# Herding in the foreign exchange market

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**Abstract**

In this paper we investigate to what extent we can identify herd behavior in the foreign exchange market. The foundation of this empirical study is a large set of survey data, which documents the individual forecasts of several large multinational banks on the future exchange rates of the Euro, the Japanese Yen and the British Pound against the US Dollar. The survey participants submitted forecasts for the 1-month, 3-month and 12-month time horizon. In this study, we first identify which banks can be detected as 'leaders' by measuring their performance using ordinary least squares regression. We classify a bank as a 'leader' if the bank outperforms its colleague banks on forecasting a certain exchange rate on a certain time horizon. In turn, we conduct Granger-causality tests in order to examine whether the forecasts of these leading banks are used by the other banks. We document substantial evidence of herd behavior in our sample, particularly for predictions on the 1-month time horizon. Furthermore we find that the average forecast is mimicked more often than the forecasts of the best performing banks.

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## 1 Introduction

The universal meaning of the word *herding* is 'to unite'; *to assemble together in a herd*. The term herding originally stems from the grouping of a number of animals (e.g. a herd of cattle, a herd of sheep). However, over the last couple of decades, the use of the word herding has expanded towards the field of economics. Particularly in the field of behavioral finance, herding has become a widely used connotation for the group behavior of economic agents.

Similar to the *meaning* of the word herding, the *explanation* of herding in behavioral finance also finds its analogy in the animal world. In his paper "Geometry for the Selfish Herd", Hamilton (1970) describes how animals, aware of being in danger, form a herd in order to decrease their individual risk. In a particular example he gives, Hamilton describes the setting of a group of frogs and one water-snake living together in a circular pond. In the example, the snake sleeps the entire day on the bottom of the pond, except for one moment, when the snakes wakes up to search for its daily meal: one frog. The frogs anticipate on the snake's daily routine and try to decrease their risk of becoming the snakes' prey by positioning themselves on the rim of the pond, which is the least favorite place for the snake to seek for its meal. Being situated on the rim of the pond, each individual frog can try to decrease its risk of being eaten, by decreasing the distance between itself and its neighbors. As a result, the frogs jump quickly towards each other on the rim looking for safer positions and as such form a herd. With the same line of reasoning, Hamilton gives many more examples of herd behavior in the animal world (e.g., sheep in the presence of a dog, schools of fish, etc.).

The important finding in the example described above, abstracting from the particular setting, is that self interested individuals, aware of being in danger, tend to engage in herd behavior in order to decrease their individual risk. Wilfred Trotter (1914) applies biological conceptions to the human society and argues that herd behavior is a psychological instinct. This provides the important insight that herd behavior in human societies might be caused by the same instinct that causes herd behavior in the animal world. For this reason, we consider the line of reasoning explaining herd behavior in the animal world to be applicable in the context of the research presented in this paper: the foreign exchange market. That is, the banks participating in the survey might abstain from publishing forecasts too far away from the 'general consensus' of their colleague banks, as they might be afraid to damage their reputation in case the forecasts turn out to be underperforming compared to the other banks. Similar to the findings of Hamilton, in this example the individuals (the participating banks) also try to decrease their individual risk by adopting herd behavior. We can conclude that there is considerable evidence that herd behavior in human societies is caused by a similar biological motivation as in the animal world. It seems that self-interested individuals exposed to risk, whether animals or human beings, try to decrease their individual risk by moving closer to others of the same kind. The remainder of this paper will focus on herd behavior in financial markets.

## 1.2 The implications of herding

The previous section provided an introduction to the phenomenon herding and to herd behavior in financial markets in particular. This section outlines the implications of herding in financial markets.

The Efficient Markets Hypothesis (EMH), introduced by Fama (1970), states that asset prices always reflect all publicly known information and that prices will instantaneously change when new information becomes available. This effectively implies that prices *become* information, as prices are a perfect reflection of the information available to the market. One of the assumptions underlying the EMH is that agents have rational expectations and behave accordingly. If that assumption is met, the *average* population's expectation is correct, even though possibly no individual agent is, and the price adapts such that the price level reflects the average expectation. This means that under the EMH, prices work as an aggregator: the price aggregates all information available. This in turn implies that if the EMH works correctly, it is impossible to consistently outperform the market based on public information.

Herd behavior jeopardizes the working of the EMH, as it reduces the information content in prices. When economic agents start forming expectations based on the expectations of others instead of following their individual rational expectations, the prevailing market price will no longer reflect all publicly available information and will move away from its fundamental value. The origination of an economic bubble is a classic example of a market in which the price is established based on others' expectations, instead of being based on each individual's rational expectation about the fundamental value. Bubbles arise when individuals start buying a particular asset because they believe its price will rise. This believe is disregarding the individuals' expectation about the fundamental value of the asset. As a result, the price of the asset will increase spectacularly, fueled by the increased demand, and move far above its fundamental value. At a certain point, investors realize the asset is excessively overpriced, which causes all investors to try to get rid of the asset as fast as possible. This causes the price of the asset to drop dramatically (often even to a level below fundamental value). Keynes (1936) compared the stock market once metaphorically to a beauty contest: The judges are not giving their own opinion on who is the most beautiful woman, but they are concerned with guessing what the other judges think is the most beautiful woman.

As becomes clear, herd behavior in financial markets can have a harmful effect, as it decreases the information content in prices. This amplifies the volatility of prices, as the setting of prices is based on very little information. Furthermore, herd behavior can cause speculative bubbles.

### 1.3 Different types of herding

In financial markets, there are several possible motivations for herd behavior. According to Bikhchandani and Sharma (2006), three types of herding can be distinguished: information-based herding, reputation-based herding and compensation-based herding. In this section, each of these types of herding will be discussed briefly. Furthermore, we will analyze the likeliness of each type of herd behavior to occur in the sample used in our study.

In the case of *information-based* herding, the behavior of certain economic agents is copied because these agents are believed to possess better private information than others. Their behavior is mimicked, as it is believed that this private information is directly reflected by their behavior. It is important to note that it is only *perceived* that these individuals possess better information. Their information might in fact be faulty, in which case herd behavior can give rise to speculative bubbles and prices moving far away from fundamental value.

*Reputation-based* herding occurs when economic agents are uncertain about their own ability to assess the market. As a result, they will base their decisions on the prior assessment of other agents. This type of herding can be particularly detrimental, since the (random) decision of one agent can cause a sequence of agents copying this decision. Since all agents make decisions based on the prior decision, all agents are effectively copying the decision of the first agent. As a result, all decisions in the market are based on very little information which leads to an inefficient market equilibrium. The phenomenon that individuals base their decision on the previous decision of others was introduced by Banerjee (1992), who uses a simple sequential decision model.

*Compensation-based* herding might occur when the compensation of agents depends on their relative performance compared to a certain benchmark (e.g. the market portfolio or a particular group of investors). In a setting in which all agents have imperfect private information about stock returns, a risk-averse agent subject to the compensation scheme illustrated above is likely to adopt herd behavior in order to decrease the risk of low compensation. Compensation-based herding does not need to be inefficient from the employer's perspective, as such compensations schemes can efficiently reduce risk in a situation in which there is asymmetric information (moral hazard and adverse selection problems). Bikhchandani and Sharma describe this as 'constrained efficiency', where constraints are put on the risks of moral hazard and adverse selection. Despite this apparent benefit of individual risk reduction, also this type of herding reduces the information content of prices, which can be detrimental for the performance of the market as a whole.

The type of herding we believe is most likely to occur in our sample is reputation-based herding, whereas we deem the other types less likely to occur. The participation of the banks in the survey was optional and the performance of the forecasters was, to our knowledge, not linked to their compensation. This would imply that *compensation* is an unlikely motivation for herding in this setting. *Information*-based herding also seems unlikely to occur, as the future exchange rates of the currencies in this dataset depend on many macro-economic variables, which is information that is publicly available. Opposed to compensation- and information-based herding, *reputation*-based herding seems a type of herding which is likely to occur in our sample. Since the forecasts of the banks participating in the survey were made publicly available, there was a clear possibility for the forecasters to measure the performance of its colleague participants and to copy their forecasts. Moreover, reputation-based herding makes intuitive sense in this setting, since there is a lot of uncertainty involved with the forecasting of exchange rates. For this reason, forecasters might feel insecure about their own ability to make good predictions and might therefore be tempted to use the expectations of their colleagues when submitting their own predictions.

### 1.4 Prior research and this paper's contribution to the existing literature

Although a considerable amount of research has focused on herd behavior in financial markets (e.g. Plott, 2000; Hey and Morone, 2004), most of this research has focused on the stock market, whereas relatively little research has been done on herding in the foreign exchange market.

The only empirical evidence on herding in the foreign exchange market using survey data has been reported in a working paper by Beine, Benassy-Quere and Colas (2008). In their study, survey data from 1990-1994 and 1996-2001 is used, providing data on the forecasts of a number of large banks on the exchange rates of the most important currencies for several time horizons. Beine *et al* document moderate support for herd behavior in the foreign exchange market. Although they identify sequential connections between exchange-rate forecasters, they could not identify a specific forecaster leading more than four other forecasters. Another important finding in their study is that herd behavior can be detected for both short-run as well as long-run time horizons. However, Beine *et al* find that forecasters seem more likely to mimic others for short-run predictions than for long-run predictions.

Although our study is similar to the study conducted by Beine *et al*, this paper presents useful contributions to the existing literature. First of all, this study provides additional quantitative evidence for the existence of herd behavior in the foreign exchange market, since we use a different dataset than Beine *et al*. Secondly; this study uses a dataset with different characteristics than the dataset used by Beine *et al*. We use more recent data, as our data documents forecasts in the period 2003-2008, whereas Beine *et al* use forecasts from the periods 1990-1994 and 1996-2001. Furthermore, our dataset consists of weekly data, contrary to Beine *et al*, who use monthly data. Using weekly data instead of monthly data gives the opportunity to detect herding at a higher frequency. As expectations change instantaneously as new market information becomes available, it is important to measure herd behavior with a short lag. The longer the lag used to check whether herding can be detected, the more noise (i.e., new information) is incorporated in the tests. This in turn, makes it more difficult to provide evidence for the existence of herding. Lastly, our sample consists of more forecasters, which increases the likelihood that our sample gives a good representation of the market as a whole. In addition, a sample consisting of more forecasters enhances the statistical power of our tests.

Since we use a different, and for some reasons a better, dataset than is used in the study of Beine *et al*, we believe this paper provides useful insights in whether, and to what extent, herd behavior can be identified in the foreign exchange market. A detailed description of the data is presented in the next chapter.

The remainder of this paper is organized as follows. Chapter 2 gives a detailed description of the data used in this study. In Chapter 3, the methodology used in this study is discussed. In Chapter 4, we report the results of the tests we conducted and we examine whether and to what extent we can detect herd behavior in the foreign exchange market. The fifth and final chapter presents some concluding remarks.

# 2 Data

In this chapter we describe the dataset used in this study. As our dataset consists of survey data, we first discuss the use of survey data in this type of study.

## 2.1 Survey data

The following section is based on a paper written by Frankel and Froot (1985), and outlines the advantages and disadvantages of the use of survey data.

Economists are generally somewhat skeptic about the use of survey data to measure expectations in financial markets. It is often claimed that these surveys are not taken very seriously by the respondents. In the same line of reasoning, opponents of the use of surveys claim that more can be learned from observing the actual behavior of economic agents than from what economic agents say. According to these opponents, survey data does not provide a correct representation of the actual expectations of the respondents, and researchers should therefore be cautious when drawing conclusions based on this type of data.

The opponents of the use of surveys present valid arguments. Nevertheless, in the context of the foreign exchange market, there is an important advantage to the use of surveys compared to observing actual behavior. Looking at 'actual behavior' to identify expectations in the foreign exchange market can be done by looking at *forward exchange rates*. However, the disadvantage of using forward exchange rates is that they include a risk premium, which forms a clear bias in measuring the expected change in the exchange rate. For this reason, survey data might in fact be more useful than looking at forward rates as surveys do not include this bias, and measure expectations directly.

A counterargument to the critique that most respondents do not take surveys very seriously can be found in the reputation of the participants. As the results of the survey are made publicly available, it could be harmful for participants' reputation to submit poor forecasts. For this reason, there is a clear incentive for the participants to take the survey seriously. Another argument in favor of the use of surveys in these kinds of studies is that the participants in these surveys are usually highly specialized in foreign exchange markets. They are experts, who have access to the latest information. This enables them to make well supported predictions about exchange rates.

As becomes clear from the above, there are valid arguments for surveys to be used in this type of study. Therefore, we will confidently use our survey data as a basis to make inferences in this study.

### 2.2 Data description

In this study, we use weekly survey data from *FX Week*, containing expectations on exchange rates in the period 2003-2008. FX Week is a weekly magazine, specialized in the foreign exchange market. The survey participants, 61 large multinational banks, were asked to predict the future value of a number of currencies on the 1-month horizon, 3-month horizon and 12-month horizon. For simplicity, we numbered the participants from 'Forecast1' up to and including 'Forecast61'. A list of the names of the participating banks can be found in Appendix I. Next to the survey data provided by FX Week, we use data on the actual exchange rates in the period for which the banks made forecasts. This data was extracted from *Datastream*, and is used in this study to measure the actual forecasting performance of the participants of the survey. In this study, we concentrate on the exchange rate of the Euro, the Great-Britain Pound and the Japanese Yen against the US-Dollar. We focus on these three exchange rates, since they represent most of the turnover volume on the foreign exchange market.

Our dataset documents expectations on future exchange rates on Mondays every week, in the period from January 13th, 2003 until February 25th, 2008. In this study, we assume the expectations on the future exchange rates to be formed on the dates the forecasts were submitted. It is important to note that the results of the survey were published *before* the next forecast was made.

Although FX Week reports weekly data, the survey was not conducted every week of the year. In the period mentioned above, the survey was held 216 times. The average number of weeks per year the survey reports data on is 42, leaving considerable ‘gaps’ in the data. Especially around the holiday periods in July and in December, there are some periods in which there is no data for two or three weeks in a row. Except for decreasing the statistical power, these gaps do not cause a problem for our tests, as we do not need the data to be perfectly sequenced in order to test for herding.

