on average anti-herd. The coefficient on the crisis dummy suggests a statistically significant negative relationship between forecaster anti-herding and extent of forecast uncertainty. The same result emerges once we substitute the RR index by the standard deviation of forecast revisions. Again the β coefficient is significantly negative indicating that in times of forecast uncertainty business cycle forecasters tend to herd while

in normal times they tend to anti-herd. Concerning the recession dummy the β coefficient is negative and of similar magnitude than in the forecast revision case, but insignificant. Compared to this, the relationship between the time-varying S statistic and the GDP per capita as measured by the γ coefficient is not significantly different from zero. Also when using the RR index and the GDP per capita as explanatory variables shows that the crisis variables is significant while the GDP per capita is not.

Insert Table 3 about here.

While forecasters thus typically anti-herd in normal times, they show a tendency towards herding in times of higher economic uncertainty. The value of about -0.07 in the RR specification for example suggests that a crisis of level 2 according to the RR index would thus be enough for forecasters to switch to herding behavior. Concerning the forecast revisions, the coefficient of -0.05 indicates that if the standard deviation of the forecast revisions increases by about 0.1 over the forecasting cycle of 24 months, the herding statistic significantly falls short of the unbiased value of 0.5. This indicates that herding behavior is more likely the more forecasters have revised their forecasts.

Our results thus show that herding and economic crisis are related, however they do not allow us to engage in a more thorough analysis concerning the causality of this relationship. From our data we cannot identify the underlying reasons driving herding behavior in times of crises or more generally in times of heightened uncertainty. A more comprehensive analysis could further scrutinize the role of model uncertainty in forecasting models and the effect of more frequent data revisions in uncertain times on forecasting behavior. However, forecasting behavior and economic uncertainty are clearly related, as suggested by our results. Prati and Sbracia (2010) provide further evidence and show that the higher forecast uncertainty of the Consensus Economics data set concerning macroeconomic variables is associated with currency crises.

6 Concluding Remarks

In this paper we use more than 226,851 growth forecasts submitted by 1,604 professional forecasters in 45 countries. The main finding of our research is that forecasters show anti-herding behavior in their prediction of real growth, at least in normal times and for industrialized countries.

Forecasters, thus, appear to make "extreme" forecasts in a smooth and predictable economic environment. However, the extent of anti-herding among the industrialized countries varies substantially. Extreme forecasts may reflect attempts to differentiate one's own forecasts from the forecasts of others. Laster et al. (1999) show how such an incentive to scatter forecasts around the consensus forecasts arises when forecasters' income (or reputation) does not only depend on the accuracy of their forecasts, but also on relative performance. An extreme forecast that is very different from the forecasts of other forecasters may predict growth rates poorly. If such an extreme forecast, however, turns out to be correct occasionally, and no other forecaster has published a similar forecast, then the income effect of such a stroke of luck may be large. In contrast to this, we document that growth forecasters in emerging economies seem to herd. They tend to place their forecasts towards the consensus.

Further, we find that the extent to which growth forecasters (anti-)herd is varying over time. Based on a rolling window estimation approach we find that forecaster (anti-)herding was somewhat less pronounced in 2001 to 2003 and became more prevalent thereafter. Using three different indicators for crisis and uncertainty a regression analysis confirms that forecasters show a tendency to approach the previous consensus forecast in more turbulent times. Thus, in an environment of elevated uncertainty, forecasters show less anti-herding and more herding behavior. Thus it seems that more uncertain economic circumstances induce professional forecasters to hide in the flock. When predictability of future real growth worsens due to the presence of an economic crisis or the like, forecasters seem to give higher weight to potential reputation losses because of wrong individual forecasts. This can be justified, as a wrong forecast made by a majority of forecasters can be considered as something unavoidable and thus will not affect the reputation of the single forecaster.

