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Anchoring Near the Lighthouse:
Bond Market Analysts' Behavior Co-ordination by
External Signal

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Anchoring Near the Lighthouse: Bond Market Analysts' Behavior Co-ordination by External Signal

This paper presents a new model variant of reputational herding, so-called externally triggered herding. The assumption is that agents undertake the alignment of their behavior not through constant mutual observation but through orientation towards an external signal. An evaluation of interest rate forecast time series (October 1990 until December 2004) of 32 US banks, insurance companies, research and consulting institutes, associations, and industrial companies shows that without exception all bond market analysts involved displayed rational herding. The actual bond market situation at the time each forecast was developed is identified as the external signal which served as the orientation point for herd members (JEL E47, D84, G21, G12).

In discussions of financial market phenomena no other animal species is referred to more often than lemmings. In the warm season these voles tend to mass reproduction, which can result in the migration of large groups. Often such migrating populations do not even stop at the shoreline, but swim out into the open sea and drown. This bizarre behavior is often used as a simile for the behavior of stock market agents. Many people feel more comfortable when they find their estimations and deeds in accordance with those of their peer group. In extreme cases they can even completely detach themselves from their own ideas of sense and advantageous behavior, so that the group can gain a momentum of its own which no group member can control. This behavior is often called herding or herd behavior and is used as an explanation of irrational investment behavior, especially in the formation of bubbles.

Often, though, an astonishingly corresponding behavior of financial analysts – who are usually not regarded as having a tendency to irrational actions – can be observed. John Maynard Keynes was the first to point out that, from the perspective of a financial analyst, it could be rational to shape one's forecasts not according to one's own knowledge, but align it mainly to the prevailing opinion of the analyst community. "Worldly wisdom teaches that it is better for reputation to fail conventionally than to succeed unconventionally."¹ This combination of circumstances is defined as rational herding.

Thus, financial analysts who show rational herding also include the behavior of their colleagues in their own decision making to achieve maximum individual benefit. Since the beginning of the 1990s, scientific research aimed to develop a model theory of the likely emergence of rational herding of financial analysts,² and to then compare these models with empirical data of the visible behavior of financial analysts (published forecasts). From this, three model fami-

¹ Keynes (1936), p. 158.

² For a thorough overview of the various theories and the relevant literature see Hirshleifer and Teoh (2003), pp. 25-66; Bikhchandani, Hirshleifer, and Welch (2002), pp. 1-23.

lies have been formed so far: reputational herding, informational cascades and investigative herding.

This study claims that these existing concepts do not sufficiently take into account the external signals which affect all group members. Therefore a new model variant of reputational herding will be presented here which can be defined as externally triggered herding. The assumption is that there is a group orientation regarding which external signal they should act upon. The behavior of each group member is determined by this external signal as long as the group recognizes it as being behavior-relevant. The process of perception of the single agent is not focused on the action of the other agents but on the external signal and the collective recognition of the relevance of this signal within the group. The different model theories and the suggested extension of the model will be discussed in Chapter I.

At present there are numerous empirical studies on rational herd behavior of portfolio managers.³ In contrast to this, the behavior of financial analysts has been the subject of only a few empirical investigations. Among these are mainly studies on the possible herd behavior of analysts of the US stock market,⁴ whereas up to now the behavior of bond market analysts has hardly found any consideration. The studies of Bewley and Fiebig (2002) and Spiwoks (2004a) are the only ones so far which have examined the possible rational herding behavior of bond market analysts (synoptic overview in Table 1). A close look at present empirical research clearly shows that the measurement of rational herd behavior raises major methodological problems. It is especially important that the methodology is adequately suited to the data base

³ As examples of further studies see: Wermers (1995), pp. 1089-1105; Golec (1997), pp. 367-381; Oehler (1998), pp. 452-465; Grinblatt, Titman, and Wermers (1999), pp. 581-621; Jones, Lee, and Weis (1999); Nofsinger and Sias (1999), pp. 2263-2295; Arnswald (2001), pp. 6-45; Sias (2001), pp. 1-42; Cohen and Shin (2002), pp. 59-67; Fong, Gallagher, Gardner, and Swan (2004); pp. 1-46; Walter and Weber (2005); Lütje and Menkhoff (2005), pp. 785-799; Oehler and Chao (without year), pp. 1-32.

⁴ Important empirical studies on rational herd behavior of stock analysts are: Trueman (1994), pp. 695-704; Olsen (1996), pp. 37-41; Graham (1999), pp. 247-262; Welch (2000), pp. 372-394; Hong, Kubik, and Solomon (2000), pp. 134-143; Cooper, Day, and Lewis (2001), pp. 383-416.

used. The measurement problem is presented in Chapter II, as well as the data base employed and the underlying examination methodology of this study.

TABLE 1 – SYNOPTIC OVERVIEW OF EXISTING LITERATURE ON HERDING BEHAVIOR OF BOND MARKET ANALYSTS

	Bewley and Fiebig (2002)	Spiwoks (2004a)
Evaluated forecast subject	3-Month interest rate for the USA, Japan, Germany, France, U.K., Italy, Canada and Australia	German 10-Year Government bond yield
Forecast horizon	3 months	3 months and 12 months
Frequency of forecast	Monthly	Monthly
Period of time	Apr. 1990 – Sep. 1996	Oct. 1989 – Dec. 1999
Source of data	Consensus Forecasts	Consensus Forecasts
Research method	Regression analysis	Correlation coefficient matrices
Results	40% of analysts do not tend towards herding; 38% of forecasters do slightly tend towards herding; 22% of analysts strongly tend towards herding.	100% of analysts show rational herding throughout the whole research period.
Remarks		In German

Chapter III analyzes 32 forecast time series of banks, insurance companies and other financial services companies, research and consulting institutes, associations and industrial companies. These are monthly forecasts of the 10-Year US Government bond yield with a forecast horizon of twelve months. It becomes obvious that the bond market analysts were extremely unsuccessful in their efforts to forecast the most important changes of the development in interest rates. But, in comparison, their endeavor to always move within the protective environment of the majority's opinion was extraordinarily successful. The analysis of the forecast time series regarding possible topically oriented trend adjustment⁵ finally shows that the financial analysts

⁵ On the notation of topically-oriented trend adjustment see Andres and Spiwoks (1999), pp. 515-516; Spiwoks and Hein (2005), pp. 7-8.

observed came to a broadly concurrent forecast due to their joint orientation towards an external signal.

A summary of the most important results of the study and their critical evaluation is given in Chapter IV.

I. Theory of Rational Herding Behavior

The models⁶ explain how possible rational herding of financial analysis can emerge. However, they do not imply that rational herding must always and inevitably appear.

The theory of reputational herding⁷ assumes that financial analysis makes strategic use of an information asymmetry. For the clients of the forecasts it remains hidden whether the market evaluation given by the analyst mirrors his actual opinion, or if he is merely imitating other analysts' market evaluations for strategic reasons. If an individual analyst comes to conclusions which differ from those of other financial analysts, he has to undergo the following calculations, which were first described by Keynes:⁸ Should the analyst's estimation – which is contrary to the common market opinion – be wrong, his reputation will suffer badly from the false forecast. Should he be right, however, his singular forecast among the many contrary forecasts would be considered a fluke. Therefore, his reputation would not benefit. If he follows the common estimation against his own better judgment, his reputation would benefit should the majority's opinion be proved correct. Yet, even if he and the other analysts were wrong in the

⁶ We refrain from giving a formal representation of the theories here. The formal model structures can be viewed in the given literature.

⁷ As important works on this theory see for example Scharfstein and Stein (1990), pp. 465-479; Hirshleifer (1993), pp. 145-160; Graham (1999), pp. 241-247; Chevalier and Ellison (1999), pp. 389-432; Ottaviani and Sørensen (2000), pp. 695-704.

⁸ See Keynes (1936), pp. 157-158.

same time and manner, this would not lead to a loss of reputation. As all analysts were wrong, the unexpected development would be regarded as unforeseeable. Considering these calculations, it would not make sense to follow one's own judgment when it is contrary to the collective estimation. The financial analyst who always joins the prevailing opinion has the best prospects of increasing or at least retaining his reputation – and his income.