As is mentioned above, 61 banks participated in the survey conducted by FX Week. However, not all participating banks submitted their forecasts every time the survey was conducted. Some banks were more actively participating in the survey than others. An overview of the response of the 61 banks is presented in Figure 1 on the next page. As the figure shows, there is a considerable number of banks who submitted their forecasts a relatively small number of times. We found a slight negative correlation between ‘number of observations’ and ‘performance’, causing a bias in our performance results in favor of the banks who submitted a small number of forecasts. To overcome this problem, we decided to remove all banks from the sample with less observations than 100 (25 out of the 61 banks), leaving us with 36 forecasters to use in this study. Our sample of 36 forecasters is still larger than the sample used by Beine *et al*, and provides us with a solid basis to draw conclusions on with regard to our research question. Appendix I presents the response per bank as well as an overview of which banks are part of the sample and which are not.

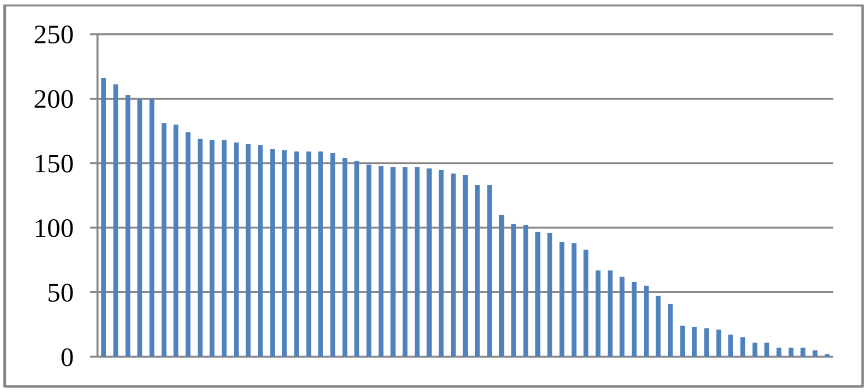


Figure 1 displays the number of responses of the 61 banks participating in the survey. The highest response is 216 out of 216, the lowest response is 2 out of 216. The average response in the (initial) sample is 111.

**Figure 1 - Survey Response of the participating 61 banks**

Table 1 below presents descriptive statistics of the survey data. We can see in the table that the banks in our sample expected the Euro, on average, to decrease slightly against the US Dollar in the sample period. The same can be concluded for the Great Britain Pound against the US Dollar and the US Dollar against the Japanese Yen. Furthermore, we find the standard deviation (for all exchange rates) to increase as the time horizon increases. This makes sense, as it is obvious that exchange rates can change more in a longer time period. Therefore, the standard deviation of the expected change of the exchange rates increases as the time horizon expands.

**Table 1**
**Descriptive Statistics**

| | EUR/USD | | | GBP/USD | | | USD/JPY | | |
|---|---|---|---|---|---|---|---|---|---|
| **Time Horizon** | **1M** | **3M** | **12M** | **1M** | **3M** | **12M** | **1M** | **3M** | **12M** |
| **Average** | -0,004 | -0,007 | -0,024 | -0,003 | -0,005 | 0,000 | -0,005 | -0,016 | -0,033 |
| **Standard Deviation** | 0,033 | 0,052 | 0,099 | 0,030 | 0,043 | 0,109 | 0,035 | 0,056 | 0,124 |
| **Minimum** | -0,119 | -0,181 | -0,320 | -0,129 | -0,193 | -0,233 | -0,143 | -0,206 | -0,318 |
| **Maximum** | 0,122 | 0,162 | 0,222 | 0,108 | 0,137 | 0,386 | 0,126 | 0,189 | 0,332 |

*Table 1 represents descriptive statistics of the forecasts made on three exchange rates and three time horizons by the 36 banks in our sample in the period 2003-2008.*

## 3 Methodology

In this chapter we will discuss the methodology used in this study. To identify the leading banks in the sample, we used *ordinary least squares regression*. In turn, we conducted *Granger Causality*-tests in order to assess whether we can detect herding.

To be able to test for herd behavior, we must first determine which banks' forecasts are most likely to be copied by the other banks. We depict the banks whose expectations are likely to be mimicked by the other forecasters as *leaders*. We recognized forecasters as being a leader if their forecasts outperformed the forecasts of all other participants. We identified one leader for each exchange rate-horizon combination. The performance of the participating banks is measured by regressing their forecasts on the actual exchange rate at the end of the particular time horizon. More specifically, we regressed the participants' expected *change* of the exchange rate on the actual change of the exchange rate. The specification used to measure performance is presented below:

$$E_t(S_{t+k}) - S_t = \alpha + \beta\,(S_{t+k} - S_t)$$

*Where:*

- $E_t(S_{t+k})$ = *the prediction of the particular bank*
- $S_t$ = *the exchange rate on the date the forecast was submitted*
- $S_{t+k}$ = *the actual exchange rate at the end of the time horizon*

The relative performance of the participants can be found by looking at the corresponding *adjusted R-squares*[1]. The forecaster with the highest adjusted R-squared is the best performer, and is thus identified as the leader. Similarly, we also measured the performance of the 'average forecast' and compared it to the performance of the participating banks.

Next to measuring the performance of the forecasters and comparing it to the average forecast, we also checked for the relative performance of the *random walk forecast*. As the random walk forecast predicts a 'zero-change' of the exchange rate on the date the forecast is made, we were not able to measure its performance directly by the regression method described above because this would leave no variance in the independent variable. For this reason, we measured the relative performance of the random walk indirectly, by comparing its 'average squared forecasting error' to those of the other forecasters.

After having identified the leaders, we conducted *Granger causality* tests in order to investigate whether and to what extent herd behavior can be detected in our sample.
The Granger causality test is based on prediction, and tests whether past values of a certain variable hold significant statistical information about the value of another variable (Granger, 1969). Thus, in a model with two variables, for example $X_1$ and $X_2$, causality is tested by

[1] The adjusted R-square provides a measure of performance on a scale from 0 to 1, where a score of 1 represents a perfect prediction.

examining whether adding lagged values of $X_1$ to lagged values of $X_2$, adds significant power in predicting $X_2$. In a similar fashion, Granger causality tests also check whether the causality runs the other way around (i.e., from $X_2$ to $X_1$), see the formulas below.

$$X_1(t) = \sum_{j=1}^{p} A_{11,j} X_1(t-j) + \sum_{j=1}^{p} A_{12,j} X_2(t-j) + E_1(t)$$

$$X_2(t) = \sum_{j=1}^{p} A_{21,j} X_1(t-j) + \sum_{j=1}^{p} A_{22,j} X_2(t-j) + E_2(t)$$ [2]

If one of the two variables helps predict the other variable significantly, but the causality does not run the other way around, there is so-called 'one-way-causality', which means that the one variable 'Granger causes' the other variable. It is also possible to find two-way Granger causality (or no causality at all), in which case it is harder to interpret the results. Although Granger causality tests are not a 'waterproof' method for testing true causality (both variables might be influenced by a third variable with different lags), it is a generally accepted method for testing causality and we therefore deem it a suitable method to use in this study for investigating whether causality runs from the leader to the other forecasters. If we can indeed find causality running from leader to other forecasters, we will denote these forecasters as 'followers'. Since the results of the survey were made publicly available by FX Week after the survey, all forecasters were able to observe the forecasts of the other participants before they submitted their forecasts the following week. Therefore, we test for *one-lag* Granger causality, which means that we test whether the participants used the leaders' forecast of the *previous* week when making their forecast. Similarly, we also test whether we can detect granger causality running from the average to the other forecasters.

In the next chapter, the results of the performance tests and Granger causality tests are presented and discussed.

# 4 Results

In this Chapter, we will present and discuss the results of the tests conducted in this study. In Section 4.1, we present the forecasting performance of the participants of the survey, and

[2] Formulas available at http://www.scholarpedia.org/article/Granger_causality#Personal_account_by_Clive_Granger

compare it to the performance of the average forecast. Additionally, we compare the performance of the survey participants to the performance of the 'random walk'. In Section 4.2, we investigate whether the forecasting performance of the participants is positively correlated to their performance for the other currencies or time horizons. In Section 4.3, we report the results of the Granger causality tests we conducted and present to what extent herding can be detected.

### 4.1 Performance and leaders

As is described in Chapter 3, we used ordinary least squares regression in order to measure the performance of the survey participants, which in turn enables us to identify the leaders in the sample. The performance of the leaders for every exchange rate-horizon combination, as well as the performance of the 'average forecast' is presented in Table 2. We also present the 'average performance'. The performance of each individual forecaster can be found in Appendix II.

**Table 2 - Leaders, performance of the average and average performance**

| **1-Month Horizon** | **EUR/USD** | **GBP/USD** | **USD/JPY** |
|---|---|---|---|
| Leader | Forecast3 | Forecast31 | Forecast49 |
| Name Leader | *Citigroup* | *Merrill Lynch* | *Investors Bank & Trust* |
| Performance of the Leader | 0.044 | 0.127 | 0.092 |
| Performance of the 'Average Forecast' | 0.000 | 0.000 | 0.012 |
| Average Performance of the sample | 0.004 | 0.016 | 0.015 |
| | | | |
| **3-Month Horizon** | **EUR/USD** | **GBP/USD** | **USD/JPY** |
| Leader | Forecast42 | Forecast41 | Forecast49 |
| Name Leader | *SEB Merchant Banking* | *Calyon* | *Investors Bank & Trust* |
| Performance of the Leader | 0.198 | 0.251 | 0.101 |
| Performance of the 'Average Forecast' | 0.014 | 0.028 | 0.001 |
| Average Performance of the sample | 0.031 | 0.042 | 0.023 |
| | | | |
| **12-Month Horizon** | **EUR/USD** | **GBP/USD** | **USD/JPY** |
| Leader | Forecast26 | Forecast5 | Forecast3 |
| Name Leader | *Dresdner Kleinwort* | *HSBC* | *Citigroup* |
| Performance of the Leader | 0.329 | 0.598 | 0.541 |
| Performance of the 'Average Forecast' | 0.031 | 0.474 | 0.201 |
| Average Performance of the sample | 0.068 | 0.205 | 0.135 |

*Performance is expressed in terms of Adjusted R-Squared*

For the interpretation of the results in Table 2, it is important to note the difference between *Performance of the 'Average Forecast'* and *Average Performance of the sample*. Although the terminology is rather similar, the meaning of the statistics is very different. The former reflects the performance of the 'average of all the forecasts', in which the average forecast is effectively treated as being a separate forecaster. The latter on the contrary, presents the 'average performance' of the sample, and is calculated by taking the simple average of all forecasters' adjusted R-squares.

We can derive several noteworthy characteristics from Table 2. First of all, we see that the forecasters tend to perform better when making forecasts over a longer time-horizon. This makes sense, as there is often a lot of 'noise' in exchange rates in the short run, whereas exchange rates tend to approach fundamental value in the long run. Secondly, we see that for every exchange rate-horizon combination, the performance of the leader by far exceeds the *'average forecast'*. Finally, we note that the average forecast only outperforms the average of the sample two out of the nine exchange rate-horizon combinations. In other words, the average forecast performs below average seven out of nine times. This is surprising, as the average forecast often performs quite well compared to the individual forecasters (Cavaglia, Verschoor and Wolff, 1993 and 1994). Our findings are therefore not in line with the Efficient Markets Hypothesis (EMH), which proposes that if all market participants have rational expectations, the average of the expectations will set the price at its 'correct' level. This means that if the EMH would work perfectly, the average forecast should outperform all individual forecasts, which is clearly not the case.

To give us more insight on the general level of performance of the forecasters in our sample, we also tested the relative performance of the 'random walk'-forecast. Meese and Rogoff (1983) found in their study that the random walk actually did not perform worse than a number of technical models often used by highly specialized exchange rate forecasters. For this reason, we thought it would be worthwhile to measure the relative performance of the random walk against the forecasters in our sample. In order to measure this, we made a performance-ranking of the forecasters in our sample including the random walk, based on their *average squared forecasting error*. As there are 36 forecasters in our sample, the rank of the random walk must lie in between 1 (highest performance) and 37 (lowest performance). The ranking of the random walk forecast compared to the other forecasters is presented in Table 3. The actual average squared forecasting error of every forecaster can be found in

Appendix III. As we can see in Table 3, the rank of the random walk is quite high for almost all exchange rate-horizon combinations, meaning that the random walk performs relatively well. These findings are even more striking than the findings of Meese and Rogoff, as the random walk in our sample actually performs *above* average compared to the other forecasters. This apparent relatively high performance of the random walk is remarkable, as there is no predictive power in the random walk (the random walk simply predicts 'no change'). Our findings therefore undermine the predictive skills of the often claimed highly specialized and well-compensated forecasters partaking in our sample.

**Table 3 – Relative Performance of the Random Walk**

| **Time Horizon** | 1 Month | 1 Month | 1 Month | 3 Month | 3 Month | 3 Month | 12 Month | 12 Month | 12Month |
|---|---|---|---|---|---|---|---|---|---|
| **Exchange Rate** | EURUSD | GPBUSD | USDJPY | EURUSD | GPBUSD | USDJPY | EURUSD | GPBUSD | USDJPY |
| **Rank Random Walk** | 8 | 3 | 2 | 8 | 11 | 2 | 13 | 23 | 3 |

*Table 3 represents the relative performance of the Random Walk compared to the 36 banks in our sample based on their* *average squared forecasting error*. *The rank of the Random Walk in the table represents its relative performance, where rank '1' ('37') would imply that the random walk performed better (worse) than all the banks in our sample.*

In line with our finding that the performance of the forecasters increases as the time horizon increases, we find that the relative performance of the random walk tends to decrease as the time horizon increases. The relatively high performance of the random walk on the 1-month time horizon makes sense because the random walk 'expects' a zero-change in exchange rate. This zero-change scenario is much more likely to occur on the 1-month horizon than for the 3-month or 12-month horizon. The last noteworthy characteristic we derive from Table 3 is that we find a surprisingly high performance of the random walk for the Japanese Yen against the US Dollar exchange rate, which could imply that the forecasters in our sample had a particularly poor performance regarding the forecasting of this exchange rate. In general, we can conclude that the random walk forecast has a rather high relative performance in our sample.