In terms of a suggested policy implication, our results indicate that in times of economic crisis the tendency to herding behavior decreases the heterogeneity which, in turn, is less pronounced than it potentially would be under no herding behavior. In contrast to this, under normal economic conditions the anti-herding behavior yields a higher forecaster heterogeneity compared to a situation of unbiased forecasts. This indicates that the disagreement of forecasters in times of economic crises is potentially even stronger as reflected in the survey data while under normal economic conditions survey forecasts report an imprecise measure of forecast disagreement since the heterogeneity of forecasts is exaggerated. An evaluation of

forecaster disagreement by means of survey data should, hence, take into account the forecasting behavior rather than relying on simple statistical measures. Policy makers as well as financial market participants should take such a behavior into account before inferring macroeconomic uncertainty from survey data.

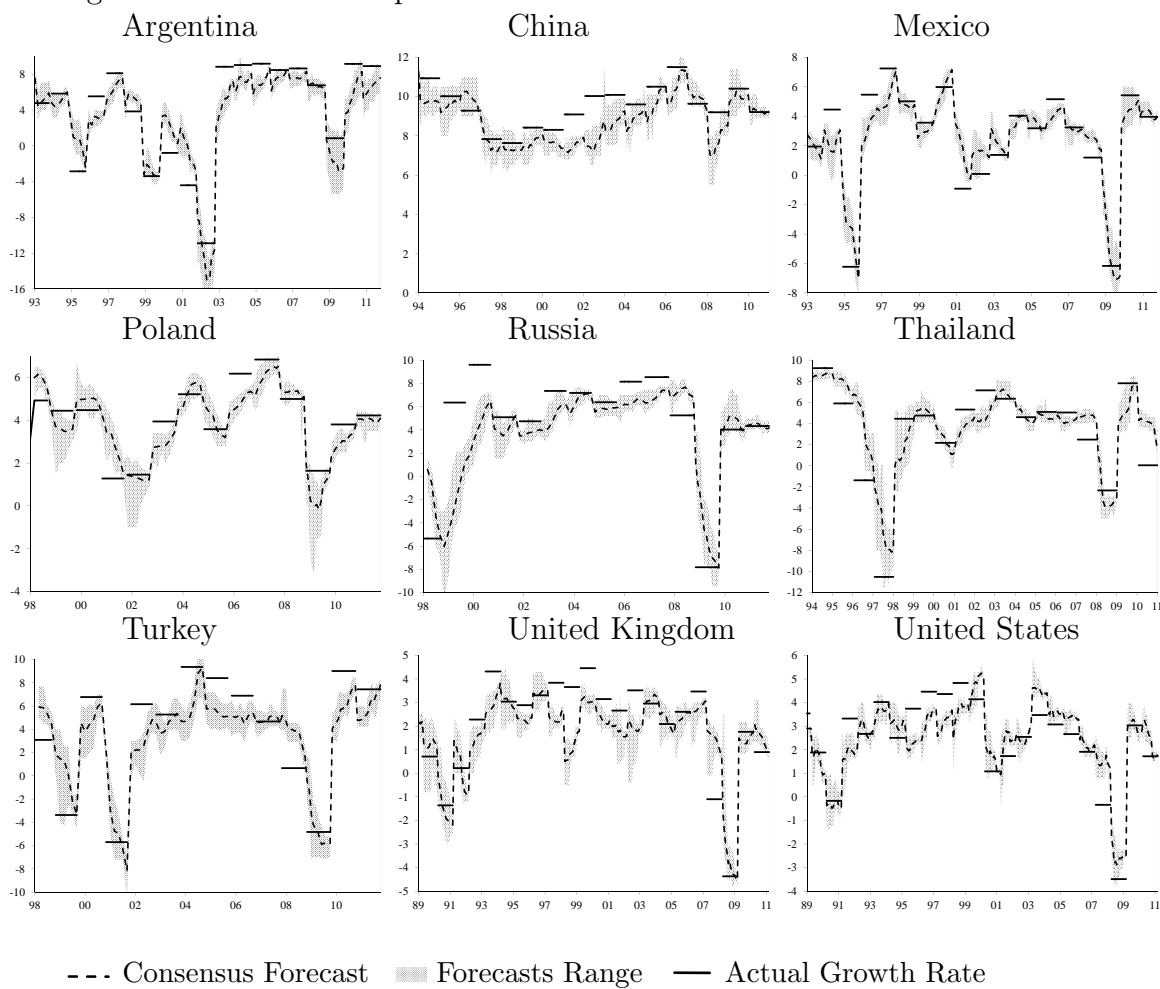
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Figure 1: Actual and Expected Growth Rates for Selected Countries



Notes: Figure 1 shows the cross-sectional consensus current-year forecast (dotted line), the forecast range (shaded area), and the actual values (solid line). The actual growth rates are taken from the database of the International Monetary Fund.