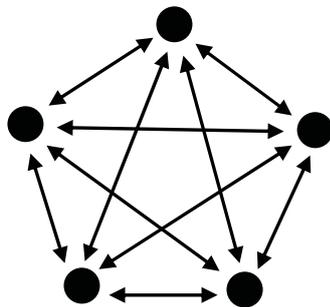


FIGURE 1. COMMUNICATION STRUCTURE OF REPUTATIONAL HERDING: ALL GROUP MEMBERS ARE WATCHING EACH OTHER

The informational cascades⁹ approach supposes that financial analysts really try hard to give the best possible forecast. At the same time they are unsure whether their own estimation correctly describes reality. Analysts presume that the estimations of the other analysts have the same value as their own. Therefore the following situation is conceivable: Analysts should compare two stock investments (A and B) with each other. The superficial impression of A is minimally better. However, all analysts have the information that B is to be preferred to alternative A. Only one analyst has contrasting information. Coincidentally, it is precisely this one who has to make and publish his decision first. He chooses investment A. The next analyst to

⁹ As important examples of work on this approach see Banerjee (1992), pp. 797-817; Bikhchandani, Hirshleifer, and Welch (1992), pp. 992-1026; Welch (1992), pp. 695-732; Lee (1993), pp. 395-411; Gul and Lundholm (1995), pp. 1039-1066; Devenow and Welch (1996), pp. 603-615; Gale (1996), pp. 617-628; Hirshleifer (1997); Zhang (1997), pp. 188-205; Anderson and Holt (1997), pp. 847-862; Bikhchandani, Hirshleifer, and Welch (1998), pp. 151-170; Avery and Zemsky (1998), pp. 724-748; Anderson, Frenzen, and Sullivan (1998); Moscarini, Ottaviani, and Smith (1998), pp. 657-665; Anderson and Holt (2000), pp. 1-7; Sanditov, Cowan, and Kool (2002), pp. 1-27.

make his decision encounters the following situation: The fact that the first colleague has chosen alternative A shows that he has the information that A is the better alternative. The second analyst has contrasting information but takes his colleague's information as seriously as his own. The two contradictory pieces of information counterbalance each other. The second analyst now has to decide according to external appearances. Thus he also chooses A. The third protagonist knows that the decision made by the second one reveals nothing about his private signal. Nevertheless he, too, will choose A, because for him the situation in which he has to make his decision is just like it was for the second one. In the end all analysts prefer A, although only one of them had the private signal that investment A was better.

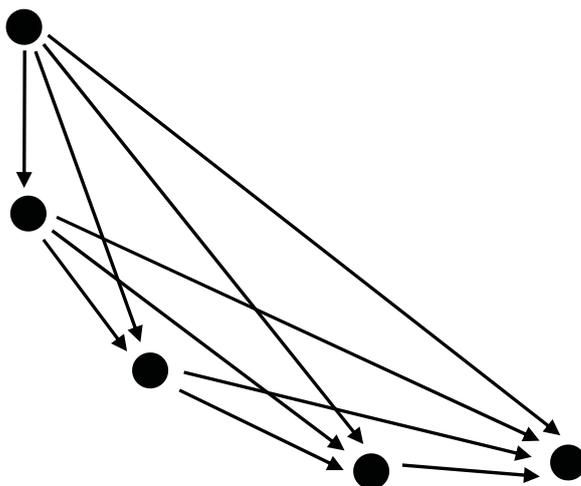


FIGURE 2. COMMUNICATION STRUCTURE OF INFORMATIONAL CASCADES: THE ACTIONS OF THE FIRST DECISION MAKERS INFLUENCE THE FOLLOWING DECISION MAKERS

The approach of investigative herding¹⁰ supposes that, in certain cases, obtaining information is only worthwhile if others also procure this information. For example, an analyst who has to work on forecasts with a short forecast horizon must not concentrate on the analysis of funda-

¹⁰ As important examples of work on this approach see Brennan (1990), pp. 709-730; Froot, Scharfstein, and Stein (1992), pp. 1461-1484; Dow and Gorton (1994), pp. 819-849; Golec (1997), pp. 367-381.

mental data which are recognized by the market only after a significant time lapse. He must grasp what the majority of market agents will consider to be promising investments in the near future. The evaluation of an investment made by his fellow analysts might, under certain circumstances, be much more important for a short time forecast than the actual fundamental facts. Therefore one's own forecast is sensibly orientated towards the forecasts made by colleagues. The model structure thus corresponds to that of reputational herding: All analysts recognize the behavior of all other group members (see Figure 1). Only the implied motivation of the analysts is judged differently: instead of an opportunist reputation maximization, an honest effort to make the best possible forecast is insinuated here.

Each of these three approaches shows specific weaknesses, however:

The investigative herding model is tailored to short-term decision situations. In particular, congruencies of the behavior of making medium to long-term capital market forecasts are not explained by this model.

The informational cascades model was, at first, received very positively, because it is a general approach which does not require the existence of principal-agent relations for the explanation of rational herd behavior. Yet this model presupposes a gradual and completely transparent decision finding process of the partaking group members. But decisions of financial analysts are often made synchronically and – at least for some time – not publicly and are therefore not transparent. Further to this, recent experimental studies show that business subjects systematically overestimate the significance of their own information, so that informational cascades usually do not develop.¹¹ The approach of informational cascades can therefore be considered as largely unsuitable for the explanation of rational herding behavior.

¹¹ See Huck and Oechssler (2000); Spiwoks, Bizer and Hein (2005). See for contrary opinion a. o. Anderson and Holt (1997).

As it can generally be assumed that financial analysts act upon an information asymmetry with regard to their clients,¹² the reputational herding model seems to be the most convincing approach to explain rational herding behavior regarding medium to long term forecast decisions. However, this approach has a significant weakness. On the one hand, the permanent observation of the behavior of the other group members is not always possible (without time lag), and on the other hand it is tied to a huge amount of transaction costs.

Generally, two possibilities are conceivable to design a more realistic model variant of reputational herding: 1. the building of random networks, and 2. the orientation towards external signals (externally triggered herding).

If the possibility of forming spontaneous networks is included in the reputational herding model it is no longer necessary to presuppose that each group member always observes all the other group members. Instead a steady, spontaneous exchange of ideas with several group members is assumed, whereby single contact cells overlap so that indirectly everybody has an exchange relationship with everyone else.¹³

The approach of externally triggered herding presented here also takes up the original thought of reputational herding and assumes that financial analysts are concerned about their reputations. But the assumption is that analysts are not constantly watching each other's concrete single decisions, but their orientation towards a certain external signal. This external signal does not reveal anything about the topic of the forecast (the future market development), but only about the behavior of the other group members. To take up the signal therefore does not lead to a better forecast performance, but merely to behavior that is adjusted to the other group members. The basic orientation towards a certain external signal is changed – if at all – only

¹² Those making enquiries or clients can never be sure whether the financial analyst really is of a certain published opinion, or whether he is stating it for strategic reasons to realize a maximum personal benefit. Only the financial analyst himself knows about the quality of his forecast and his motivation. Therefore information asymmetry is a constitutive element of every client-analyst relationship.

¹³ Re the approach of random networks e. g. Cont and Bouchaud (2000), pp. 170-196; Eguiluz and Zimmermann (2000), pp. 5659-5662; D'Hulst and Rodgers (1999), pp. 1-8.

over longer periods of time. In contrast to this, concrete forecast decisions are made on a daily basis. If the analysts observed each other's single forecast decisions this would be very time consuming and would thus involve high transaction costs. Thus the approach of externally triggered herding seems to be more realistic because it assumes that mutual observation is only carried out regarding the procedure of forecast generation and therefore has to be done less frequently.

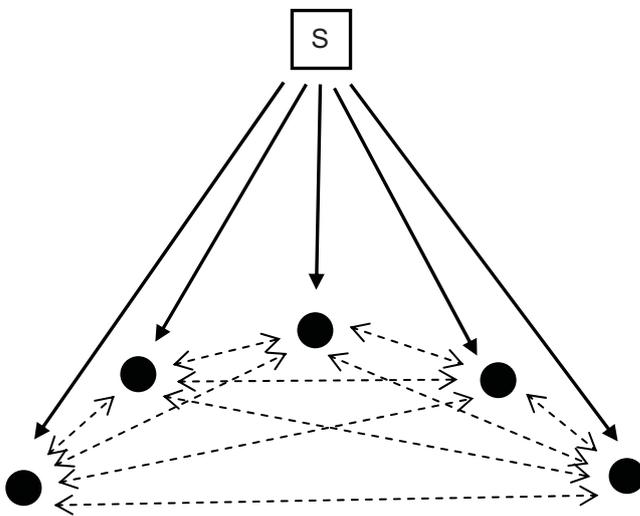


FIGURE 3. COMMUNICATION STRUCTURE OF EXTERNALLY TRIGGERED HERDING: AN EXTERNAL SIGNAL DETERMINES THE DECISION MAKING BEHAVIOR OF THE GROUP MEMBERS

The model structure of externally triggered herding thus includes an external signal that enables a coordination of behavior within the group which is favorable in terms of transaction costs. The interaction processes among the group members only refer to the sporadic examination of the (unchanged) acceptance of the external signal by the other group members.

For financial analysts it is very important that their own forecasts do not vary too much from the forecasts of other analysts. As an observation of each single decision of all group members could be made only at disproportionately high information costs, analysts concentrate on ensur-

ing that they orient themselves towards that external signal which serves as an orientation point for the majority of their fellow analysts.

One advantage of the externally triggered herding model – as opposed to the random networks approach – lies in the fact that each decision maker usually needs to pick up only one signal. The transaction costs incurred therefore decrease to a negligible amount. Another advantage is that an empirical examination of this model is easier. Any possible external signal must be empirically visible.