### 4.2 Correlation of Performance

To broaden our understanding of the data, we investigated whether the performance of the individual forecasters for a certain exchange rate-horizon combination is positively correlated with their performance for the other exchange rate-horizon combinations. More interestingly, we also examined whether this correlation is higher for forecasts within the same exchange rate or the same time horizon. In other words, does a forecaster who performs well for a certain exchange rate (time horizon), also perform well for the same exchange rate (time horizon) for a different time horizon (exchange rate). If our results confirm this, we infer to observe ‘specialization’, meaning that certain forecasters are relatively good or bad in predicting specific exchange rates (or time horizons).

As can be derived from Table 4, forecasting performance is generally positively related to forecasting performance for other exchange rate-horizon combinations. This is demonstrated by the fact that 24 out of the 36 correlation coefficients are positive, as well as by the finding that the average correlation coefficient is positive (which is 0.084). Moreover, we detect specialization in the forecasting of particular exchange rates. This is demonstrated by the shaded areas in the upper right part of Table 4, which represent the relevant exchange rate-horizon combinations. As we can see, seven out of the nine coefficients are positive, and the average of these coefficients is 0.155, which is significantly higher than the overall average discussed before. This finding holds also true when we look at the three exchange rates separately.

**Table 4: Correlation Matrix 1**

| | EURUSD1 | EURUSD12 | EURUSD3 | GBPUSD1 | GBPUSD12 | GBPUSD3 | USDJPY1 | USDJPY12 | USDJPY3 |
|---|---|---|---|---|---|---|---|---|---|
| **EURUSD1** | 1 | 0.300 | 0.077 | 0.033 | 0.226 | 0.319 | 0.156 | 0.248 | 0.133 |
| **EURUSD12** | 0.300 | 1 | -0.019 | 0.029 | 0.469 | 0.272 | -0.002 | 0.098 | 0.008 |
| **EURUSD3** | 0.077 | -0.019 | 1 | -0.099 | 0.012 | -0.017 | -0.223 | 0.041 | -0.014 |
| **GBPUSD1** | 0.033 | 0.029 | -0.099 | 1 | 0.056 | 0.438 | 0.034 | -0.265 | 0.176 |
| **GBPUSD12** | 0.226 | 0.469 | 0.012 | 0.056 | 1 | 0.273 | -0.063 | -0.023 | 0.038 |
| **GBPUSD3** | 0.319 | 0.272 | -0.017 | 0.438 | 0.273 | 1 | -0.084 | 0.211 | -0.085 |
| **USDJPY1** | 0.156 | -0.002 | -0.223 | 0.034 | -0.063 | -0.084 | 1 | -0.121 | 0.106 |
| **USDJPY12** | 0.248 | 0.098 | 0.041 | -0.265 | -0.023 | 0.211 | -0.121 | 1 | 0.285 |
| **USDJPY3** | 0.133 | 0.008 | -0.014 | 0.176 | 0.038 | -0.085 | 0.106 | 0.285 | 1 |

*The shaded areas in the upper right part of the table represent the correlation coefficients for leadership within the same exchange rate forecast. The shaded areas in the lower left part of the table represent the correlation coefficients for leadership within the same forecast horizon.*

In a similar fashion, we investigated whether we can detect specialization for particular time horizons. The correlation coefficients for the three different time horizons are represented by the shaded cells in lower left part of Table 4. Contradictory to our findings regarding the correlation of performance on the same exchange rate, we do not find specialization regarding the time horizons the forecasts are made on. Only five out of the nine relevant coefficients are positive, and the average of these coefficients is 0.072, which is lower than the overall average coefficient of 0.084. Furthermore, the average correlation coefficient exceeds the overall average only for the 12-month horizon.

In conclusion, the performance of the forecasters is positively related to the performance of their other forecasts. Moreover, we detect specialization for particular exchange rates, whereas banks do not appear to be specialized in making predictions for a certain time horizon.

**4.3 Granger Causality Results**

In order to detect herd behavior in our sample, we performed one-lag Granger causality tests on the leaders we selected for every exchange rate-horizon combination. The null-hypothesis of our test is '*Leader does not Granger Cause Forecast-x*', where the leader is the best performer of that specific exchange rate-horizon, and forecast-x is one of the other forecasters in the sample. This test is performed on each individual forecaster and each exchange rate-horizon combination. The results of these tests are presented in Table 5, in which the highlighted cells represent the forecasters for which we reject the null-hypothesis at the 5% significance level.

From the results in Table 5 we conclude that herd behavior can be detected in our sample for almost every exchange rate and time horizon. Only for the 12-month Euro-US dollar forecasts we do not detect any herding at all. A second noteworthy finding can be derived from Table 5 by looking at the frequency of herding. It seems that herding occurs substantially more on the 1-month horizon than on the 3-month or 12-month horizon. This finding is similar to the findings of Beine *et al*, and makes sense intuitively as well. As already mentioned, there is a lot more noise involved in short term future exchange rates than in long term future exchange rates. Therefore, for predictions with a short time horizon, forecasters rely more heavily on their individual technical models, whereas predictions on the long run can be done more easily with publicly available macroeconomic information. Making predictions with a short time horizon is therefore found to be more difficult, which is proved by the results presented earlier in this chapter. For this reason, forecasters might doubt their own models for making short run predictions, and as a consequence they might copy the forecasts of the other forecasters. Therefore, herding is possibly more likely to occur on forecasts with a short horizon compared to forecasts with a long horizon. If this line of reasoning is indeed correct, we can label this type of herding as 'reputation-based herding', as the herd behavior is rooted in forecasters' uncertainty about their own ability to make accurate forecasts. A third result worth mentioning is that the selected leaders in our sample engage in herd behavior themselves for the other exchange rate-horizon combinations. In fact, the leaders we found are, on average, herding even *more* than the other forecasters. This remarkable, as we would not expect banks who lead the other banks for a certain exchange rate-horizon combination, to be involved in herd behavior an above average amount of times when making predictions for the other exchange rates and time horizons.

**Table 5: Granger Probabilities**

| **Horizon/Currency** | **1M-EURUSD** | **1M-GBPUSD** | **1M-USDJPY** | **3M-EURUSD** | **3M-GBPUSD** | **3M-USDJPY** | **12M-EURUSD** | **12M-GBPUSD** | **12M-USDJPY** |
|---|---|---|---|---|---|---|---|---|---|
| Leader | Forecast 3 | Forecast 31 | Forecast 49 | Forecast 42 | Forecast 41 | Forecast 49 | Forecast 26 | Forecast5 | Forecast3 |
| Forecast3 | 0.0001 | 0.0326 | 0.0496 | 0.3160 | 0.3299 | 0.6029 | 0.1378 | 0.9210 | 0.3372 |
| Forecast4 | 0.5086 | 0.1423 | 0.1026 | 0.9269 | 0.3889 | 0.0731 | 0.0512 | 0.3969 | 0.0047 |
| Forecast5 | 0.7637 | 0.0478 | 0.3004 | 0.2198 | 0.3811 | 0.0463 | 0.6965 | 0.0677 | 0.0029 |
| Forecast6 | 0.2950 | 0.2128 | 0.6257 | 0.1623 | 0.3844 | 0.8618 | 0.6030 | 0.3170 | 0.5451 |
| Forecast8 | 0.5124 | 0.0675 | 0.8846 | 0.9236 | 0.9023 | 0.5252 | 0.6570 | 0.9861 | 0.9847 |
| Forecast9 | 0.0992 | 0.0033 | 0.1372 | 0.1391 | 0.9268 | 0.5599 | 0.3154 | 0.5184 | 0.2942 |
| Forecast10 | 0.3998 | 0.0339 | 0.0765 | 0.9254 | 0.2476 | 0.6295 | 0.2978 | 0.7202 | 0.0100 |
| Forecast11 | 0.9866 | 0.0196 | 0.6638 | 0.0022 | 0.2240 | 0.4206 | 0.2839 | 0.8173 | 0.9798 |
| Forecast12 | 0.9132 | 0.0907 | 0.3838 | 0.9845 | 0.8452 | 0.4476 | 0.7232 | 0.6001 | 0.8254 |
| Forecast13 | 0.2190 | 0.0066 | 0.1143 | 0.2974 | 0.3815 | 0.4905 | 0.7489 | 0.8633 | 0.2063 |
| Forecast15 | 0.4253 | 0.0128 | 0.3996 | 0.8625 | 0.8054 | 0.1714 | 0.9236 | 0.1234 | 0.1112 |
| Forecast18 | 0.5508 | 0.0289 | 0.9426 | 0.7862 | 0.4588 | 0.9387 | 0.7558 | 0.4410 | 0.2297 |
| Forecast19 | 0.0218 | 0.0066 | 0.3259 | 0.6185 | 0.7708 | 0.1616 | 0.9626 | 0.8450 | 0.4636 |
| Forecast20 | 0.0081 | 0.0006 | 0.0432 | 0.5951 | 0.5607 | 0.9709 | 0.3433 | 0.7305 | 0.7872 |
| Forecast22 | 0.5042 | 0.0038 | 0.3680 | 0.3337 | 0.7421 | 0.2214 | 0.7877 | 0.0290 | 0.3255 |
| Forecast24 | 0.0271 | 0.0306 | 0.1632 | 0.7373 | 0.7734 | 0.5289 | 0.1867 | 0.7903 | 0.2711 |
| Forecast26 | 0.2164 | 0.0057 | 0.0147 | 0.4948 | 0.5159 | 0.5782 | 0.2397 | 0.0785 | 0.2323 |
| Forecast27 | 0.3051 | 0.0005 | 0.3921 | 0.0344 | 0.1062 | 0.7804 | 0.8382 | 0.2196 | 0.6222 |
| Forecast28 | 0.0694 | 0.0001 | 0.0080 | 0.1110 | 0.4236 | 0.3253 | 0.8161 | 0.6528 | 0.8502 |
| Forecast29 | 0.8444 | 0.0621 | 0.8208 | 0.2046 | 0.9406 | 0.8166 | 0.4163 | 0.4228 | 0.4316 |
| Forecast30 | 0.0111 | 0.0511 | 0.0007 | 0.1039 | 0.0477 | 0.9782 | 0.3442 | 0.6023 | 0.7061 |
| Forecast31 | 0.3656 | 0.0002 | 0.3585 | 0.3522 | 0.7076 | 0.1297 | 0.3615 | 0.3067 | 0.0213 |
| Forecast33 | 0.8230 | 0.2385 | 0.5315 | 0.2011 | 0.2109 | 0.2450 | 0.8680 | 0.7432 | 0.3735 |
| Forecast34 | 0.0614 | 0.1299 | 0.5416 | 0.8515 | 0.7233 | 0.7749 | 0.9982 | 0.4238 | 0.0637 |
| Forecast36 | 0.3500 | 0.0082 | 0.0065 | 0.1845 | 0.5222 | 0.9079 | 0.8995 | 0.6480 | 0.8256 |
| Forecast37 | 0.9765 | 0.0616 | 0.3579 | 0.2456 | 0.5835 | 0.3291 | 0.0823 | 0.0261 | 0.0272 |
| Forecast39 | 0.0938 | 0.0095 | 0.0204 | 0.3788 | 0.8654 | 0.9564 | 0.0593 | 0.0324 | 0.6925 |
| Forecast40 | 0.0042 | 0.0015 | 0.1157 | 0.0161 | 0.2523 | 0.5547 | 0.1486 | 0.0088 | 0.9625 |
| Forecast41 | 0.0169 | 0.0049 | 0.0262 | 0.1792 | 0.0127 | 0.4999 | 0.1040 | 0.7466 | 0.6255 |

| Horizon/Currency | 1M-EURUSD | 1M-GBPUSD | 1M-USDJPY | 3M-EURUSD | 3M-GBPUSD | 3M-USDJPY | 12M-EURUSD | 12M-GBPUSD | 12M-USDJPY |
|---|---|---|---|---|---|---|---|---|---|
| Forecast42 | 0.0701 | 0.0148 | 0.0318 | 0.0103 | 0.9459 | 0.8809 | 0.5090 | 0.2267 | 0.1228 |
| Forecast43 | 0.5591 | 0.0080 | 0.3283 | 0.0918 | 0.0170 | 0.4998 | 0.4411 | 0.9484 | 0.2643 |
| Forecast44 | 0.6334 | 0.0137 | 0.0427 | 0.0816 | 0.4006 | 0.4823 | 0.9604 | 0.6582 | 0.6880 |
| Forecast45 | 0.0915 | 0.0147 | 0.0182 | 0.0530 | 0.2961 | 0.2294 | 0.3271 | 0.8896 | 0.8070 |
| Forecast46 | 0.1504 | 0.1152 | 0.1012 | 0.1605 | 0.8860 | 0.1788 | 0.8172 | 0.4609 | 0.0361 |
| Forecast49 | 0.0103 | 0.0422 | 0.0005 | 0.0034 | 0.1259 | 0.9507 | 0.0908 | 0.0862 | 0.2714 |
| Forecast51 | 0.2056 | 0.0230 | 0.2544 | 0.1864 | 0.4018 | 0.6587 | 0.0718 | 0.0089 | 0.1428 |
| Frequency | 7 | 25 | 11 | 4 | 2 | 1 | 0 | 5 | 6 |
| Significant at 5% | Leader | | | | | | | | |

To increase the robustness of our results, we also checked whether we could find causality running the other way around, thus from the follower to the leader. The results of these 'robustness'-tests can be found in Appendix IV. As can be concluded from the results, the causality we find running from leader to followers, is hardly ever found to also run the other way around. This finding further strengthens our results.