Table 1: Empirical Results

Country (Period)	Year	S stat.	Stand. Error	Lower 99 %	Upper 99 %	Obs.	Forecaster
Argentina	current	0.485 ⁺	0.01	0.462	0.508	3,306	53
(1993–2011)	next	0.465*	0.01	0.440	0.490	2,769	53
Australia	current	0.545*	0.01	0.524	0.565	4,155	41
(1990–2011)	next	0.661*	0.01	0.640	0.682	3,965	41
Brazil	current	0.503	0.01	0.479	0.527	3,059	53
(1993–2011)	next	0.515	0.01	0.490	0.540	2,829	53
Bulgaria	current	0.660*	0.02	0.600	0.720	481	13
(1998–2011)	next	0.582*	0.02	0.529	0.635	609	13
Canada	current	0.495	0.01	0.474	0.516	4,010	37
(1999–2011)	next	0.534*	0.01	0.513	0.556	3,812	37
Chile	current	0.525*	0.01	0.501	0.550	2,936	43
(1993–2011)	next	0.497	0.01	0.471	0.522	2,699	43
China	current	0.543*	0.01	0.521	0.565	3,572	46
(1994–2011)	next	0.601*	0.01	0.578	0.624	3,295	46
Colombia	current	0.496	0.01	0.464	0.527	1,747	34
(1997–2011)	next	0.474 ⁺	0.01	0.440	0.507	1,567	34
Croatia	current	0.580*	0.02	0.521	0.639	533	12
(1998–2011)	next	0.517	0.02	0.453	0.581	427	12
Czech Republic	current	0.511	0.01	0.481	0.541	1,872	32
(1998–2011)	next	0.553*	0.01	0.520	0.585	1,674	32
Estonia	current	0.428*	0.02	0.368	0.487	492	13
(1998–2011)	next	0.419*	0.03	0.351	0.486	393	13
France	current	0.568*	0.01	0.548	0.587	4,741	40
(1999–2011)	next	0.553*	0.01	0.532	0.573	4,247	40
Germany	current	0.525*	0.01	0.510	0.541	7,197	54
(1999–2011)	next	0.505	0.01	0.489	0.521	6,630	54
Hong Kong	current	0.519 ⁺	0.01	0.496	0.541	3,284	44
(1994–2011)	next	0.530*	0.01	0.506	0.554	3,006	44
Hungary	current	0.487	0.01	0.455	0.519	1,725	29
(1998–2011)	next	0.580*	0.01	0.546	0.614	1,560	29
India	current	0.516	0.01	0.490	0.542	2,506	45
(1994–2011)	next	0.587*	0.01	0.559	0.616	2,124	45
Indonesia	current	0.583*	0.01	0.558	0.608	2,736	46
(1994–2011)	next	0.591*	0.01	0.565	0.617	2,553	46
Italy	current	0.498	0.01	0.476	0.520	3,625	40
(1999–2011)	next	0.499	0.01	0.476	0.522	3,377	40
Japan	current	0.598*	0.01	0.580	0.616	5,263	45
(1999–2011)	next	0.607*	0.01	0.587	0.628	4,228	45
Latvia	current	0.459 ⁺	0.02	0.398	0.519	474	13
(1994–2011)	next	0.440 ⁺	0.03	0.372	0.507	383	13
Lithuania	current	0.435*	0.02	0.371	0.498	434	12
(1994–2011)	next	0.460 ⁺	0.03	0.389	0.531	347	12
Malaysia	current	0.518 ⁺	0.01	0.494	0.541	3,122	52
(1994–2011)	next	0.554*	0.01	0.529	0.578	2,919	52
Mexico	current	0.460*	0.01	0.437	0.482	3,492	50
(1993–2011)	next	0.543*	0.01	0.520	0.566	3,239	50

Notes: Stand. Error = standard error. p-value = significance level of $H_0: S = 0.5$. Obs. = number of forecasts. No. = number of forecasters. * (+) = significance level on a one (ten) percent level ($H_0: S = 0.5$).