The hypothesis on which this study is based can be defined as follows: Possible herding behavior of financial analysts regarding medium to long term forecast decisions can be correctly described by the externally triggered herding model.

II. Data and Methodology

The forecast data used for the empirical examination of the externally triggered herding approach of bond market analysts were published in the international periodical on economic forecasting “Consensus Forecasts”.¹⁴ The concept of this periodical, published by the British company Consensus Economics, is quite simple. Local banks, insurance companies, consulting and research institutes, associations and industrial companies of each examined economy deliver their forecasts for their specific country to Consensus Forecasts. They are published monthly and are additionally summarized into a consensus forecast. The consensus forecast is calculated by the unweighted average of the individual forecasts, and can be interpreted as an average market estimation.

¹⁴ See Consensus Forecasts, years 1989-2003.

This study scrutinizes the forecasts of the ten-year US Government bond yield with a forecast horizon of 12 months. The forecasts are available as monthly data. All those companies which delivered their interest rate forecasts to Consensus Forecasts for at least five years without interruption are included in the data evaluation.¹⁵ This applies to 32 companies in total, among which are banks, insurance companies, and other financial services companies such as U. S. Trust, Northern Trust, Merrill Lynch, Credit Suisse First Boston, J. P. Morgan, Chase Manhattan, Smith Barney, Wells Fargo, Chemical Bank, Nations Bank, Continental Bank, First Union, Fannie Mae and Metropolitan Life. Research and consulting companies as well as associations are also represented, such as Interindustry Forecasting at the University of Maryland (Inforum), Research Seminar in Quantitative Economics at the University of Michigan (RSQE), Oxford Economic Forecasting (OEF), Wharton Econometric Forecasting Associates (WEFA), Conference Board, Standard & Poor's, Regional Financial Association / Economy.com, Consensus Economics, Dun & Bradstreet, Griggs & Santow, National Association of Homebuilders, and the National Association of Manufacturers. Major industrial companies act as analysts too, such as General Motors, Ford Motors, Daimler/Chrysler, Amoco, DuPont and the Eaton Corp.

The research period is October 1989 to December 2004.¹⁶ The 32 forecast time series contain a total of 3555 data. The shortest examined time series is 60 months, the longest 171 months. On average each of the 32 time series provides 108 monthly data.

An empirical analysis of possible rational herding behavior raises serious methodological problems. Often only qualitative data ("buy" or "sell") are available for the evaluation of behavior of stock fund managers or stock analysts. Furthermore, these appear at irregular intervals and

¹⁵ Occasionally some forecast data are missing in the time series, because there was no or no timely delivery of the forecasts to Consensus Economics. The gaps were closed by later research and supplementation of the forecast data after contacting the respective forecasting companies. In some cases this was not possible because the company does not exist any more or was not willing to cooperate. Then the data gaps were closed by linear interpolation.

¹⁶ The research period begins with the founding of the periodical Consensus Forecasts in October 1989. The forecasts up to delivery date December 2003 (which corresponds to the validity time of December 2004) were considered.

have no determined forecast horizons, so that they cannot necessarily be formulated as time series. To take these facts into account, two principal methods of measurement were developed: the so-called LSV measure¹⁷ focuses on the number of identical purchase and selling orders per period of time for certain stocks. The so-called portfolio-change measure¹⁸ (PCM) determines whether the relative weights of single stocks of the examined security portfolios change in the same way. Both procedures have serious faults, however.¹⁹

Objections against the LSV measure can be summarized as follows: 1. Only the behavior alternatives selling or purchasing are examined. The respective scale of each order is not considered, which can lead to grave misinterpretations. 2. The whole examination time frame is split into several observation units. These units are evaluated irrespective of each other. Thus when herding behavior is established, it is not possible to recognize whether it is always the same or always different market agents who tend towards herding. 3. The LSV measure registers the actions regarding single stocks. Possible herding behavior at a higher aggregation level (e. g. at sector level) is therefore not taken into account. 4. The determination of each observation unit can lead to a bias of the results. If a short period of time is chosen, for example two weeks, possible cases of herd behavior are overlooked because the subsequent action falls into the next observation unit. Or, if a long period of time is examined, for example three months, it can result in the misinterpretation of independent transactions as herding behavior. If A buys a stock at the beginning of a quarter, which B also buys at the end of the same quarter, it will be interpreted as resultant behavior, although the two transactions may not be connected to each other.

¹⁷ Named after its inventors Lakonishok, Shleifer, and Vishny. See Lakonishok, Shleifer, and Vishny (1992); Bikhchandani and Sharma (2000), pp. 14-19.

¹⁸ PCM was developed by Wermers. See Wermers (1995); Bikhchandani and Sharma (2000), pp. 19-20.

¹⁹ Bikhchandani and Sharma present the problems of LSV- and PCM measures. See Bikhchandani and Sharma (2000), pp. 18-20.

The main problem of the PCM measure, however, is that it is based on the relative weights of single titles within the security portfolio. The result is that stock market price increases of single stocks, which, consecutively, also result in a bigger weight within the portfolios, suggest herd behavior, although no transaction – neither sale nor purchase – was carried out. Both LSV and PCM measurement methods have the additional problem that they do not offer any possibility for differentiating between true, or intentional herding, and spurious, or unintentional herding.

If the forecasts are available as quantitative data which can be represented as time series due to the regular forecast delivery and the fixed forecast horizon, further possibilities for measuring possible herding behavior emerge. Spiwoks (2004a) thus establishes herding behavior of German bond market analysts with the help of correlation coefficient matrices. Here the correlation coefficients of each forecast time series is computed with each other forecast time series and represented in the shape of a matrix. This procedure is supplemented by a graphical analysis of the forecast time series and a conventional forecast error measurement with Theil's U_2 . With the help of regression analyses, Bewley and Fiebig (2002) investigated the correlation between the examined forecast time series and the respective time series of the consensus forecasts to determine whether the analysts showed herd behavior. In general these procedures grant a good insight into the behavior of bond market analysts. However, the use of regression analysis and correlation coefficients was criticized, because although interest rate developments can have a stationary character in the long run, there can still be non-stationarity when single periods of time are examined. This can lead to biased results as a consequence of co-integrations.

This study therefore introduces a methodological innovation. The instrument of the rate of turning point errors is adopted from the classical forecast error measurement and geared anew to establish possible herd behavior.

The starting point of this methodological approach is the following question: what can or must be sensibly expected from a successful bond market analyst? Surely it is not realistic to expect that a bond market analyst would be able to predict all market movements including all short term oscillations down to the last detail for a period of 12 months. To be able to earn money on the bond market with active portfolio management strategies much less is actually needed. When an analyst is able to broadly predict the most important turning points of increasing to decreasing interest rates and vice versa, all requirements are fulfilled to realize major capital gain, limit capital loss, and therefore generate systematic surplus yield.

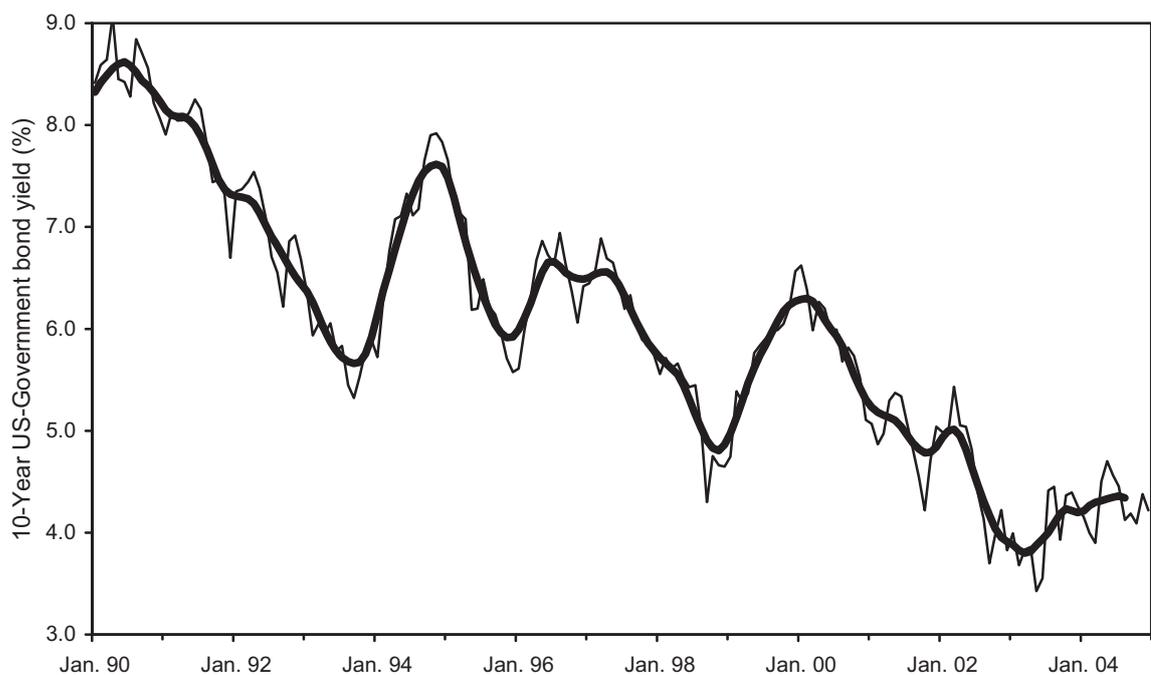


FIGURE 4. DEVELOPMENT OF THE 10-YEAR US GOVERNMENT BOND YIELD (THIN LINE) AND RESPECTIVE SMOOTHED INTEREST RATE DEVELOPMENT (BOLD LINE) FROM JANUARY 1990 TO DECEMBER 2004