In addition to testing for Granger causality from the leaders to the other forecasters, we also tested for Granger causality using the average forecast as the leader. Even though the performance of the average forecast was quite poor, there is still a valid possibility for the average forecast to be copied by the forecasters, because forecasters might take the EMH into account. As is already mentioned, the EMH proposes that the average expectation in the market is correct. As a result, there is reason for the forecasters to believe that the average forecast is in fact the best guess. Our results confirm this, as the average forecast seems to be used more often by the forecasters than the forecast of the best performing forecaster (see Table 6). In other words, we find more evidence for herding using the average forecast as the leader than for the best performing forecaster. Our results therefore suggest that it is not the actual performance of certain forecasters that is the predominant factor triggering herd behavior, but the *belief* about performance. As the average forecast is *believed* to perform well, even though it might in fact not be well-performing at all, the average forecast is more likely to be taken into account when making an own forecast than the forecast of the best performer. Furthermore, the hypothesis we presented earlier that herding occurs more for predictions on the short-run is also confirmed by the results in Table 6, which can be seen by the frequency of herding.

**Table 6: Granger Probabilities**

| Horizon/Currency | 1M-EURUSD | 1M-GBPUSD | 1M-USD-JPY | 3M-EURUSD | 3M-GBPUSD | 3M-USD-JPY | 12M-EURUSD | 12M-GBPUSD | 12M-USD-JPY |
|---|---|---|---|---|---|---|---|---|---|
| Leader | Average | Average | Average | Average | Average | Average | Average | Average | Average |
| Forecast3 | 0.0122 | 0.1050 | 0.2789 | 0.0354 | 0.6355 | 0.3994 | 0.7918 | 0.8703 | 0.0790 |
| Forecast4 | 0.0011 | 0.0016 | 0.0021 | 0.8081 | 0.8664 | 0.7962 | 0.1050 | 0.0540 | 0.0063 |
| Forecast5 | 0.0422 | 0.0350 | 0.2402 | 0.9069 | 0.7520 | 0.6347 | 0.9196 | 0.5362 | 0.0019 |
| Forecast6 | 0.0002 | 0.0063 | 0.0107 | 0.0778 | 0.7316 | 0.0262 | 0.8753 | 0.5428 | 0.8580 |
| Forecast8 | 0.0007 | 0.0439 | 0.0226 | 0.1479 | 0.3471 | 0.1169 | 0.1936 | 0.5566 | 0.1510 |
| Forecast9 | 0.0000 | 0.0000 | 0.0010 | 0.8793 | 0.7775 | 0.7607 | 0.3277 | 0.1743 | 0.0070 |
| Forecast10 | 0.0000 | 0.0035 | 0.0621 | 0.5638 | 0.9575 | 0.3394 | 0.3489 | 0.8800 | 0.0030 |
| Forecast11 | 0.0029 | 0.0059 | 0.0285 | 0.0239 | 0.0441 | 0.6821 | 0.3583 | 0.8872 | 0.2137 |
| Forecast12 | 0.0427 | 0.0040 | 0.0946 | 0.1511 | 0.1150 | 0.3279 | 0.9967 | 0.8339 | 0.3208 |
| Forecast13 | 0.0000 | 0.0000 | 0.0202 | 0.1229 | 0.1575 | 0.2951 | 0.8399 | 0.9208 | 0.2436 |
| Forecast15 | 0.0024 | 0.0638 | 0.9260 | 0.1988 | 0.6238 | 0.8753 | 0.8054 | 0.1149 | 0.1870 |
| Forecast18 | 0.0902 | 0.2929 | 0.8379 | 0.8774 | 0.6917 | 0.2178 | 0.6521 | 0.2776 | 0.3376 |
| Forecast19 | 0.0007 | 0.0591 | 0.0260 | 0.1623 | 0.5059 | 0.3167 | 0.9008 | 0.8549 | 0.0134 |
| Forecast20 | 0.0000 | 0.0000 | 0.0002 | 0.4210 | 0.5802 | 0.1593 | 0.0724 | 0.8836 | 0.5624 |
| Forecast22 | 0.0004 | 0.0295 | 0.5735 | 0.1268 | 0.9619 | 0.9545 | 0.3359 | 0.0535 | 0.0876 |
| Forecast24 | 0.0078 | 0.0819 | 0.0711 | 0.1661 | 0.5829 | 0.8067 | 0.6582 | 0.8365 | 0.1564 |
| Forecast26 | 0.0010 | 0.0151 | 0.0258 | 0.2445 | 0.8780 | 0.6859 | 0.4221 | 0.0835 | 0.0625 |
| Forecast27 | 0.0000 | 0.0004 | 0.1281 | 0.0015 | 0.0531 | 0.0856 | 0.6180 | 0.2816 | 0.5035 |
| Forecast28 | 0.0000 | 0.0001 | 0.0000 | 0.0210 | 0.6064 | 0.2024 | 0.9969 | 0.8554 | 0.1711 |
| Forecast29 | 0.0138 | 0.2187 | 0.1096 | 0.1427 | 0.7878 | 0.3120 | 0.9503 | 0.4237 | 0.3040 |
| Forecast30 | 0.0000 | 0.0131 | 0.0006 | 0.0176 | 0.0461 | 0.3103 | 0.7112 | 0.8375 | 0.0061 |
| Forecast31 | 0.0454 | 0.3352 | 0.0585 | 0.2725 | 0.7730 | 0.7383 | 0.0930 | 0.2887 | 0.0562 |
| Forecast33 | 0.1256 | 0.3758 | 0.4195 | 0.0036 | 0.0277 | 0.6933 | 0.6646 | 0.9465 | 0.3030 |
| Forecast34 | 0.0007 | 0.1663 | 0.1134 | 0.0398 | 0.3403 | 0.4702 | 0.3493 | 0.5531 | 0.0116 |
| Forecast36 | 0.0014 | 0.0003 | 0.0001 | 0.0493 | 0.2732 | 0.1370 | 0.7007 | 0.3551 | 0.8431 |
| Forecast37 | 0.0526 | 0.1774 | 0.0168 | 0.1148 | 0.3059 | 0.1407 | 0.0074 | 0.0161 | 0.0170 |
| Forecast39 | 0.0000 | 0.0015 | 0.0003 | 0.0931 | 0.3518 | 0.1980 | 0.0724 | 0.0238 | 0.2484 |
| Forecast40 | 0.0000 | 0.0001 | 0.0015 | 0.0048 | 0.1568 | 0.0060 | 0.3241 | 0.0080 | 0.8359 |
| Forecast41 | 0.0000 | 0.0000 | 0.0011 | 0.0360 | 0.1166 | 0.0184 | 0.1553 | 0.4905 | 0.0787 |
| Forecast42 | 0.0011 | 0.0086 | 0.0444 | 0.1469 | 0.6073 | 0.1125 | 0.7785 | 0.2345 | 0.1874 |
| Forecast43 | 0.0590 | 0.1585 | 0.6891 | 0.0119 | 0.0017 | 0.1600 | 0.8106 | 0.8924 | 0.4939 |
| Forecast44 | 0.0019 | 0.0076 | 0.0101 | 0.0182 | 0.0506 | 0.3649 | 0.8874 | 0.6908 | 0.8482 |
| Forecast45 | 0.0002 | 0.0036 | 0.0001 | 0.0463 | 0.2293 | 0.2110 | 0.0829 | 0.9022 | 0.3999 |
| Forecast46 | 0.0000 | 0.0091 | 0.0931 | 0.0302 | 0.5324 | 0.1925 | 0.3962 | 0.4523 | 0.0132 |
| Forecast49 | 0.0003 | 0.0287 | 0.0284 | 0.0012 | 0.0248 | 0.2596 | 0.0368 | 0.2038 | 0.7918 |
| Forecast51 | 0.0062 | 0.0018 | 0.3154 | 0.0773 | 0.0974 | 0.4221 | 0.0420 | 0.0120 | 0.0483 |
| Frequency | 32 | 26 | 21 | 15 | 5 | 4 | 3 | 4 | 10 |
| Significant at 5% | Leader | | | | | | | | |

Similar to the robustness tests we conducted using the best performing bank as a leader, we also carried out this robustness check using the average forecast as the leader. The results of these tests are presented in Appendix V and are comparable to the results on robustness presented earlier. That is, the causality seems to run from average forecast to the forecasters, and for most of the occasions not the other way around.

## 5 Concluding remarks

This paper provides ample evidence for the existence of herd behavior in the foreign exchange market. It seems that the average forecast is more popular to be used by forecasters than the forecast of the best performing colleague. Furthermore, it appears that herd behavior occurs substantially more for predictions with a short time horizon than for predictions with a longer time horizon.

Another result worth mentioning is the low performance of the average forecast. Although the EMH hypothesizes that the average expectation in the market represents the correct value, our results do not confirm this hypothesis at all. In addition, we find the performance of the random walk to be relatively high compared to the survey participants, implying that we find relatively poor predictive power in the forecasts of the banks in our sample.

We conclude this paper by giving some recommendations for further research. In this study, we assumed the best performing bank to be leading the other banks. Although this is a sensible assumption, we found more evidence for herding using the average forecast as a leader, despite its relatively poor performance. This made clear that it is not necessarily the actual performance that leads to herd behavior, but the *belief* about performance. To be able to measure herd behavior based on such beliefs, we would have to know who the forecasters *believed* would perform well in the survey. Furthermore, it could be interesting to measure the forecasters' believe about their own performance. In order to attain this information, it might be possible to design a survey incorporating particular questions about such beliefs. We believe this information would open doors to new research possibilities in the field of behavioral finance, and particularly for research on herd behavior. As the measurement of the beliefs of forecasters potentially adds a valuable dimension to research on herd behavior, our recommendation to future research in this field is to consider the need for such information.

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## Appendices

### Appendix I – Bank names, number of observations, and removals from sample

| BANK CODE | BANK NAME | NUMBER OF OBSERVATIONS | |
|---|---|---|---|
| FORECAST1 | BTM | 7 | Removed |
| FORECAST2 | CAI | 47 | Removed |
| FORECAST3 | Citigroup | 103 | |
| FORECAST4 | Deutsche Bank | 141 | |
| FORECAST5 | HSBC | 216 | |
| FORECAST6 | JP Morgan | 180 | |
| FORECAST7 | Pronet Analytics | 88 | Removed |
| FORECAST8 | RBS | 211 | |
| FORECAST9 | Societe Generale | 174 | |
| FORECAST10 | UBS | 203 | |
| FORECAST11 | ABN Amro | 200 | |
| FORECAST12 | Bank of America | 181 | |
| FORECAST13 | Barclays Capital | 200 | |
| FORECAST14 | Bank One | 17 | Removed |
| FORECAST15 | HBOS Treasury Services | 159 | |
| FORECAST16 | Mellon Bank | 67 | Removed |
| FORECAST17 | Nordea | 15 | Removed |
| FORECAST18 | Standard Chartered | 160 | |
| FORECAST19 | Westpac | 165 | |
| FORECAST20 | 4Cast | 166 | |
| FORECAST21 | Bank of New York | 55 | Removed |
| FORECAST22 | Scotia Capital | 142 | |
| FORECAST23 | Brown Brothers Harriman | 41 | Removed |
| FORECAST24 | Commonwealth Bank of Australia | 148 | |
| FORECAST25 | Credit Agricole Indosuez | 11 | Removed |
| FORECAST26 | Dresdner Kleinwort | 159 | |
| FORECAST27 | Informa Global Markets | 169 | |
| FORECAST28 | Rabobank | 168 | |
| FORECAST29 | RBC | 147 | |
| FORECAST30 | SAXO Bank | 152 | |
| FORECAST31 | Merrill Lynch | 168 | |
| FORECAST32 | Treasury Management Services | 21 | Removed |
| FORECAST33 | ANZ | 133 | |
| FORECAST34 | Bank of China | 164 | |
| FORECAST35 | HVB | 96 | Removed |
| FORECAST36 | Danske Bank | 161 | |
| FORECAST37 | Lehman Brothers | 147 | |
| FORECAST38 | WestLB | 22 | Removed |
| FORECAST39 | Lloyds TSB Corporate Markets | 159 | |
| FORECAST40 | Gain Capital | 158 | |
| FORECAST41 | Calyon | 154 | |

| | | | |
|---|---|---|---|
| FORECAST42 | SEB Merchant Banking | 146 | |
| FORECAST43 | GFT | 149 | |
| FORECAST44 | FXCM | 145 | |
| FORECAST45 | TMS Brokers | 147 | |
| FORECAST46 | BNP Paribas | 133 | |
| FORECAST47 | MG Financial Group | 83 | Removed |
| FORECAST48 | IDEAglobal | 23 | Removed |
| FORECAST49 | Investors Bank & Trust | 102 | |
| FORECAST50 | TD Securities | 11 | Removed |
| FORECAST51 | Bank of Montreal | 110 | |
| FORECAST52 | Toronto Dominion Securities | 97 | Removed |
| FORECAST53 | Thomson | 89 | Removed |
| FORECAST54 | National Australia Bank | 67 | Removed |
| FORECAST55 | UniCredit MIB | 62 | Removed |
| FORECAST56 | CMC Markets | 58 | Removed |
| FORECAST57 | ING Wholesale Banking | 5 | Removed |
| FORECAST58 | CIBC World Markets | 24 | Removed |
| FORECAST59 | Bank of New Zealand | 7 | Removed |
| FORECAST60 | St. George Bank | 7 | Removed |
| FORECAST61 | Forex Capital Markets | 2 | Removed |