Table 1: Empirical Results (continued)

Country (Period)	Year	S stat.	Stand. Error	Lower 99 %	Upper 99 %	Obs.	Forecaster
Netherlands	current	0.498	0.01	0.467	0.529	1,782	29
(1995–2011)	next	0.542*	0.01	0.510	0.575	1,641	29
New Zealand	current	0.584*	0.01	0.559	0.610	2,668	27
(1994–2011)	next	0.608*	0.01	0.581	0.634	2,485	27
Norway	current	0.549*	0.01	0.515	0.583	1,489	20
(1998–2011)	next	0.573*	0.01	0.538	0.609	1,400	20
Peru	current	0.461*	0.01	0.429	0.493	1,726	33
(1997–2011)	next	0.490	0.01	0.456	0.523	1,526	33
Philippines	current	0.499	0.02	0.440	0.558	491	18
(2009–2011)	next	0.595*	0.03	0.518	0.672	293	18
Poland	current	0.471*	0.01	0.441	0.500	1,979	36
(1998–2011)	next	0.497	0.01	0.465	0.528	1,783	36
Romania	current	0.515	0.01	0.477	0.553	1,194	29
(1998–2011)	next	0.528 ⁺	0.02	0.488	0.568	1,078	29
Russia	current	0.474 ⁺	0.01	0.442	0.505	1,733	40
(1998–2011)	next	0.565*	0.01	0.532	0.599	1,561	40
Singapore	current	0.510	0.01	0.486	0.534	2,978	44
(1994–2011)	next	0.536*	0.01	0.511	0.561	2,787	44
Slovakia	current	0.506	0.01	0.468	0.544	1,204	27
(1998–2011)	next	0.583*	0.02	0.542	0.623	1,090	27
Slovenia	current	0.453 ⁺	0.02	0.397	0.510	561	13
(1998–2011)	next	0.538	0.02	0.474	0.602	451	13
South Korea	current	0.578*	0.01	0.555	0.601	3,186	40
(1994–2011)	next	0.524 ⁺	0.01	0.499	0.548	2,842	40
Spain	current	0.544*	0.01	0.518	0.569	2,694	28
(1995–2011)	next	0.546*	0.01	0.518	0.573	2,355	28
Sweden	current	0.504	0.01	0.478	0.529	2,718	32
(1995–2011)	next	0.490	0.01	0.464	0.516	2,533	32
Switzerland	current	0.564*	0.01	0.534	0.593	2,016	19
(1998–2011)	next	0.553*	0.01	0.522	0.584	1,842	19
Taiwan	current	0.513	0.01	0.489	0.537	2,968	36
(1994–2011)	next	0.566*	0.01	0.541	0.592	2,733	36
Thailand	current	0.508	0.01	0.483	0.533	2,741	45
(1994–2011)	next	0.537*	0.01	0.511	0.564	2,475	45
Turkey	current	0.456*	0.01	0.424	0.488	1,664	38
(1998–2011)	next	0.467 ⁺	0.01	0.431	0.502	1,419	38
Ukraine	current	0.499	0.01	0.463	0.534	1,352	28
(1998–2011)	next	0.505	0.01	0.466	0.544	1,163	28
United Kingdom	current	0.543*	0.01	0.528	0.559	7,516	68
(1999–2011)	next	0.599*	0.01	0.583	0.614	7,241	68
United States	current	0.551*	0.01	0.535	0.567	6,941	65
(1999–2011)	next	0.535*	0.01	0.518	0.551	6,334	65
Venezuela	current	0.518 ⁺	0.01	0.492	0.544	2,551	42
(1993–2011)	next	0.597*	0.01	0.569	0.624	2,253	42

Notes: Stand. Error = standard error. p-value = significance level of $H_0: S = 0.5$. Obs. = number of forecasts. No. = number of forecasters. * (+) = significance level on a one (ten) percent level ($H_0 S = 0.5$).