If the interest rate development is smoothed centrally,²⁰ the significant turning points become more visible (Figure 4). A successful bond market analyst should be expected to be able at least by and large to forecast the upper turning points in June 1990, November 1994, July 1996 and February 2000, as well as the lower turning points in September 1993, November 1995, November 1998 and March 2003. The average interval between these turning points is 22 months. Systematic surplus yields can even be achieved if the turning points are reflected not more than two or three months too early or late in the forecasts. If, within the framework of 12-month forecasts, an analyst predicted the lower turning point, which actually came up in September 1993, for June 1993 or only for December 1993, the due shortening of maturities in the bond portfolio would have been effected a little too early, or late, for an optimal investment result. Yet these forecasts would have contributed significantly to a performance superior to a passive investment strategy.

An upper (lower) turning point exists at the point of time t_0 , if both the values before (t_{-1}) and after (t_{+1}) are lower (higher). Due to short term fluctuations, a normal time series with financial market data or with financial market forecasts provides a large number of turning points. An evaluation of turning point errors for unsmoothed time series usually leads to nonsensical, coincidental results. Rates of turning point errors can therefore only be considered powerful judgment measures if the forecast time series and the comparative time series are smoothed. Both the epistemological interest of this study, “are the major turning points predicted?”, and the methodological requirements of the turning point errors suggest a smoothing of the time series.

If the major turning points are forecast for the right point in time, or if the forecasts miss these major turning points by three months at the most, they are not to be defined as turning point errors. A turning point error exists if the smoothed forecast time series shows no relevant turn-

²⁰ A centered smoothing out was carried out over three months, and another centered smoothing out over seven months was put on top of this.

ing point for the period of time of three months before and after the actual turning point. A turning point error also exists if a lower (upper) turning point was predicted, but in fact an upper (lower) turning point came up.

The so-called rate of turning-point errors $RTPE$ is defined as follows:

$$(1) \quad RTPE = \frac{TPE}{TP}$$

with $RTPE$ = rate of turning point errors

TPE = number of turning point errors

TP = number of actually existing turning points

An $RTPE = 0.2$ indicates that 20% of the actual existing turning points were not recognized by the relevant analyst – even considering the 3 months time tolerance. Correspondingly to this an $RTPE = 0.2$ indicates that the analyst predicted 80% of the actual turning points correctly, i.e. with three months deviation at the most.

This corresponds to the classic forecast error measurement, which at first has no relation to the establishment of possible rational herding behavior. Such a relation is only created by the calculation of a ratio for each forecast time series, and which follows the turning point errors. This ratio is called $RTPE^*$ and reflects how well the forecast time series register the major turning points of the consensus forecast from Consensus Economics. Here too, the time series are centrally smoothed accordingly, and a 3-months tolerance area around the turning points of the consensus forecast time series is acceptable. An $RTPE^* = 0.3$ means that 30% of the turning points of the time series of the consensus forecasts do not appear in the examined forecast time series – again taking into account the three months time tolerance. On the other hand, an $RTPE^* = 0.3$ indicates that 70% of the turning points of the time series of consensus forecasts in the examined forecast time series were predicted with three months deviation at the most.

By comparing the *RPTE* and *RPTE** results one can draw conclusions regarding the possible herding behavior of the analysts. If the *RPTE** results are < 0.25 , herding behavior can be expected, because then 75% of the turning points of the single forecast time series are identical to the turning points of the consensus forecast, and thus identical to the opinions in the market. If at the same time the *RPTE* results are > 0.75 , the conclusion is that true or intentional herding is apparent. This also means that less than every fourth actual turning point was registered by the forecast time series – and the efforts of the forecast can be judged as being unsuccessful.

Forecast time series which on the one hand show no significant agreement with the later, actual events, but which on the other hand strongly resemble each other, allow the following conclusion: the aligned behavior of the analysts must be based on rational herding behavior. Had the analysts acted independently from each other it should have been expected that they would fail in different ways – considering the unlimited number of possibilities for a false estimation of the future. An analyst can base his forecast generation on numerous different interest rate theories and many fundamental and technical analysis tools, and he can include many different data and events while drawing up his forecast. Misinterpretations of the interrelations or the data are also possible in plenty of variations.²¹ So when many analysts design forecasts which are not in accordance with reality, but are very similar to each other, conscious and intentional herd behavior is the only plausible explanation.

²¹ Spiwoks (2004a), pp. 68-69 gives a short overview of the various approaches of interest rate theories, the many known procedures of financial market analysis, and the different data and events which can be included in forecast generation.

III. Results

A graphical representation of the interest rate development and the interest rate forecast time series (Figures 5 and 6) alone makes it perfectly clear that the forecasting efforts totally failed. The analysts expected the lower turning point of September 1993 only 12 to 15 months later. In reality however, an upper turning point was already emerging at that time. This upper turning point of November 1994 is indicated in the forecasts with a delay of 12 to 15 months again. At that moment, however, (November 1995) another lower turning point appeared in reality, which once again had been expected by the analysts for 12 to 15 months later. The same long delay is visible for the lower turning point of November 1998, the upper turning point of February 2000, and the lower turning point of March 2003: all these turning points were reflected in the forecast time series with a delay of 12 to 15 months.

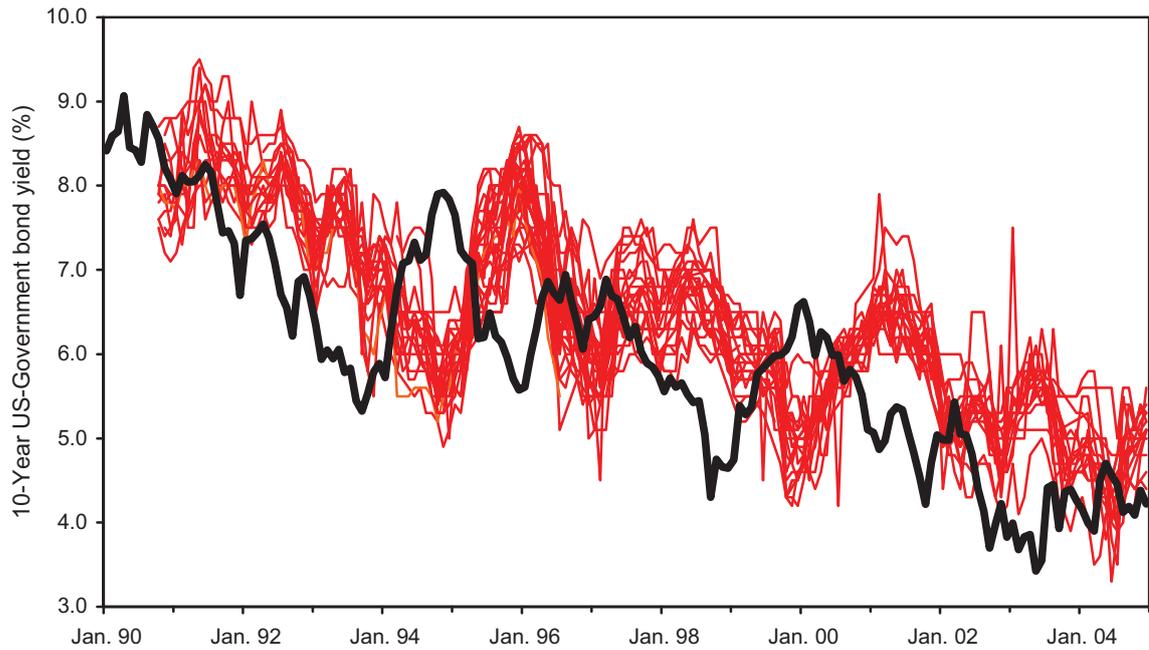


FIGURE 5. DEVELOPMENT OF THE 10-YEAR US GOVERNMENT BOND YIELD (BOLD BLACK LINE) AND RESPECTIVE FORECAST TIME SERIES (THIN RED LINES) FROM JANUARY 1990 TO DECEMBER 2004