## Appendix II

Performance in $R^2$

| Forecast | Bank | 1M EURUSD | 1M GBPUSD | 1M USDJPY | 3M EURUSD | 3M GBPUSD | 3M USDJPY | 12M EURUSD | 12M GBPUSD | 12M USDJPY |
|---|---|---|---|---|---|---|---|---|---|---|
| Forecast3 | Citigroup | 0.044 | -0.007 | 0.007 | 0.069 | 0.164 | -0.008 | 0.039 | 0.078 | 0.541 |
| Forecast4 | Deutsche Bank | -0.001 | 0.011 | -0.003 | 0.013 | 0.008 | -0.004 | 0.055 | 0.003 | 0.046 |
| Forecast5 | HSBC | -0.002 | 0.005 | 0.028 | 0.011 | 0.000 | -0.001 | 0.166 | 0.598 | 0.049 |
| Forecast6 | JP Morgan | -0.002 | -0.003 | 0.037 | 0.004 | 0.001 | 0.002 | -0.004 | 0.031 | -0.005 |
| Forecast8 | RBS | -0.005 | -0.004 | 0.002 | -0.004 | 0.018 | 0.005 | 0.017 | 0.282 | 0.094 |
| Forecast9 | Societe Generale | 0.003 | -0.005 | 0.005 | 0.084 | -0.005 | 0.034 | -0.004 | 0.253 | 0.147 |
| Forecast10 | UBS | 0.017 | -0.005 | 0.002 | 0.057 | 0.025 | -0.005 | 0.059 | 0.278 | -0.002 |
| Forecast11 | ABN Amro | -0.002 | 0.005 | -0.001 | 0.090 | 0.004 | 0.022 | 0.027 | 0.017 | 0.290 |
| Forecast12 | Bank of America | -0.002 | -0.002 | 0.067 | 0.012 | -0.005 | -0.004 | 0.052 | 0.212 | -0.003 |
| Forecast13 | Barclays Capital | 0.028 | -0.004 | 0.076 | 0.031 | 0.004 | 0.028 | 0.130 | 0.198 | 0.215 |
| Forecast15 | HBOS Treasury Services | 0.012 | 0.003 | 0.006 | 0.006 | 0.023 | 0.014 | -0.003 | 0.036 | 0.236 |
| Forecast18 | Standard Chartered | -0.006 | 0.000 | 0.019 | 0.044 | 0.026 | -0.001 | 0.059 | 0.045 | 0.014 |
| Forecast19 | Westpac | -0.005 | 0.044 | 0.014 | 0.058 | -0.001 | 0.013 | 0.087 | 0.008 | -0.002 |
| Forecast20 | 4Cast | -0.005 | -0.006 | -0.006 | 0.020 | 0.007 | 0.048 | 0.010 | 0.331 | 0.432 |
| Forecast22 | Scotia Capital | -0.006 | -0.001 | 0.028 | -0.007 | 0.000 | -0.006 | 0.000 | 0.027 | 0.076 |
| Forecast24 | Commonw. Bank of Aus. | 0.030 | -0.003 | -0.004 | 0.021 | -0.007 | 0.056 | 0.241 | 0.233 | 0.171 |
| Forecast26 | Dresdner Kleinwort | 0.030 | 0.050 | 0.011 | 0.047 | 0.105 | 0.002 | 0.329 | 0.562 | 0.020 |
| Forecast27 | Informa Global Markets | 0.004 | 0.023 | 0.037 | 0.016 | 0.007 | 0.099 | 0.021 | 0.023 | -0.004 |
| Forecast28 | Rabobank | 0.010 | 0.009 | 0.014 | -0.002 | -0.002 | 0.011 | 0.000 | 0.245 | -0.001 |
| Forecast29 | RBC | 0.004 | -0.002 | 0.003 | -0.004 | 0.057 | 0.091 | 0.207 | 0.336 | 0.414 |
| Forecast30 | SAXO Bank | 0.010 | 0.014 | -0.006 | 0.056 | 0.113 | 0.024 | 0.060 | 0.518 | 0.278 |
| Forecast31 | Merrill Lynch | 0.009 | 0.127 | -0.005 | 0.004 | 0.122 | 0.052 | -0.006 | 0.038 | 0.049 |
| Forecast33 | ANZ | -0.008 | 0.019 | -0.008 | -0.004 | 0.011 | 0.000 | -0.007 | -0.006 | 0.018 |
| Forecast34 | Bank of China | -0.003 | -0.006 | -0.002 | -0.005 | -0.006 | 0.090 | 0.056 | -0.006 | 0.451 |
| Forecast36 | Danske Bank | -0.006 | -0.006 | 0.008 | 0.005 | -0.006 | -0.005 | 0.085 | -0.001 | 0.247 |
| Forecast37 | Lehman Brothers | -0.007 | 0.040 | 0.013 | 0.076 | 0.005 | -0.005 | -0.005 | 0.070 | -0.006 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Forecast39 | Lloyds TSB CM | 0.008 | 0.009 | -0.006 | 0.134 | 0.006 | 0.033 | 0.075 | 0.584 | -0.003 |
| Forecast40 | Gain Capital | 0.002 | 0.030 | 0.028 | -0.001 | 0.141 | -0.006 | 0.157 | 0.594 | 0.294 |
| Forecast41 | Calyon | 0.009 | 0.026 | -0.007 | -0.006 | 0.251 | -0.006 | 0.103 | 0.320 | 0.011 |
| Forecast42 | SEB Merchant Banking | -0.005 | 0.015 | 0.013 | 0.198 | 0.099 | 0.025 | 0.088 | -0.006 | 0.255 |
| Forecast43 | GFT | -0.007 | 0.037 | 0.053 | -0.007 | 0.113 | 0.034 | 0.183 | 0.141 | 0.112 |
| Forecast44 | FXCM | -0.001 | -0.002 | 0.047 | -0.006 | -0.006 | -0.006 | 0.011 | 0.004 | 0.027 |
| Forecast45 | TMS Brokers | 0.000 | 0.013 | -0.006 | 0.103 | 0.012 | 0.057 | 0.012 | 0.270 | 0.024 |
| Forecast46 | BNP Paribas | -0.007 | 0.028 | -0.006 | 0.000 | 0.046 | 0.036 | 0.078 | 0.510 | 0.010 |
| Forecast49 | Investors Bank & Trust | 0.024 | 0.065 | 0.092 | -0.009 | 0.085 | 0.101 | -0.010 | 0.324 | 0.188 |
| Forecast51 | Bank of Montreal | -0.009 | 0.046 | -0.009 | -0.006 | 0.081 | -0.007 | 0.089 | 0.229 | 0.165 |
| | | | | | | | | | | |
| Average Forecast | | 0.000 | 0.000 | 0.012 | 0.014 | 0.028 | 0.001 | 0.031 | 0.474 | 0.201 |
| Average Performance Performance Random Walk | | 0.004 | 0.016 | 0.015 | 0.031 | 0.042 | 0.023 | 0.068 | 0.205 | 0.135 |

## Appendix III – Relative performance of the random walk forecast

| 1M EURUSD | BANK | ERROR | 1M GPBUSD | BANK | ERROR | 1M USDJPY | BANK | ERROR |
|---|---|---|---|---|---|---|---|---|
| Forecast49 | Investors Bank & Trust | 0.00096 | Forecast40 | Gain Capital | 0.00215 | Forecast49 | Investors Bank & Trust | 8.117 |
| Forecast3 | Citigroup | 0.00154 | Forecast51 | Bank of Montreal | 0.00220 | **Randomwalk** | | 9.372 |
| Forecast4 | Deutsche Bank | 0.00176 | **Randomwalk** | | 0.0022 | Forecast13 | Barclays Capital | 10.359 |
| Forecast40 | Gain Capital | 0.00118 | Forecast41 | Calyon | 0.00222 | Forecast44 | FXCM | 10.727 |
| Forecast41 | Calyon | 0.00123 | Forecast43 | GFT | 0.00239 | Forecast12 | Bank of America | 11.200 |
| Forecast26 | Dresdner Kleinwort | 0.00123 | Forecast45 | TMS Brokers | 0.00245 | Forecast40 | Gain Capital | 11.411 |
| Forecast45 | TMS Brokers | 0.00124 | Forecast26 | Dresdner Kleinwort | 0.00250 | Forecast36 | Danske Bank | 11.991 |
| **Randomwalk** | | 0.00125 | Forecast39 | Lloyds TSB CM | 0.00256 | Forecast28 | Rabobank | 12.051 |
| Forecast27 | Informa Global Markets | 0.00130 | Forecast49 | Investors Bank & Trust | 0.00256 | Forecast27 | Informa Global Markets | 12.279 |
| Forecast29 | RBC | 0.00138 | Forecast31 | Merrill Lynch | 0.00261 | Forecast41 | Calyon | 12.476 |
| Forecast51 | Bank of Montreal | 0.00138 | Forecast27 | Informa Global Markets | 0.00263 | Forecast45 | TMS Brokers | 12.601 |
| Forecast44 | FXCM | 0.00139 | Forecast42 | SEB Merchant Banking | 0.00273 | Forecast43 | GFT | 12.704 |
| Forecast20 | 4Cast | 0.00141 | Forecast28 | Rabobank | 0.00273 | Forecast20 | 4Cast | 13.391 |
| Forecast19 | Westpac | 0.00145 | Forecast19 | Westpac | 0.00279 | Forecast42 | SEB Merchant Banking | 13.402 |
| Forecast28 | Rabobank | 0.00147 | Forecast44 | FXCM | 0.00290 | Forecast4 | Deutsche Bank | 13.481 |
| Forecast36 | Danske Bank | 0.00155 | Forecast20 | 4Cast | 0.00291 | Forecast39 | Lloyds TSB CM | 14.116 |
| Forecast42 | SEB Merchant Banking | 0.00159 | Forecast18 | Standard Chartered | 0.00294 | Forecast19 | Westpac | 14.194 |
| Forecast46 | BNP Paribas | 0.00163 | Forecast46 | BNP Paribas | 0.00298 | Forecast8 | RBS | 14.418 |
| Forecast39 | Lloyds TSB CM | 0.00163 | Forecast11 | ABN Amro | 0.00299 | Forecast11 | ABN Amro | 14.728 |
| Forecast18 | Standard Chartered | 0.00165 | Forecast30 | SAXO Bank | 0.00302 | Forecast10 | UBS | 14.895 |
| Forecast43 | GFT | 0.00173 | Forecast36 | Danske Bank | 0.00304 | Forecast22 | Scotia Capital | 15.044 |
| Forecast11 | ABN Amro | 0.00177 | Forecast4 | Deutsche Bank | 0.00317 | Forecast29 | RBC | 15.212 |
| Forecast34 | Bank of China | 0.00181 | Forecast33 | ANZ | 0.00318 | Forecast51 | Bank of Montreal | 15.384 |
| Forecast22 | Scotia Capital | 0.00181 | Forecast37 | Lehman Brothers | 0.00321 | Forecast9 | Societe Generale | 15.455 |
| Forecast37 | Lehman Brothers | 0.00182 | Forecast29 | RBC | 0.00323 | Forecast15 | HBOS Treasury Services | 15.714 |
| Forecast9 | Societe Generale | 0.00187 | Forecast13 | Barclays Capital | 0.00332 | Forecast3 | Citigroup | 16.299 |
| Forecast33 | ANZ | 0.00188 | Forecast9 | Societe Generale | 0.00334 | Forecast18 | Standard Chartered | 16.488 |
| Forecast30 | SAXO Bank | 0.00202 | Forecast22 | Scotia Capital | 0.00336 | Forecast5 | HSBC | 16.608 |
| Forecast31 | Merrill Lynch | 0.00210 | Forecast3 | Citigroup | 0.00353 | Forecast26 | Dresdner Kleinwort | 16.734 |
| Forecast5 | HSBC | 0.00216 | Forecast5 | HSBC | 0.00354 | Forecast37 | Lehman Brothers | 17.264 |
| Forecast13 | Barclays Capital | 0.00216 | Forecast10 | UBS | 0.00366 | Forecast6 | JP Morgan | 18.146 |
| Forecast12 | Bank of America | 0.00224 | Forecast8 | RBS | 0.00377 | Forecast24 | Commonw.Bank of Austr. | 18.439 |
| Forecast8 | RBS | 0.00226 | Forecast15 | HBOS Treasury Services | 0.00386 | Forecast46 | BNP Paribas | 18.533 |
| Forecast10 | UBS | 0.00227 | Forecast24 | Commonw.Bank of Austr. | 0.00409 | Forecast33 | ANZ | 19.120 |
| Forecast15 | HBOS Treasury Services | 0.00227 | Forecast12 | Bank of America | 0.00412 | Forecast30 | SAXO Bank | 19.404 |
| Forecast24 | Commonw.Bank of Austr. | 0.00234 | Forecast6 | JP Morgan | 0.00441 | Forecast34 | Bank of China | 22.504 |
| Forecast6 | JP Morgan | 0.00256 | Forecast34 | Bank of China | 0.00616 | Forecast31 | Merrill Lynch | 33.237 |