Table 2: Correlation of Crisis Variables

	<i>S</i> statistic	Reinhart-Rogoff	Forecast Revisions	Recession Dummy
<i>S</i> statistic	1			
Reinhart-Rogoff	-0.063*	1		
Forecast Revisions	-0.066*	0.233*	1	
Recession Dummy	-0.019	0.209*	0.494*	1

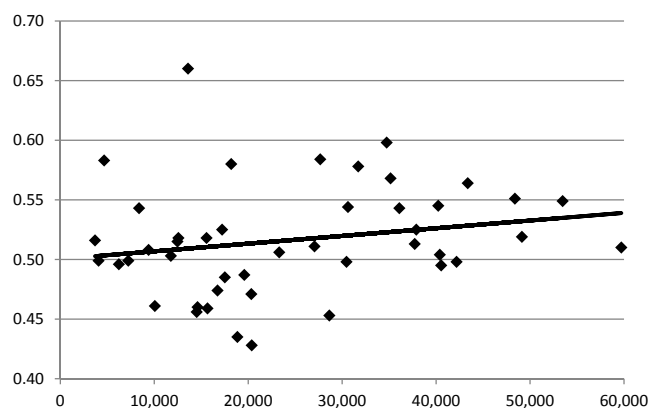
Note: Table 2 reports the Bravais-Pearson correlation coefficient; * indicates significance on a one percent level.

Table 3: Relationship of (Anti-)Herding and Crises

Estimator	Revisions		Recession		RR		GDPpc		RR & GDPpc	
	OLS	FE	OLS	FE	OLS	FE	OLS	FE	OLS	FE
α	.575** (.00)	.575** (.00)	.573** (.00)	.573** (.00)	.574** (.00)	.575** (.00)	.565** (.01)	.565** (.00)	.571** (.01)	.57** (.01)
β	-.054* (.02)	-.052** (.01)	-.048 (.08)	-.043 (.03)	-.074** (.03)	-.096** (.01)	– (–)	– (–)	-.071** (.03)	-.096** (.01)
γ	– (–)	– (–)	– (–)	– (–)	– (–)	– (–)	.023 (.03)	.021 (.02)	.012 (.03)	.003 (.02)
Obs.	7,317	7,317	6,464	6,464	7,403	7,403	7,403	7,403	7,403	7,403
R ²	.01	.01	.01	.01	.01	.01	.00	.00	.01	.01

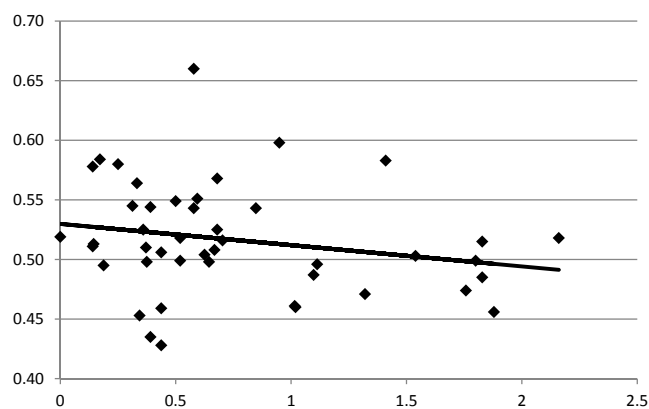
Note: Table 3 reports the estimation results of Equation (5): $S_{i,t} = \alpha_i + \beta Crisis_{i,t} + \gamma GDPpc_{i,t} + \epsilon_{i,t}$ where $i(t)$ is a country (time) index; results are either based on the Newey-West (1987) panel estimator or the fixed-effects estimator (FE); robust standard errors in parentheses; * (**) indicates significance on a ten (one) percent significance level.