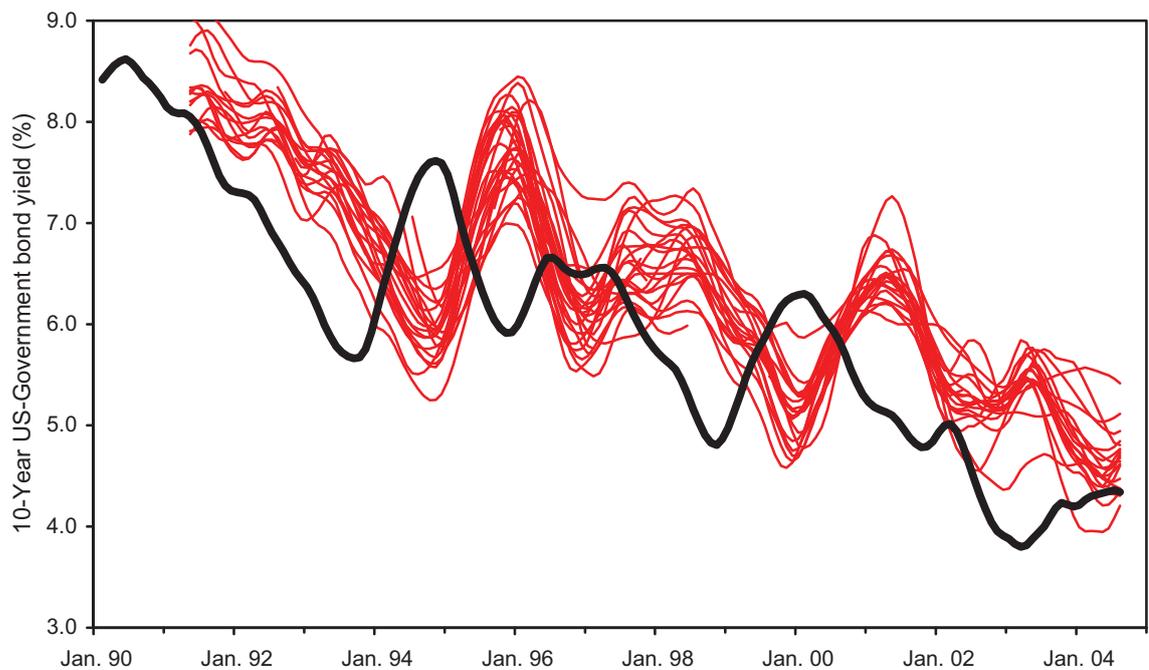


FIGURE 6. SMOOTHED DEVELOPMENT OF THE 10-YEAR US GOVERNMENT BOND YIELD (BOLD BLACK LINE) AND SMOOTHED FORECAST TIME SERIES (THIN RED LINES) FROM JANUARY 1990 TO DECEMBER 2004

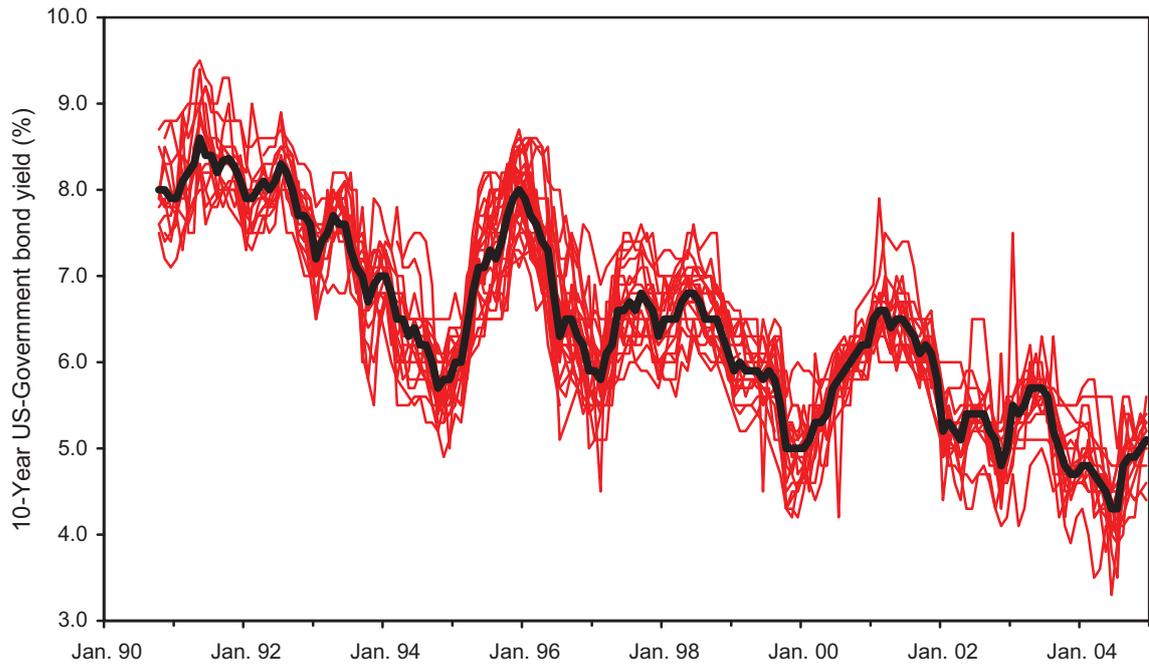


FIGURE 7. MARKET ESTIMATION OR CONSENSUS FORECAST FOR THE 10-YEAR US GOVERNMENT BOND YIELD (BOLD BLACK LINE) AND RESPECTIVE FORECAST TIME SERIES (THIN RED LINES) FROM JANUARY 1990 TO DECEMBER 2004

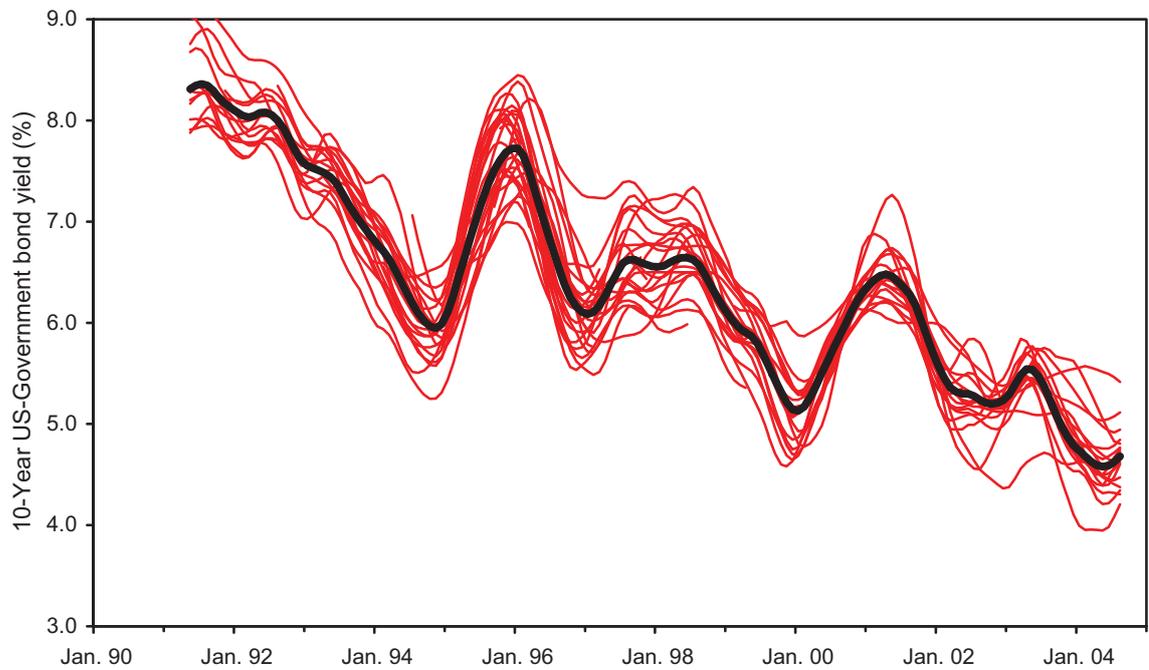


FIGURE 8. SMOOTHED DEVELOPMENT OF THE MARKET ESTIMATION OR CONSENSUS FORECAST FOR THE 10-YEAR US GOVERNMENT BOND YIELD (BOLD BLACK LINE) AND SMOOTHED FORECAST TIME SERIES (THIN RED LINES) FROM JANUARY 1990 TO DECEMBER 2004

TABLE 2 – SUCCESS OF FORECASTS OF FUTURE INTEREST RATE DEVELOPMENT (RATE OF TURNING POINT ERRORS IN REGARD TO THE TRUE INTEREST RATE DEVELOPMENT = *RTPE*) AND SUCCESS FOR HERD ORIENTATION (RATE OF TURNING POINT ERRORS IN REGARD TO THE OPINION OF MAJORITY = *RTPE**) PER ANALYSTS