*Error represents the performance measure 'average squared forecasting error'*

| **3M EURUSD** | **BANK** | **ERROR** | **3M GPBUSD** | **BANK** | **ERROR** | **3M USDJPY** | **BANK** | **ERROR** |
|---|---|---|---|---|---|---|---|---|
| Forecast49 | Investors Bank & Trust | 0.00242 | Forecast3 | Citigroup | 0.00257 | Forecast49 | Investors Bank & Trust | 18.709 |
| Forecast40 | Gain Capital | 0.00266 | Forecast41 | Calyon | 0.00326 | **Randomwalk** | | 21.756 |
| Forecast51 | Bank of Montreal | 0.00271 | Forecast43 | GFT | 0.00326 | Forecast27 | Informa Global Markets | 22.254 |
| Forecast3 | Citigroup | 0.00272 | Forecast40 | Gain Capital | 0.00331 | Forecast43 | GFT | 25.389 |
| Forecast26 | Dresdner Kleinwort | 0.00274 | Forecast51 | Bank of Montreal | 0.00342 | Forecast42 | SEB Merchant Banking | 25.410 |
| Forecast20 | 4Cast | 0.00307 | Forecast30 | SAXO Bank | 0.00443 | Forecast44 | FXCM | 27.307 |
| Forecast44 | FXCM | 0.00316 | Forecast44 | FXCM | 0.00453 | Forecast13 | Barclays Capital | 28.680 |
| **Randomwalk** | | 0.00320 | Forecast26 | Dresdner Kleinwort | 0.00461 | Forecast41 | Calyon | 29.046 |
| Forecast27 | Informa Global Markets | 0.00323 | Forecast29 | RBC | 0.00478 | Forecast51 | Bank of Montreal | 30.931 |
| Forecast43 | GFT | 0.00330 | Forecast31 | Merrill Lynch | 0.00478 | Forecast15 | HBOS Treasury Services | 30.951 |
| Forecast33 | ANZ | 0.00332 | **Randomwalk** | | 0.00483 | Forecast12 | Bank of America | 31.118 |
| Forecast29 | RBC | 0.00339 | Forecast46 | BNP Paribas | 0.00492 | Forecast40 | Gain Capital | 31.619 |
| Forecast42 | SEB Merchant Banking | 0.00347 | Forecast20 | 4Cast | 0.00522 | Forecast36 | Danske Bank | 32.386 |
| Forecast19 | Westpac | 0.00349 | Forecast49 | Investors Bank & Trust | 0.00529 | Forecast46 | BNP Paribas | 34.367 |
| Forecast41 | Calyon | 0.00357 | Forecast27 | Informa Global Markets | 0.00534 | Forecast33 | ANZ | 34.741 |
| Forecast4 | Deutsche Bank | 0.00381 | Forecast19 | Westpac | 0.00547 | Forecast39 | Lloyds TSB CM | 37.805 |
| Forecast22 | Scotia Capital | 0.00391 | Forecast45 | TMS Brokers | 0.00579 | Forecast22 | Scotia Capital | 37.886 |
| Forecast46 | BNP Paribas | 0.00441 | Forecast33 | ANZ | 0.00588 | Forecast10 | UBS | 37.981 |
| Forecast31 | Merrill Lynch | 0.00444 | Forecast18 | Standard Chartered | 0.00589 | Forecast28 | Rabobank | 38.058 |
| Forecast36 | Danske Bank | 0.00469 | Forecast42 | SEB Merchant Banking | 0.00613 | Forecast20 | 4Cast | 39.495 |
| Forecast5 | HSBC | 0.00489 | Forecast28 | Rabobank | 0.00618 | Forecast8 | RBS | 40.082 |
| Forecast45 | TMS Brokers | 0.00492 | Forecast39 | Lloyds TSB CM | 0.00631 | Forecast3 | Citigroup | 40.298 |
| Forecast28 | Rabobank | 0.00493 | Forecast37 | Lehman Brothers | 0.00646 | Forecast11 | ABN Amro | 40.755 |
| Forecast12 | Bank of America | 0.00503 | Forecast22 | Scotia Capital | 0.00647 | Forecast37 | Lehman Brothers | 41.385 |
| Forecast37 | Lehman Brothers | 0.00503 | Forecast36 | Danske Bank | 0.00675 | Forecast19 | Westpac | 42.780 |
| Forecast8 | RBS | 0.00510 | Forecast11 | ABN Amro | 0.00681 | Forecast45 | TMS Brokers | 43.411 |
| Forecast18 | Standard Chartered | 0.00527 | Forecast10 | UBS | 0.00718 | Forecast5 | HSBC | 46.069 |
| Forecast34 | Bank of China | 0.00529 | Forecast13 | Barclays Capital | 0.00724 | Forecast9 | Societe Generale | 46.942 |
| Forecast6 | JP Morgan | 0.00543 | Forecast4 | Deutsche Bank | 0.00725 | Forecast6 | JP Morgan | 49.517 |
| Forecast9 | Societe Generale | 0.00545 | Forecast8 | RBS | 0.00726 | Forecast30 | SAXO Bank | 51.442 |
| Forecast13 | Barclays Capital | 0.00548 | Forecast5 | HSBC | 0.00729 | Forecast4 | Deutsche Bank | 53.878 |
| Forecast30 | SAXO Bank | 0.00573 | Forecast24 | Commonw.Bank of Austr. | 0.00834 | Forecast26 | Dresdner Kleinwort | 54.004 |
| Forecast10 | UBS | 0.00599 | Forecast15 | HBOS Treasury Services | 0.00849 | Forecast18 | Standard Chartered | 58.040 |
| Forecast24 | Commonw.Bank of Austr. | 0.00604 | Forecast9 | Societe Generale | 0.00865 | Forecast24 | Commonw.Bank of Austr. | 62.653 |
| Forecast39 | Lloyds TSB CM | 0.00607 | Forecast6 | JP Morgan | 0.00871 | Forecast29 | RBC | 67.197 |
| Forecast11 | ABN Amro | 0.00615 | Forecast12 | Bank of America | 0.00961 | Forecast34 | Bank of China | 67.758 |
| Forecast15 | HBOS Treasury Services | 0.00640 | Forecast34 | Bank of China | 0.01579 | Forecast31 | Merrill Lynch | 104.228 |

*Error represents the performance measure 'average squared forecasting error'*

| 12 EURUSD | BANK | ERROR | 12 GPBUSD | BANK | ERROR | 12 USDJPY | BANK | ERROR |
|---|---|---|---|---|---|---|---|---|
| Forecast4 | Deutsche Bank | 0.0111 | Forecast9 | Societe Generale | 0.0176 | Forecast49 | Investors Bank & Trust | 74.732 |
| Forecast5 | HSBC | 0.0117 | Forecast39 | Lloyds TSB CM | 0.0204 | Forecast15 | HBOS Treasury Services | 75.948 |
| Forecast26 | Dresdner Kleinwort | 0.0121 | Forecast5 | HSBC | 0.0229 | **Randomwalk** | | 96.375 |
| Forecast40 | Gain Capital | 0.0124 | Forecast4 | Deutsche Bank | 0.0235 | Forecast43 | GFT | 98.189 |
| Forecast6 | JP Morgan | 0.0131 | Forecast30 | SAXO Bank | 0.0275 | Forecast6 | JP Morgan | 113.666 |
| Forecast43 | GFT | 0.0132 | Forecast46 | BNP Paribas | 0.0284 | Forecast41 | Calyon | 116.127 |
| Forecast9 | Societe Generale | 0.0134 | Forecast10 | UBS | 0.0285 | Forecast28 | Rabobank | 125.851 |
| Forecast51 | Bank of Montreal | 0.0137 | Forecast41 | Calyon | 0.0287 | Forecast44 | FXCM | 128.160 |
| Forecast8 | RBS | 0.0138 | Forecast26 | Dresdner Kleinwort | 0.0301 | Forecast33 | ANZ | 132.750 |
| Forecast13 | Barclays Capital | 0.0143 | Forecast20 | 4Cast | 0.0306 | Forecast27 | Informa Global Markets | 133.646 |
| Forecast10 | UBS | 0.0146 | Forecast8 | RBS | 0.0306 | Forecast12 | Bank of America | 144.480 |
| Forecast29 | RBC | 0.0149 | Forecast45 | TMS Brokers | 0.0310 | Forecast10 | UBS | 149.307 |
| Forecast30 | SAXO Bank | 0.0151 | Forecast29 | RBC | 0.0310 | Forecast19 | Westpac | 157.573 |
| **Randomwalk** | | 0.0152 | Forecast6 | JP Morgan | 0.0315 | Forecast8 | RBS | 168.534 |
| Forecast42 | SEB Merchant Banking | 0.0153 | Forecast28 | Rabobank | 0.0325 | Forecast39 | Lloyds TSB CM | 172.976 |
| Forecast20 | 4Cast | 0.0160 | Forecast40 | Gain Capital | 0.0327 | Forecast51 | Bank of Montreal | 174.003 |
| Forecast46 | BNP Paribas | 0.0166 | Forecast24 | Commonw.Bank of Austr. | 0.0336 | Forecast13 | Barclays Capital | 175.510 |
| Forecast39 | Lloyds TSB CM | 0.0170 | Forecast49 | Investors Bank & Trust | 0.0342 | Forecast5 | HSBC | 178.932 |
| Forecast44 | FXCM | 0.0176 | Forecast13 | Barclays Capital | 0.0343 | Forecast18 | Standard Chartered | 182.858 |
| Forecast41 | Calyon | 0.0181 | Forecast51 | Bank of Montreal | 0.0357 | Forecast45 | TMS Brokers | 189.056 |
| Forecast18 | Standard Chartered | 0.0181 | Forecast18 | Standard Chartered | 0.0362 | Forecast40 | Gain Capital | 193.214 |
| Forecast19 | Westpac | 0.0183 | Forecast27 | Informa Global Markets | 0.0381 | Forecast37 | Lehman Brothers | 194.252 |
| Forecast31 | Merrill Lynch | 0.0196 | **Randomwalk** | | 0.0384 | Forecast42 | SEB Merchant Banking | 203.587 |
| Forecast24 | Commonw.Bank of Austr. | 0.0200 | Forecast19 | Westpac | 0.0385 | Forecast20 | 4Cast | 205.947 |
| Forecast22 | Scotia Capital | 0.0205 | Forecast31 | Merrill Lynch | 0.0394 | Forecast11 | ABN Amro | 207.317 |
| Forecast11 | ABN Amro | 0.0210 | Forecast43 | GFT | 0.0400 | Forecast36 | Danske Bank | 208.788 |
| Forecast37 | Lehman Brothers | 0.0210 | Forecast37 | Lehman Brothers | 0.0418 | Forecast30 | SAXO Bank | 213.835 |
| Forecast12 | Bank of America | 0.0218 | Forecast12 | Bank of America | 0.0445 | Forecast22 | Scotia Capital | 228.425 |
| Forecast28 | Rabobank | 0.0218 | Forecast42 | SEB Merchant Banking | 0.0457 | Forecast4 | Deutsche Bank | 237.630 |
| Forecast27 | Informa Global Markets | 0.0219 | Forecast44 | FXCM | 0.0457 | Forecast9 | Societe Generale | 248.591 |
| Forecast45 | TMS Brokers | 0.0236 | Forecast36 | Danske Bank | 0.0496 | Forecast46 | BNP Paribas | 257.592 |
| Forecast33 | ANZ | 0.0237 | Forecast33 | ANZ | 0.0497 | Forecast29 | RBC | 262.796 |
| Forecast49 | Investors Bank & Trust | 0.0251 | Forecast3 | Citigroup | 0.0519 | Forecast26 | Dresdner Kleinwort | 271.759 |
| Forecast36 | Danske Bank | 0.0283 | Forecast11 | ABN Amro | 0.0519 | Forecast24 | Commonw.Bank of Austr. | 287.978 |
| Forecast34 | Bank of China | 0.0292 | Forecast22 | Scotia Capital | 0.0526 | Forecast3 | Citigroup | 295.176 |
| Forecast3 | Citigroup | 0.0304 | Forecast15 | HBOS Treasury Services | 0.0563 | Forecast34 | Bank of China | 296.132 |
| Forecast15 | HBOS Treasury Services | 0.0330 | Forecast34 | Bank of China | 0.0601 | Forecast31 | Merrill Lynch | 329.619 |

*Error represents the performance measure 'average squared forecasting error'*

## Appendix IV - Results Granger Causality Tests Best Performers

| **1 Month Horizon** | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Exchange rate** | | **EURUSD** | | **GBPUSD** | | **USDJPY** | |
| **Leader** | | **Forecast3** | | **Forecast31** | | **Forecast49 Investors Bank & Tr.** | |
| **Name Bank** | | **Citigroup** | | **Merrill Lynch** | | | |
| **Granger prob.** | | Causality from Leader to forecaster | Forecaster to leader | Causality from Leader to forecaster | Forecaster to leader | Causality from Leader to forecaster | Forecaster to leader |
| Forecast3 | Citigroup | 0.000 | 0.044 | 0.033 | 0.922 | 0.050 | 0.259 |
| Forecast4 | Deutsche Bank | 0.509 | 0.067 | 0.142 | 0.262 | 0.103 | 0.197 |
| Forecast5 | HSBC | 0.764 | 0.017 | 0.048 | 0.578 | 0.300 | 0.412 |
| Forecast6 | JP Morgan | 0.295 | 0.109 | 0.213 | 0.057 | 0.626 | 0.564 |
| Forecast8 | RBS | 0.512 | 0.029 | 0.068 | 0.180 | 0.885 | 0.287 |
| Forecast9 | Societe Generale | 0.099 | 0.204 | 0.003 | 0.458 | 0.137 | 0.633 |
| Forecast10 | UBS | 0.400 | 0.090 | 0.034 | 0.286 | 0.076 | 0.164 |
| Forecast11 | ABN Amro | 0.987 | 0.244 | 0.020 | 0.545 | 0.664 | 0.520 |
| Forecast12 | Bank of America | 0.913 | 0.292 | 0.091 | 0.162 | 0.384 | 0.667 |
| Forecast13 | Barclays Capital | 0.219 | 0.345 | 0.007 | 0.359 | 0.114 | 0.370 |
| Forecast15 | HBOS Treasury Services | 0.425 | 0.245 | 0.013 | 0.338 | 0.400 | 0.500 |
| Forecast18 | Standard Chartered | 0.551 | 0.375 | 0.029 | 0.828 | 0.943 | 0.257 |
| Forecast19 | Westpac | 0.022 | 0.957 | 0.007 | 0.537 | 0.326 | 0.174 |
| Forecast20 | 4Cast | 0.008 | 0.559 | 0.001 | 0.283 | 0.043 | 0.235 |
| Forecast22 | Scotia Capital | 0.504 | 0.219 | 0.004 | 0.249 | 0.368 | 0.752 |
| Forecast24 | Commonw. Bank of Aus. | 0.027 | 0.223 | 0.031 | 0.376 | 0.163 | 0.474 |
| Forecast26 | Dresdner Kleinwort | 0.216 | 0.397 | 0.006 | 0.952 | 0.015 | 0.192 |
| Forecast27 | Informa Global Markets | 0.305 | 0.240 | 0.000 | 0.553 | 0.392 | 0.414 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Forecast28 | Rabobank | 0.069 | 0.303 | 0.000 | 0.389 | 0.008 | 0.178 |
| Forecast29 | RBC | 0.844 | 0.608 | 0.062 | 0.423 | 0.821 | 0.288 |
| Forecast30 | SAXO Bank | 0.011 | 0.636 | 0.051 | 0.215 | 0.001 | 0.032 |
| Forecast31 | Merrill Lynch | 0.366 | 0.158 | 0.000 | 0.967 | 0.359 | 0.119 |
| Forecast33 | ANZ | 0.823 | 0.896 | 0.239 | 0.523 | 0.531 | 0.932 |
| Forecast34 | Bank of China | 0.061 | 0.222 | 0.130 | 0.642 | 0.542 | 0.357 |
| Forecast36 | Danske Bank | 0.350 | 0.186 | 0.008 | 0.579 | 0.007 | 0.212 |
| Forecast37 | Lehman Brothers | 0.977 | 0.151 | 0.062 | 0.419 | 0.358 | 0.202 |
| Forecast39 | Lloyds TSB CM | 0.094 | 0.372 | 0.010 | 0.295 | 0.020 | 0.114 |
| Forecast40 | Gain Capital | 0.004 | 0.348 | 0.001 | 0.401 | 0.116 | 0.137 |
| Forecast41 | Calyon | 0.017 | 0.351 | 0.005 | 0.342 | 0.026 | 0.306 |
| Forecast42 | SEB Merchant Banking | 0.070 | 0.563 | 0.015 | 0.182 | 0.032 | 0.215 |
| Forecast43 | GFT | 0.559 | 0.287 | 0.008 | 0.464 | 0.328 | 0.919 |
| Forecast44 | FXCM | 0.633 | 0.979 | 0.014 | 0.104 | 0.043 | 0.138 |
| Forecast45 | TMS Brokers | 0.091 | 0.295 | 0.015 | 0.277 | 0.018 | 0.068 |
| Forecast46 | BNP Paribas | 0.150 | 0.298 | 0.115 | 0.285 | 0.101 | 0.161 |
| Forecast49 | Investors Bank & Trust | 0.010 | 0.300 | 0.042 | 0.446 | 0.000 | 0.296 |
| Forecast51 | Bank of Montreal | 0.206 | 0.378 | 0.023 | 0.204 | 0.254 | 0.709 |