Figure 2: (Anti-)Herding Statistic and the GDP per capita

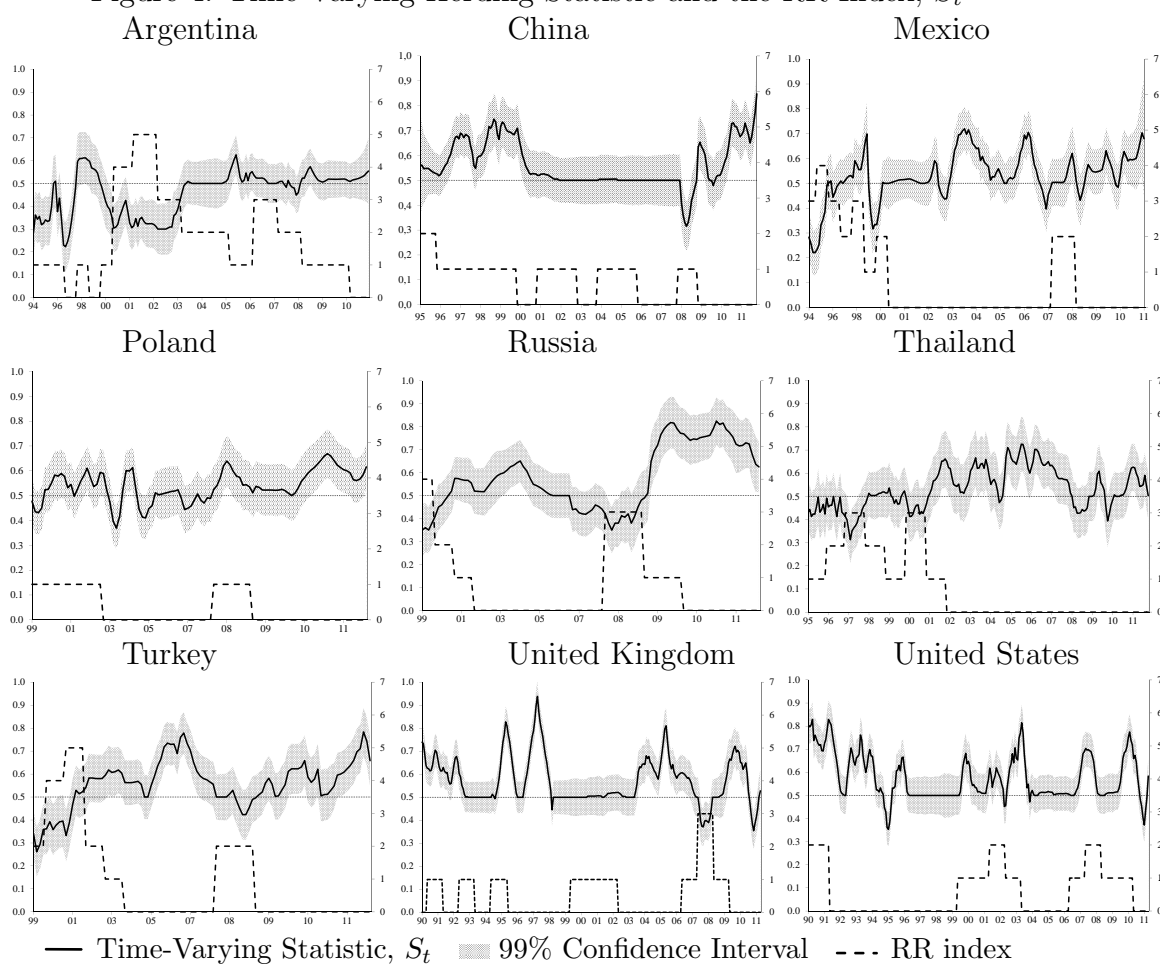


Notes: Figure 2 shows for the current-year forecasts the (anti-)herding S statistic (see Table 1) on the vertical axis and the GDP per capita on the horizontal axis. The solid line reflects a regression line: $S = 0.50(36.8) + 0.001(1.35)$ GDP p.c., $R^2 = .02$. t-values in parentheses.

Figure 3: (Anti-)Herding Statistic and the Reinhart-Rogoff index



Notes: Figure 3 shows for the current-year forecasts the (anti-)herding S statistic (see Table 1) on the vertical axis and the average Reinhart-Rogoff index on the horizontal axis. The solid line reflects a regression line: $S = 0.53(45.9) - 0.02(1.90)$ RR, $R^2 = .04$. t-values in parentheses.

Figure 4: Time-Varying Herding Statistic and the RR Index, S_t 

Notes: Figure 4 shows the unbiased value of 0.5 (fine dotted line), the Reinhart-Rogoff index (dotted line), the time-varying S_t statistic (solid line), and the 99% confidence interval (shaded area).