Institution	Forecasting period	Months	<i>RTPE</i>	<i>RTPE*</i>
Consensus Economics	Oct. 1990 – Dec. 2004	171	1.00	0.00
Core States / First Union	Oct. 1990 – Dec. 2004	171	1.00	0.00
Ford Motors	Oct. 1990 – Dec. 2004	171	0.86	0.33
Standard & Poor's	July 1991 – Dec. 2004	162	0.86	0.17
Eaton Corp.	Nov. 1992 – Dec. 2004	146	1.00	0.00
DuPont	Oct. 1993 – Dec. 2004	135	1.00	0.17
Wells Fargo	Mar. 1994 – Dec. 2004	130	1.00	0.00
Griggs & Santow	Nov. 1990 – July 2001	129	1.00	0.00
U. S. Trust	Oct. 1994 – Dec. 2004	123	1.00	0.00
Conference Board	Oct. 1994 – Dec. 2004	123	0.80	0.00
J. P. Morgan Chase	Oct. 1994 – Dec. 2004	123	1.00	0.20
General Motors	Jan. 1995 – Dec. 2004	120	1.00	0.00
Daimler/Chrysler	Apr. 1995 – Dec. 2004	117	1.00	0.00
RFA / Economy.com	May 1995 – Dec. 2004	116	0.60	0.00
Nat. Assn. Homebuilders	June 1995 – Dec. 2004	115	1.00	0.00
WEFA Group	July 1992 – June 2001	108	1.00	0.00
Fannie Mae	Feb. 1996 – Dec. 2004	107	1.00	0.20
Northern Trust	Oct. 1990 – Feb. 1999	101	1.00	0.00
Smith Barney	Oct. 1990 – Oct. 1998	97	1.00	0.00
RSQE - Univ. of Michigan	Mar. 1997 – Dec. 2004	94	1.00	0.00
Chase Manhattan	Oct. 1990 – Mar. 1998	90	1.00	0.00
Merrill Lynch	Oct. 1990 – Feb. 1998	89	1.00	0.00
Metropolitan Life	Oct. 1990 – Sep. 1997	84	1.00	0.00
Amoco Corp.	Oct. 1990 – June 1997	81	1.00	0.00
Chemical Bank	Nov. 1990 – Jan. 1997	75	0.75	0.00
Oxford Economic Forec.	Oct. 1998 – Dec. 2004	75	0.50	0.00
Nat. Assn. Manufacturers	Oct. 1990 – Dec. 1996	75	1.00	0.00
Credit Suisse First Boston	Oct. 1990 – July 1996	70	1.00	0.00
Inforum - Univ. of Maryland	Apr. 1999 – Dec. 2004	69	1.00	0.00
Dun & Bradstreet	Apr. 1992 – July 1997	64	1.00	0.00
Nations Bank	Aug. 1994 – Aug. 1999	61	1.00	0.00
Continental Bank	Oct. 1990 – Sep. 1995	60	1.00	0.00
Average		108	0.95	0.03

The rates of turning point errors fully confirm the impression of the graphical analysis (Table 2). 26 out of 32 forecasters did not predict a single turning point correctly – despite allowing for the time tolerance of three months before and after an actual turning point event. This means that more than 81% of the analysts examined reached a rate of turning point errors of 1.00. For the average of all analysts the *RTPE* is 0.95. The timing of only 5% of all turning

points was predicted by the analysts reasonably correctly. If one assumes that the analysts were really willing to predict the future interest rate development as well as possible, this result can only be called a catastrophe; their forecasting efforts were utter failures.

The situation is completely different if one assumes that Keynes (1936) was right with his estimation of analysts. If the analysts only strive to always remain within the protection of the herd with their own forecasts, they were very successful (Table 2). 27 out of the 32 examined forecast time series reflect all major turning points of the consensus forecast. More than 84% of forecast time series thus have an *RTPE** of 0.00. On average 97% of turning points of the consensus forecast were identified by the forecast time series. The graphical analysis (Figures 7 and 8) displays this strict orientation of the analysts towards the forecasting behavior of the other analysts very well. The time series of the consensus forecasts marks the direction which the single forecast time series follow with only fairly insignificant variations. Thus the forecast time series present a tight compound in the midst of which the consensus forecast can always be found. This way the alignment of the single forecasts towards the respective prevailing market opinion becomes particularly obvious.

The possible objection that the construction of the consensus forecast as an unweighted average of single forecasts would automatically lead to the results displayed does not hold for two reasons:

1. There is a strong correspondence between the single forecast time series and the time series of the consensus forecasts only if the estimations of the analysts always move within a tight corridor. If the analysts act independently and therefore present differing estimations of the future, a time series of consensus forecasts results which has no similarity to any of the forecast time series (see the fictitious example in the Appendix, Figure 13).

2. Apart from the forecasts examined here, the consensus forecasts always contain a large number of further forecasts by market experts which find no explicit consideration in this study, because their presence in the Consensus Forecasts periodical is shorter than five years.

If the results are differentiated not according to analysts as in Table 2, and the forecast success is instead judged according to the single turning points (Table 3), it can be determined whether the analysts recognized distinct turning points significantly better than others. This is not the case, however. Concerning the seven major turning points there are hardly any differences worth mentioning regarding the actual forecast success. The lower turning point of March 2003 was predicted a little more often than the others. But here too, 76% of the analysts did not forecast the change from decreasing to increasing interest rates – even allowing for the three months tolerance before and after the event. On average only 6% of the institutions recognized the actual turning points correctly (as Table 2 shows the institutions unfortunately differed from case to case!). On the contrary: across all turning points of the consensus forecast the analysts managed to almost constantly imitate market opinion (Table 3). The percentage of market experts whose forecasts coincided with the major turning points of the consensus forecast varies from turning point to turning point between 100% and 89%, and is 95% on average.

TABLE 3 – PROPORTIONS OF ANALYSTS FAILING THE FORECAST TASK PER TURNING POINT AND PROPORTIONS OF ANALYSTS FAILING DUE TO HERD ORIENTATION BEHAVIOR PER TURNING POINT

Turning Points of interest rate time series	Proportion of failed forecasters	Turning points of consensus forecast time series	Proportion of failed forecasters
Lower Turning Point: Sep. 1993	0.94	Lower Turning Point: Nov. 1994	0.05
Upper Turning Point: Nov. 1994	1.00	Upper Turning Point: Jan. 1996	0.04
Lower Turning Point: Nov. 1995	1.00	Lower Turning Point: Jan. 1997	0.04
Upper Turning Point: June 1996	0.96	Upper Turning Point: June 1998	0.11
Lower Turning Point: Nov. 1998	1.00	Lower Turning Point: Jan. 2000	0.00
Upper Turning Point: Feb. 2000	0.95	Upper Turning Point: Apr. 2001	0.06
Lower Turning Point: Mar. 2003	0.76		
Average	0.94	Average	0.05

An important intermediate result can be established as follows: the bond market experts delivered very similar forecasts for the time period from 1990 to 2004. With few exceptions the major turning points of the consensus forecast completely correlate with the turning points of the single examined forecast time series. This is therefore a case of herding behavior.²²

It still needs to be decided whether this is intentional or unintentional herding behavior. It is at least conceivable that all analysts have mastered their craft and are able to draw up correct forecasts. In such a case it is possible that the market experts come to broadly agreeing forecasts independently of each other. Such a combination of circumstances would be called unintentional herding, because there is herding behavior despite the fact that the actors have no intention to act in this way.

The examined forecast results leave no space for such an interpretation, however. Due to the high rates of turning point errors the forecasting efforts of the institutions and companies

²² The theory of Zitzewitz (2001), pp. 1-26, and Laux and Probst (2004), pp. 45-66, that for a number of the analysts there were incentives for consciously stepping out of the line of the mainstream opinion cannot be confirmed by the existing results, nor considering Figures 5-8. Neither can the data support the approach of Effinger and Polborn (2001), pp. 385-403, which claims that an anti-herding strategy could emerge, at least under certain circumstances.

evaluated must be judged as complete failures.²³ As mentioned above, analysts can fail in many different ways: There are very many interest rate theories, a vast variety of fundamental and technical analysis instruments, a lot of different data and events to be included in the forecast design and, finally, unlimited opportunities for misinterpretations and errors.²⁴ So when a large number of analysts do not foresee the actual market development, but, at the same time, correspond so strongly with their faulty forecasts, there is only one plausible explanation: the large degree of agreement of the forecasts is a result of the actors trying to achieve such an agreement. Therefore, this is a case of intentional herding behavior.

Finally, it can be investigated whether this is a case of externally triggered herding. Should this be the case, the external signal which causes the analysts to align their behavior towards reasonably good transaction costs must be visible. Merely by looking at Figure 5 a supposition regarding the external signal can be made. The forecast time series seem to be a delayed reflex of the actual interest rate development. This becomes obvious when the smoothed course of the interest rate is compared with the smoothed forecast time series (Figure 6).

Figures 9 and 10 show that the time series of consensus forecasts strongly reflects the actual interest rate development. With 12 to 15 months delay the forecasts re-live the actual proceedings of the bond market. This becomes especially obvious when the forecasts are moved left by their forecast horizon, so that they are no longer depicted at their time of validity, but at the time they were generated (Figures 11 and 12). The deviations between forecasts and the actual interest rate level at the time of forecast generation are minimal. Only in the extraordinary low interest rate phase after 2002 do the forecasts detach themselves more clearly from the actual market situation. To a certain extent this reflects the excessive precaution of the bond analysts:

²³ An evaluation of the forecast quality with the help of Theil's U_2 also leads to the result that the forecast efforts must be seen as complete failures. See Spiwoks and Hein (2005).