Follower at 5% level

Causality unclear

| **3 Month Horizon** | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Exchange rate** | | **EURUSD** | | **GBPUSD** | | **USDJPY** | |
| **Leader** | | **Forecast42** | | **Forecast41** | | **Forecast49** | |
| **Name Bank** | | **SEB Merchant Banking** | | **Calyon** | | **Investors Bank & Trust** | |
| **Granger prob.** | | Causality from Leader to forecaster | Forecaster to leader | Causality from Leader to forecaster | Forecaster to leader | Causality from Leader to forecaster | Forecaster to leader |
| Forecast3 | Citigroup | 0.316 | 0.191 | 0.330 | 0.859 | 0.603 | 0.044 |
| Forecast4 | Deutsche Bank | 0.927 | 0.602 | 0.389 | 0.169 | 0.073 | 0.082 |
| Forecast5 | HSBC | 0.220 | 0.417 | 0.381 | 0.487 | 0.046 | 0.259 |
| Forecast6 | JP Morgan | 0.162 | 0.253 | 0.384 | 0.333 | 0.862 | 0.010 |
| Forecast8 | RBS | 0.924 | 0.308 | 0.902 | 0.378 | 0.525 | 0.357 |
| Forecast9 | Societe Generale | 0.139 | 0.020 | 0.927 | 0.527 | 0.560 | 0.102 |
| Forecast10 | UBS | 0.925 | 0.430 | 0.248 | 0.835 | 0.630 | 0.301 |
| Forecast11 | ABN Amro | 0.002 | 0.267 | 0.224 | 0.532 | 0.421 | 0.020 |
| Forecast12 | Bank of America | 0.984 | 0.788 | 0.845 | 0.376 | 0.448 | 0.187 |
| Forecast13 | Barclays Capital | 0.297 | 0.661 | 0.381 | 0.604 | 0.490 | 0.162 |
| Forecast15 | HBOS Treasury Services | 0.863 | 0.337 | 0.805 | 0.041 | 0.171 | 0.095 |
| Forecast18 | Standard Chartered | 0.786 | 0.582 | 0.459 | 0.460 | 0.939 | 0.232 |
| Forecast19 | Westpac | 0.618 | 0.831 | 0.771 | 0.323 | 0.162 | 0.111 |
| Forecast20 | 4Cast | 0.595 | 0.402 | 0.561 | 0.513 | 0.971 | 0.106 |
| Forecast22 | Scotia Capital | 0.334 | 0.670 | 0.742 | 0.425 | 0.221 | 0.160 |
| Forecast24 | Commonw. Bank of Aus. | 0.737 | 0.257 | 0.773 | 0.197 | 0.529 | 0.368 |
| Forecast26 | Dresdner Kleinwort | 0.495 | 0.543 | 0.516 | 0.592 | 0.578 | 0.001 |
| Forecast27 | Informa Global Markets | 0.034 | 0.410 | 0.106 | 0.167 | 0.780 | 0.599 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Forecast28 | Rabobank | 0.111 | 0.190 | 0.424 | 0.222 | 0.325 | 0.125 |
| Forecast29 | RBC | 0.205 | 0.435 | 0.941 | 0.242 | 0.817 | 0.251 |
| Forecast30 | SAXO Bank | 0.104 | 0.310 | 0.048 | 0.277 | 0.978 | 0.119 |
| Forecast31 | Merrill Lynch | 0.352 | 0.756 | 0.708 | 0.928 | 0.130 | 0.305 |
| Forecast33 | ANZ | 0.201 | 0.842 | 0.211 | 0.279 | 0.245 | 0.058 |
| Forecast34 | Bank of China | 0.852 | 0.582 | 0.723 | 0.289 | 0.775 | 0.274 |
| Forecast36 | Danske Bank | 0.185 | 0.105 | 0.522 | 0.453 | 0.908 | 0.066 |
| Forecast37 | Lehman Brothers | 0.246 | 0.323 | 0.583 | 0.460 | 0.329 | 0.247 |
| Forecast39 | Lloyds TSB CM | 0.379 | 0.401 | 0.865 | 0.041 | 0.956 | 0.190 |
| Forecast40 | Gain Capital | 0.016 | 0.371 | 0.252 | 0.521 | 0.555 | 0.048 |
| Forecast41 | Calyon | 0.179 | 0.511 | 0.013 | 0.927 | 0.500 | 0.099 |
| Forecast42 | SEB Merchant Banking | 0.010 | 0.691 | 0.946 | 0.640 | 0.881 | 0.303 |
| Forecast43 | GFT | 0.092 | 0.429 | 0.017 | 0.204 | 0.500 | 0.394 |
| Forecast44 | FXCM | 0.082 | 0.850 | 0.401 | 0.347 | 0.482 | 0.041 |
| Forecast45 | TMS Brokers | 0.053 | 0.203 | 0.296 | 0.124 | 0.229 | 0.095 |
| Forecast46 | BNP Paribas | 0.161 | 0.905 | 0.886 | 0.687 | 0.179 | 0.849 |
| Forecast49 | Investors Bank & Trust | 0.003 | 0.144 | 0.126 | 0.443 | 0.951 | 0.242 |
| Forecast51 | Bank of Montreal | 0.186 | 0.854 | 0.402 | 0.573 | 0.659 | 0.250 |

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|---|
| Follower at 5% level |
| Causality unclear |

| **12 Month Horizon** | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Exchange rate** | | **EURUSD** | | **GBPUSD** | | **USDJPY** | |
| **Leader** | | **Forecast 26** | | **Forecast5** | | **Forecast3** | |
| **Name Bank** | | **Dresdner Kleinwort** | | **HSBC** | | **Citigroup** | |
| **Granger prob.** | | Causality from Leader to forecaster | Forecaster to leader | Causality from Leader to forecaster | Forecaster to leader | Causality from Leader to forecaster | Forecaster to leader |
| Forecast3 | Citigroup | 0.138 | 0.030 | 0.921 | 0.687 | 0.337 | 0.748 |
| Forecast4 | Deutsche Bank | 0.051 | 0.288 | 0.397 | 0.067 | 0.005 | 0.975 |
| Forecast5 | HSBC | 0.697 | 0.224 | 0.068 | 0.953 | 0.003 | 0.812 |
| Forecast6 | JP Morgan | 0.603 | 0.300 | 0.317 | 0.226 | 0.545 | 0.500 |
| Forecast8 | RBS | 0.657 | 0.686 | 0.986 | 0.041 | 0.985 | 0.132 |
| Forecast9 | Societe Generale | 0.315 | 0.163 | 0.518 | 0.414 | 0.294 | 0.965 |
| Forecast10 | UBS | 0.298 | 0.384 | 0.720 | 0.183 | 0.010 | 0.219 |
| Forecast11 | ABN Amro | 0.284 | 0.819 | 0.817 | 0.074 | 0.980 | 0.245 |
| Forecast12 | Bank of America | 0.723 | 0.931 | 0.600 | 0.412 | 0.825 | 0.272 |
| Forecast13 | Barclays Capital | 0.749 | 0.398 | 0.863 | 0.283 | 0.206 | 0.939 |
| Forecast15 | HBOS Treasury Services | 0.924 | 0.760 | 0.123 | 0.007 | 0.111 | 0.702 |
| Forecast18 | Standard Chartered | 0.756 | 0.331 | 0.441 | 0.014 | 0.230 | 0.006 |
| Forecast19 | Westpac | 0.963 | 0.567 | 0.845 | 0.010 | 0.464 | 0.499 |
| Forecast20 | 4Cast | 0.343 | 0.893 | 0.730 | 0.594 | 0.787 | 0.027 |
| Forecast22 | Scotia Capital | 0.788 | 0.663 | 0.029 | 0.358 | 0.326 | 0.871 |
| Forecast24 | Commonw. Bank of Aus. | 0.187 | 0.129 | 0.790 | 0.306 | 0.271 | 0.086 |
| Forecast26 | Dresdner Kleinwort | 0.240 | 0.011 | 0.079 | 0.802 | 0.232 | 0.631 |
| Forecast27 | Informa Global Markets | 0.838 | 0.800 | 0.220 | 0.008 | 0.622 | 0.772 |
| Forecast28 | Rabobank | 0.816 | 0.730 | 0.653 | 0.115 | 0.850 | 0.542 |
| Forecast29 | RBC | 0.416 | 0.851 | 0.423 | 0.113 | 0.432 | 0.160 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Forecast30 | SAXO Bank | 0.344 | 0.820 | 0.602 | 0.343 | 0.706 | 0.114 |
| Forecast31 | Merrill Lynch | 0.362 | 0.439 | 0.307 | 0.025 | 0.021 | 0.221 |
| Forecast33 | ANZ | 0.868 | 0.582 | 0.743 | 0.223 | 0.374 | 0.954 |
| Forecast34 | Bank of China | 0.998 | 0.347 | 0.424 | 0.564 | 0.064 | 0.670 |
| Forecast36 | Danske Bank | 0.900 | 0.687 | 0.648 | 0.078 | 0.826 | 0.737 |
| Forecast37 | Lehman Brothers | 0.082 | 0.776 | 0.026 | 0.095 | 0.027 | 0.257 |
| Forecast39 | Lloyds TSB CM | 0.059 | 0.509 | 0.032 | 0.954 | 0.692 | 0.017 |
| Forecast40 | Gain Capital | 0.149 | 0.820 | 0.009 | 0.052 | 0.962 | 0.202 |
| Forecast41 | Calyon | 0.104 | 0.127 | 0.747 | 0.641 | 0.625 | 0.377 |
| Forecast42 | SEB Merchant Banking | 0.509 | 0.590 | 0.227 | 0.023 | 0.123 | 0.544 |
| Forecast43 | GFT | 0.441 | 0.838 | 0.948 | 0.031 | 0.264 | 0.153 |
| Forecast44 | FXCM | 0.960 | 0.668 | 0.658 | 0.010 | 0.688 | 0.179 |
| Forecast45 | TMS Brokers | 0.327 | 0.739 | 0.890 | 0.981 | 0.807 | 0.038 |
| Forecast46 | BNP Paribas | 0.817 | 0.218 | 0.461 | 0.088 | 0.036 | 0.203 |
| Forecast49 | Investors Bank & Trust | 0.091 | 0.353 | 0.086 | 0.056 | 0.271 | 0.405 |
| Forecast51 | Bank of Montreal | 0.072 | 0.319 | 0.009 | 0.254 | 0.143 | 0.591 |