²⁴ Spiwoks (2004a) pp. 68-69 gives a short overview of the various approaches of interest rate theory, of the many known procedures of financial market analysis, and the different data and events which can be included in the forecast design.

The forecasts immediately mirror increasing interest rates, while during decreasing interest rates the analysts are hesitant and want to ensure that the trend is lasting. Historically low interest rates are not fully reflected in the forecasts.

The phenomenon that the forecasts are constantly aligned to the current market situation is called topically oriented trend adjustment. Since Andres and Spiwoks (1999) various studies have furnished proof of its existence for interest rate forecast time series as well as for stock index and exchange rate forecast time series.²⁵ It equally occurs for forecasts with various forecast horizons (1, 3, 6, 12, and 24 months).

Figures 5 and 6 clearly show that to a limited degree the individual analysts hold different opinions. By and large, though, they move within the protective environment of the herd, and the herd is oriented towards the current market situation. Thus it becomes obvious that the external signal towards which the analysts orient themselves to always design their own forecast in line with the herd of analysts is the actual market situation at the time of each forecast generation.

The crucial advantage of this form of behavior alignment lies in the low costs connected with the observation of the external signal. It would take much more exertion to always observe the behavior of all fellow herd members.

²⁵ See e.g. Spiwoks (2003, 2004b), Bofinger and Schmidt (2003, 2004).

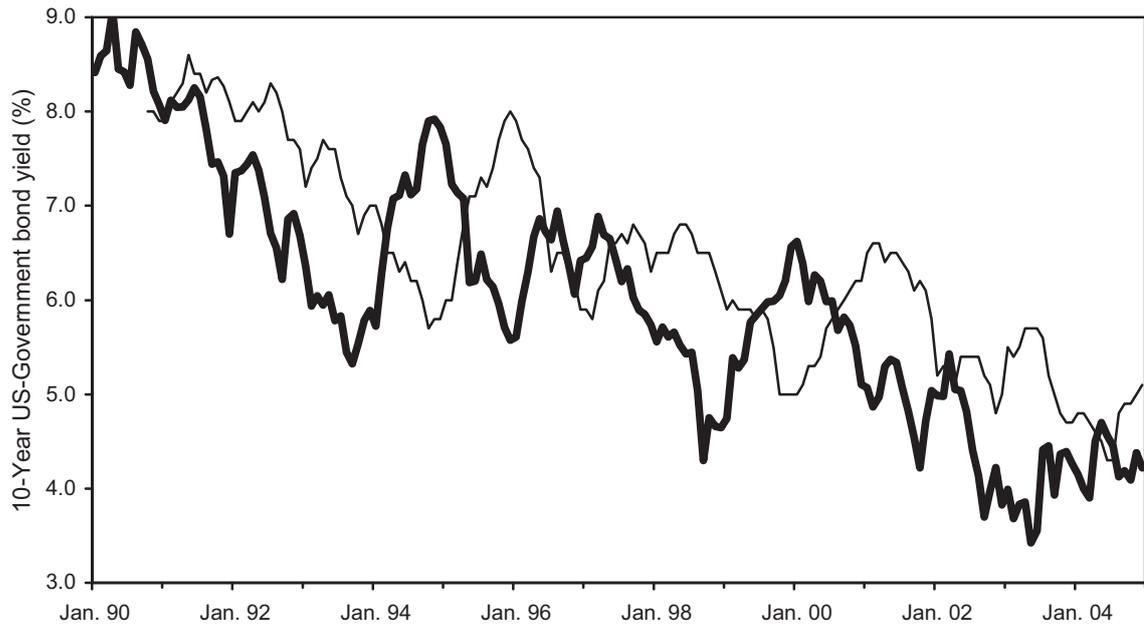


FIGURE 9. DEVELOPMENT OF THE 10-YEAR US GOVERNMENT BOND YIELD (BOLD LINE) AND RESPECTIVE TIME SERIES OF THE CONSENSUS FORECASTS (THIN LINE) FROM JANUARY 1990 TO DECEMBER 2004

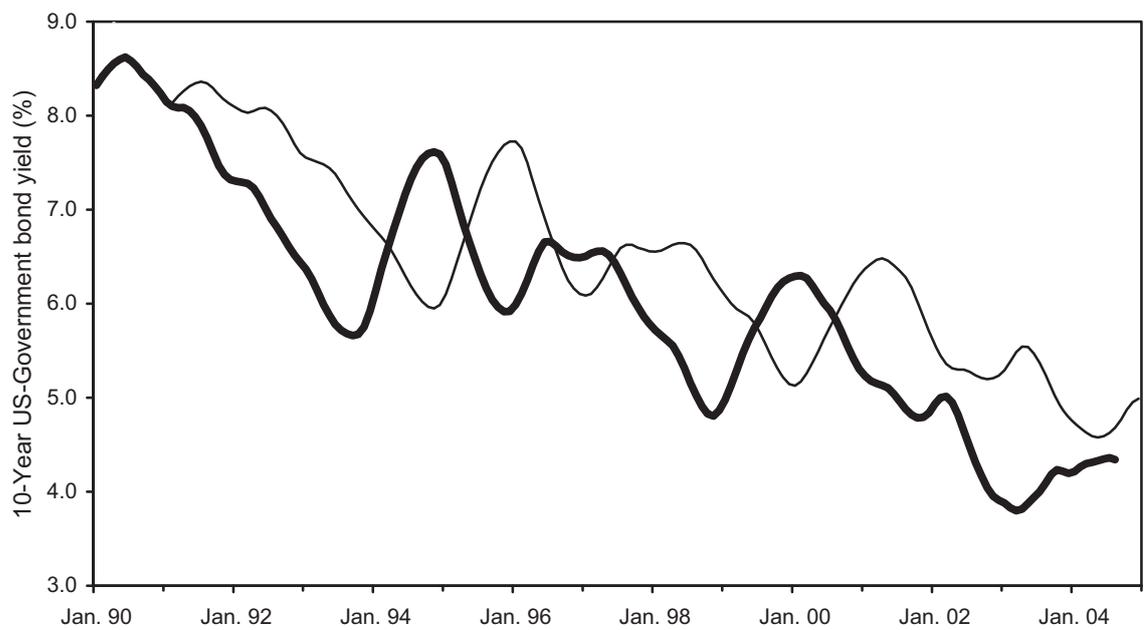


FIGURE 10. SMOOTHED DEVELOPMENT OF THE 10-YEAR US GOVERNMENT BOND YIELD (BOLD LINE) AND SMOOTHED TIME SERIES OF THE CONSENSUS FORECASTS (THIN LINE) FROM JANUARY 1990 TO DECEMBER 2004

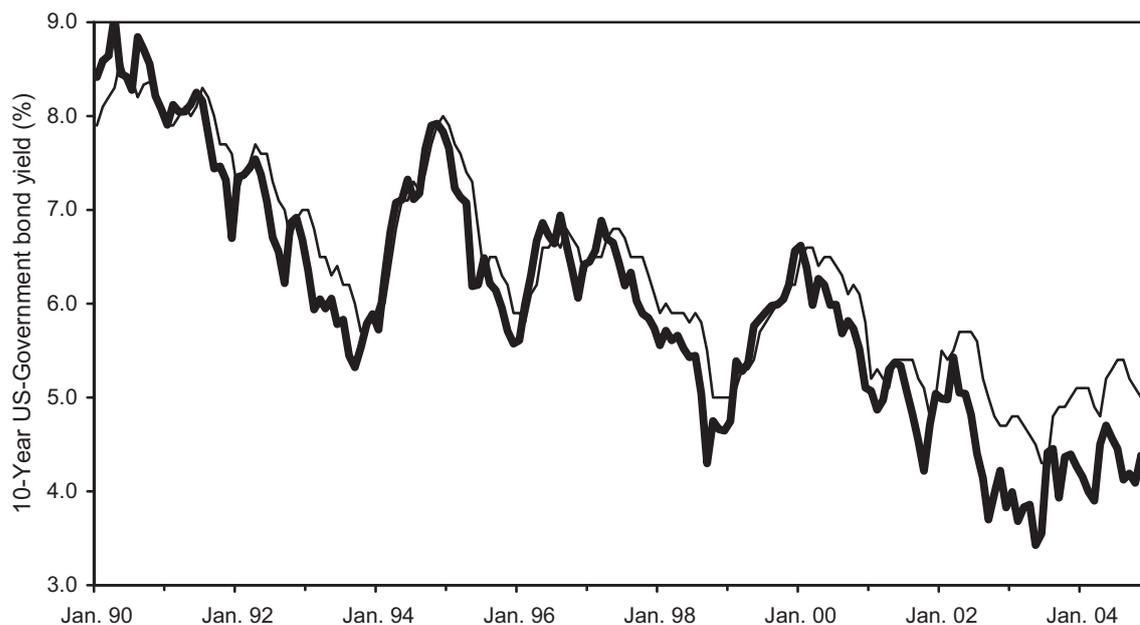


FIGURE 11. DEVELOPMENT OF THE 10-YEAR US GOVERNMENT BOND YIELD (BOLD LINE) AND CONSENSUS FORECASTS MOVED TO THE LEFT BY THE FORECAST HORIZON (THIN LINE) FROM JANUARY 1990 TO DECEMBER 2004

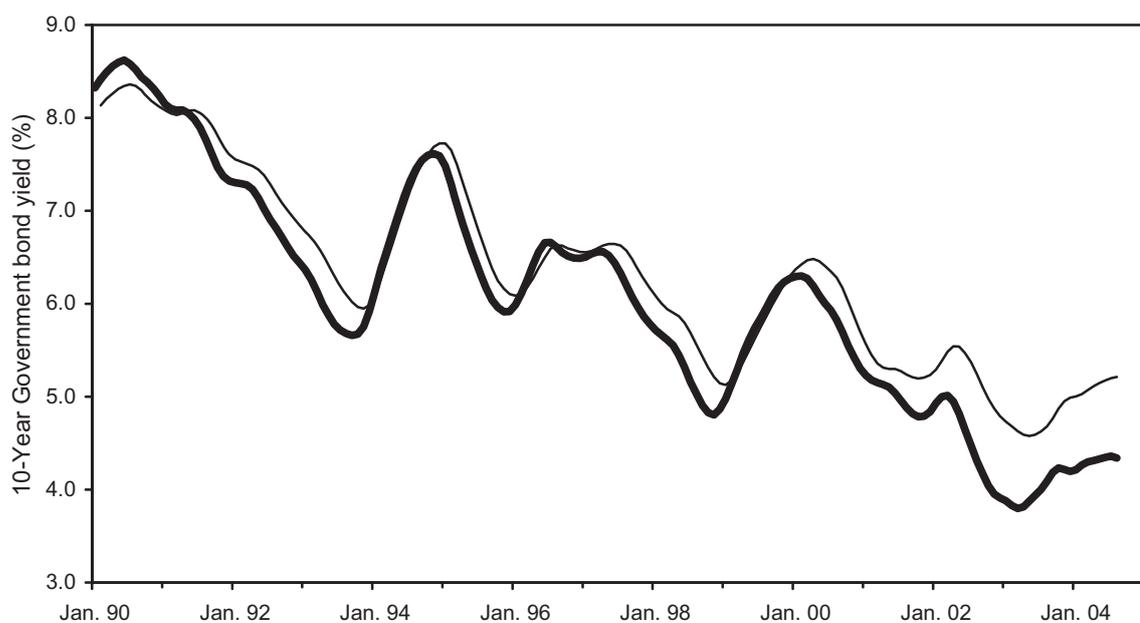


FIGURE 12. SMOOTHED DEVELOPMENT OF THE 10-YEAR US GOVERNMENT BOND YIELD (BOLD LINE) AND SMOOTHED CONSENSUS FORECASTS MOVED TO THE LEFT BY THE FORECAST HORIZON (THIN LINE) FROM JANUARY 1990 TO DECEMBER 2004

IV. Conclusions from the research results

The evaluation of the empirical data permits the following conclusions:

1. During the whole research period (1990 – 2004) the financial analysts under scrutiny drew up yield forecasts which show extensive correspondences (Figures 7 and 8).
2. The forecast quality of the examined forecast time series has to be described as poor. The 32 smoothed forecast time series have average rates of turning point errors of 0.95 (Table 2). The broad agreement of the forecast time series cannot therefore be explained by a successful forecasting procedure. But if all forecast time series are unsuited to correctly predicting the future, it could be expected that independent actions of the analysts would lead to them failing in different ways. After all, there are unlimited ways of wrongly predicting the future. As the analysts fail in almost identical ways it must be presumed that there is an underlying mechanism of behavior alignment and that this is also active. A case of rational herding behavior can therefore be postulated.
3. To empirically prove that externally triggered herding is the case, it is necessary to identify the external signal. In this study the analysts oriented their own forecast decisions to a large extent towards the respective actual market situation. This becomes obvious in Figures 9 to 12.
4. The hypothesis underlying this study, namely that the financial analysts' behavior can be correctly described with the approach of the externally triggered herding model, must be regarded as confirmed for the time being.

If the results given are summarized, and it is assumed that the examined forecasts of the 10-Year US Government bond yield are not solitary phenomena but possibly typical cases of fi-

nancial market forecasting,²⁶ the following picture emerges: It is obviously no easy task to generate capital market forecasts of a high forecast quality. Therefore financial analysts need to develop special survival techniques. On the one hand they must try to conceal the fact that the chances of their analysis being successful are low. On the other hand they need to shape the unavoidable failures in a way that holds no negative consequences for them. This can be achieved most easily if the forecasts of the individual analyst do not deviate too much from the collective market estimation of the analyst community. To this extent, the calculations exactly correspond to the basic combination of circumstances found in reputational herding, which Keynes developed in 1936. Regarding the particular build-up of the agreement process among the respective analysts, the aspect of transaction costs arising due to the communication process must be considered. It becomes obvious that the analysts are oriented towards an external signal, in this case the actual market situation. This signal is available for all group members. Picking up the signal needs only minimal efforts, the analysts only need to make spot checks from time to time to see whether their fellow group members are still maintaining their orientation towards this concrete external signal. If there is no sign of a general re-orientation of the analyst community, the observation of the external signal is sufficient to safely ensure that one's own forecasts are cradled within the protective environment of the collective majority's opinion.

²⁶ Against the background of extensively corresponding results of the evaluation of German bond market analysts, it can be assumed that this is no unique phenomenon. See Spiwoks (2004a).

Appendix

Given an example of fictitious forecast time series which obviously show no herding behavior, but represent individually differing theories of the phases of high and low interest rates, the following becomes clear: in such a situation the time series of consensus forecasts has no similarity with any individual forecast time series. The strong correlation of the consensus forecast time series with the single forecast time series of Figures 7 and 8 cannot simply be explained by the fact that the consensus forecast is calculated as the average of the single forecasts. Rather, a strong similarity of the forecast time series is necessary so that the time series of the consensus forecasts can adopt an extensively corresponding course.

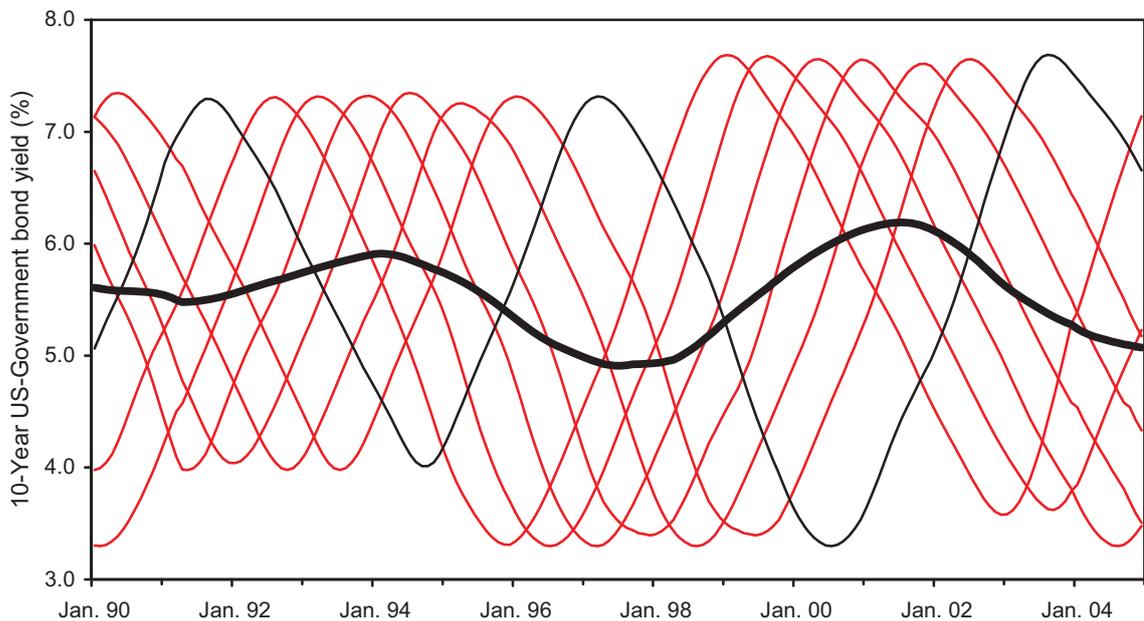


FIGURE 13. FICTITIOUS FORECAST TIME SERIES WHICH DO NOT UNDERLY ANY HERDING BEHAVIOR (THIN LINES), AND THE RESULTING TIME SERIES OF CONSENSUS FORECASTS (BOLD LINE)

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