Follower at 5% level

Causality unclear

# Appendix V - Results Granger Causality Tests – Average Forecast

| **1 Month Horizon** | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Exchange rate** | | **EURUSD** | | **GBPUSD** | | **USDJPY** | |
| **Leader** | | Average | | Average | | Average | |
| **Granger prob.** | | | | | | | |
| **Causality from** | | Causality from Leader to forecaster | Forecaster to leader | Causality from Leader to forecaster | Forecaster to leader | Causality from Leader to forecaster | Forecaster to leader |
| Forecast3 | Citigroup | 0.012 | 0.013 | 0.105 | 0.188 | 0.279 | 0.750 |
| Forecast4 | Deutsche Bank | 0.001 | 0.108 | 0.002 | 0.268 | 0.002 | 0.081 |
| Forecast5 | HSBC | 0.042 | 0.780 | 0.035 | 0.336 | 0.240 | 0.320 |
| Forecast6 | JP Morgan | 0.000 | 0.414 | 0.006 | 0.142 | 0.011 | 0.626 |
| Forecast8 | RBS | 0.001 | 0.751 | 0.044 | 0.205 | 0.023 | 0.124 |
| Forecast9 | Societe Generale | 0.000 | 0.032 | 0.000 | 0.109 | 0.001 | 0.303 |
| Forecast10 | UBS | 0.000 | 0.974 | 0.004 | 0.256 | 0.062 | 0.228 |
| Forecast11 | ABN Amro | 0.003 | 0.852 | 0.006 | 0.300 | 0.029 | 0.319 |
| Forecast12 | Bank of America | 0.043 | 0.755 | 0.004 | 0.039 | 0.095 | 0.568 |
| Forecast13 | Barclays Capital | 0.000 | 0.769 | 0.000 | 0.070 | 0.020 | 0.524 |
| Forecast15 | HBOS Treasury Services | 0.002 | 0.790 | 0.064 | 0.392 | 0.926 | 0.908 |
| Forecast18 | Standard Chartered | 0.090 | 0.750 | 0.293 | 0.694 | 0.838 | 0.186 |
| Forecast19 | Westpac | 0.001 | 0.762 | 0.059 | 0.614 | 0.026 | 0.190 |
| Forecast20 | 4Cast | 0.000 | 0.901 | 0.000 | 0.125 | 0.000 | 0.222 |
| Forecast22 | Scotia Capital | 0.000 | 0.641 | 0.029 | 0.491 | 0.574 | 0.910 |
| Forecast24 | Commonw. Bank of Aus. | 0.008 | 0.682 | 0.082 | 0.376 | 0.071 | 0.345 |
| Forecast26 | Dresdner Kleinwort | 0.001 | 0.351 | 0.015 | 0.911 | 0.026 | 0.328 |
| Forecast27 | Informa Global Markets | 0.000 | 0.882 | 0.000 | 0.124 | 0.128 | 0.601 |
| Forecast28 | Rabobank | 0.000 | 0.657 | 0.000 | 0.221 | 0.000 | 0.264 |
| Forecast29 | RBC | 0.014 | 0.649 | 0.219 | 0.282 | 0.110 | 0.234 |
| Forecast30 | SAXO Bank | 0.000 | 0.774 | 0.013 | 0.190 | 0.001 | 0.040 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Forecast31 | Merrill Lynch | 0.045 | 0.586 | 0.335 | 0.944 | 0.058 | 0.045 |
| Forecast33 | ANZ | 0.126 | 0.133 | 0.376 | 0.529 | 0.420 | 0.596 |
| Forecast34 | Bank of China | 0.001 | 0.803 | 0.166 | 0.359 | 0.113 | 0.548 |
| Forecast36 | Danske Bank | 0.001 | 0.846 | 0.000 | 0.171 | 0.000 | 0.315 |
| Forecast37 | Lehman Brothers | 0.053 | 0.244 | 0.177 | 0.491 | 0.017 | 0.475 |
| Forecast39 | Lloyds TSB CM | 0.000 | 0.951 | 0.002 | 0.144 | 0.000 | 0.149 |
| Forecast40 | Gain Capital | 0.000 | 0.716 | 0.000 | 0.203 | 0.002 | 0.160 |
| Forecast41 | Calyon | 0.000 | 0.648 | 0.000 | 0.118 | 0.001 | 0.366 |
| Forecast42 | SEB Merchant Banking | 0.001 | 0.759 | 0.009 | 0.104 | 0.044 | 0.422 |
| Forecast43 | GFT | 0.059 | 0.291 | 0.159 | 0.493 | 0.689 | 0.630 |
| Forecast44 | FXCM | 0.002 | 0.855 | 0.008 | 0.122 | 0.010 | 0.163 |
| Forecast45 | TMS Brokers | 0.000 | 0.959 | 0.004 | 0.137 | 0.000 | 0.074 |
| Forecast46 | BNP Paribas | 0.000 | 0.693 | 0.009 | 0.199 | 0.093 | 0.322 |
| Forecast49 | Investors Bank & Trust | 0.000 | 0.434 | 0.029 | 0.863 | 0.028 | 0.061 |
| Forecast51 | Bank of Montreal | 0.006 | 0.295 | 0.002 | 0.635 | 0.315 | 0.875 |

Follower at 5% level

Causality unclear

| 3 Month Horizon<br>**Exchange rate**<br>**Leader**<br>**Granger probabilities**<br>**Causality from** | | **EURUSD**<br>Average<br>Causality from Leader to forecaster | <br><br>Forecaster to leader | **GBPUSD**<br>Average<br>Causality from Leader to forecaster | <br><br>Forecaster to leader | **USDJPY**<br>Average<br>Causality from Leader to forecaster | <br><br>Forecaster to leader |
|---|---|---|---|---|---|---|---|
| Forecast3 | Citigroup | 0.035 | 0.038 | 0.635 | 0.556 | 0.399 | 0.262 |
| Forecast4 | Deutsche Bank | 0.808 | 0.727 | 0.866 | 0.414 | 0.796 | 0.228 |
| Forecast5 | HSBC | 0.907 | 0.377 | 0.752 | 0.357 | 0.635 | 0.051 |
| Forecast6 | JP Morgan | 0.078 | 0.783 | 0.732 | 0.332 | 0.026 | 0.019 |
| Forecast8 | RBS | 0.148 | 0.996 | 0.347 | 0.182 | 0.117 | 0.038 |
| Forecast9 | Societe Generale | 0.879 | 0.127 | 0.778 | 0.295 | 0.761 | 0.074 |
| Forecast10 | UBS | 0.564 | 0.665 | 0.958 | 0.827 | 0.339 | 0.178 |
| Forecast11 | ABN Amro | 0.024 | 0.755 | 0.044 | 0.104 | 0.682 | 0.016 |
| Forecast12 | Bank of America | 0.151 | 0.661 | 0.115 | 0.070 | 0.328 | 0.033 |
| Forecast13 | Barclays Capital | 0.123 | 0.467 | 0.158 | 0.351 | 0.295 | 0.074 |
| Forecast15 | HBOS Treasury Services | 0.199 | 0.998 | 0.624 | 0.296 | 0.875 | 0.470 |
| Forecast18 | Standard Chartered | 0.877 | 0.246 | 0.692 | 0.582 | 0.218 | 0.283 |
| Forecast19 | Westpac | 0.162 | 0.237 | 0.506 | 0.371 | 0.317 | 0.149 |
| Forecast20 | 4Cast | 0.421 | 0.419 | 0.580 | 0.946 | 0.159 | 0.063 |
| Forecast22 | Scotia Capital | 0.127 | 0.485 | 0.962 | 0.698 | 0.955 | 0.054 |
| Forecast24 | Commonw. Bank of Aus. | 0.166 | 0.803 | 0.583 | 0.224 | 0.807 | 0.102 |
| Forecast26 | Dresdner Kleinwort | 0.244 | 0.221 | 0.878 | 0.748 | 0.686 | 0.150 |
| Forecast27 | Informa Global Markets | 0.002 | 0.804 | 0.053 | 0.221 | 0.086 | 0.317 |
| Forecast28 | Rabobank | 0.021 | 0.803 | 0.606 | 0.486 | 0.202 | 0.047 |
| Forecast29 | RBC | 0.143 | 0.133 | 0.788 | 0.277 | 0.312 | 0.043 |
| Forecast30 | SAXO Bank | 0.018 | 0.402 | 0.046 | 0.811 | 0.310 | 0.024 |
| Forecast31 | Merrill Lynch | 0.272 | 0.428 | 0.773 | 0.845 | 0.738 | 0.046 |
| Forecast33 | ANZ | 0.004 | 0.556 | 0.028 | 0.482 | 0.693 | 0.183 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Forecast34 | Bank of China | 0.040 | 0.493 | 0.340 | 0.078 | 0.470 | 0.080 |
| Forecast36 | Danske Bank | 0.049 | 0.927 | 0.273 | 0.296 | 0.137 | 0.196 |
| Forecast37 | Lehman Brothers | 0.115 | 0.524 | 0.306 | 0.428 | 0.141 | 0.294 |
| Forecast39 | Lloyds TSB CM | 0.093 | 0.716 | 0.352 | 0.109 | 0.198 | 0.066 |
| Forecast40 | Gain Capital | 0.005 | 0.586 | 0.157 | 0.640 | 0.006 | 0.050 |
| Forecast41 | Calyon | 0.036 | 0.512 | 0.117 | 0.913 | 0.018 | 0.085 |
| Forecast42 | SEB Merchant Banking | 0.147 | 0.512 | 0.607 | 0.688 | 0.112 | 0.322 |
| Forecast43 | GFT | 0.012 | 0.625 | 0.002 | 0.261 | 0.160 | 0.111 |
| Forecast44 | FXCM | 0.018 | 0.251 | 0.051 | 0.512 | 0.365 | 0.131 |
| Forecast45 | TMS Brokers | 0.046 | 0.874 | 0.229 | 0.297 | 0.211 | 0.012 |
| Forecast46 | BNP Paribas | 0.030 | 0.010 | 0.532 | 0.507 | 0.193 | 0.178 |
| Forecast49 | Investors Bank & Trust | 0.001 | 0.648 | 0.025 | 0.634 | 0.260 | 0.130 |
| Forecast51 | Bank of Montreal | 0.077 | 0.181 | 0.097 | 0.814 | 0.422 | 0.342 |

Follower at 5% level

Causality unclear

| **12 Month Horizon** | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Exchange rate** | | **EURUSD** | | **GBPUSD** | | **USDJPY** | |
| **Leader** | | Average | | Average | | Average | |
| **Granger probabilities** | | | | | | | |
| **Causality from** | | Causality from Leader to forecaster | Forecaster to leader | Causality from Leader to forecaster | Forecaster to leader | Causality from Leader to forecaster | Forecaster to leader |
| Forecast3 | Citigroup | 0.792 | 0.062 | 0.870 | 0.286 | 0.079 | 0.163 |
| Forecast4 | Deutsche Bank | 0.105 | 0.294 | 0.054 | 0.384 | 0.006 | 0.733 |
| Forecast5 | HSBC | 0.920 | 0.023 | 0.536 | 0.689 | 0.002 | 0.696 |
| Forecast6 | JP Morgan | 0.875 | 0.096 | 0.543 | 0.369 | 0.858 | 0.785 |
| Forecast8 | RBS | 0.194 | 0.241 | 0.557 | 0.363 | 0.151 | 0.740 |
| Forecast9 | Societe Generale | 0.328 | 0.001 | 0.174 | 0.790 | 0.007 | 0.815 |
| Forecast10 | UBS | 0.349 | 0.215 | 0.880 | 0.624 | 0.003 | 0.279 |
| Forecast11 | ABN Amro | 0.358 | 0.720 | 0.887 | 0.178 | 0.214 | 0.139 |
| Forecast12 | Bank of America | 0.997 | 0.781 | 0.834 | 0.594 | 0.321 | 0.379 |
| Forecast13 | Barclays Capital | 0.840 | 0.771 | 0.921 | 0.589 | 0.244 | 0.574 |
| Forecast15 | HBOS Treasury Services | 0.805 | 0.377 | 0.115 | 0.025 | 0.187 | 0.869 |
| Forecast18 | Standard Chartered | 0.652 | 0.789 | 0.278 | 0.033 | 0.338 | 0.020 |
| Forecast19 | Westpac | 0.901 | 0.161 | 0.855 | 0.053 | 0.013 | 0.390 |
| Forecast20 | 4Cast | 0.072 | 0.888 | 0.884 | 0.682 | 0.562 | 0.005 |
| Forecast22 | Scotia Capital | 0.336 | 0.965 | 0.053 | 0.948 | 0.088 | 0.845 |
| Forecast24 | Commonw. Bank of Aus. | 0.658 | 0.232 | 0.836 | 0.432 | 0.156 | 0.387 |
| Forecast26 | Dresdner Kleinwort | 0.422 | 0.130 | 0.084 | 0.785 | 0.063 | 0.591 |
| Forecast27 | Informa Global Markets | 0.618 | 0.126 | 0.282 | 0.003 | 0.503 | 0.932 |
| Forecast28 | Rabobank | 0.997 | 0.617 | 0.855 | 0.061 | 0.171 | 0.892 |
| Forecast29 | RBC | 0.950 | 0.600 | 0.424 | 0.070 | 0.304 | 0.037 |
| Forecast30 | SAXO Bank | 0.711 | 0.744 | 0.838 | 0.135 | 0.006 | 0.262 |
| Forecast31 | Merrill Lynch | 0.093 | 0.705 | 0.289 | 0.062 | 0.056 | 0.233 |
| Forecast33 | ANZ | 0.665 | 0.194 | 0.947 | 0.090 | 0.303 | 0.548 |
| Forecast34 | Bank of China | 0.349 | 0.030 | 0.553 | 0.784 | 0.012 | 0.284 |
| Forecast36 | Danske Bank | 0.701 | 0.119 | 0.355 | 0.376 | 0.843 | 0.117 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Forecast37 | Lehman Brothers | 0.007 | 0.735 | 0.016 | 0.548 | 0.017 | 0.727 |
| Forecast39 | Lloyds TSB CM | 0.072 | 0.749 | 0.024 | 0.407 | 0.248 | 0.020 |
| Forecast40 | Gain Capital | 0.324 | 0.330 | 0.008 | 0.024 | 0.836 | 0.024 |
| Forecast41 | Calyon | 0.155 | 0.259 | 0.490 | 0.747 | 0.079 | 0.935 |
| Forecast42 | SEB Merchant Banking | 0.778 | 0.543 | 0.234 | 0.034 | 0.187 | 0.238 |
| Forecast43 | GFT | 0.811 | 0.261 | 0.892 | 0.029 | 0.494 | 0.398 |
| Forecast44 | FXCM | 0.887 | 0.068 | 0.691 | 0.008 | 0.848 | 0.153 |
| Forecast45 | TMS Brokers | 0.083 | 0.873 | 0.902 | 0.798 | 0.400 | 0.082 |
| Forecast46 | BNP Paribas | 0.396 | 0.258 | 0.452 | 0.029 | 0.013 | 0.605 |
| Forecast49 | Investors Bank & Trust | 0.037 | 0.554 | 0.204 | 0.225 | 0.792 | 0.387 |
| Forecast51 | Bank of Montreal | 0.042 | 0.910 | 0.012 | 0.146 | 0.048 | 0.732 |

Follower at 5% level

Causality unclear