Information Transmission in the Euribor

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Abstract

The Euribor is a survey-based benchmark for interbank term deposit rates. In this paper I interpret panel banks' submissions to the Euribor survey as forecasts of the interest rate prevailing in the market. I investigate whether the forecasting errors are independent of any event in the banks' information sets. There is strong empirical evidence against this hypothesis. Banks' forecasts exhibit a similar contrarian bias as has been documented among other professional forecasters, e.g. equity research analysts. I discuss possible causes for this behavior and implications for the reform of IBOR benchmark rates.

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1 Introduction

Euribor is the "Euro Interbank Offered Rate", the Euro area equivalent to the even more prominent Libor. There are many similar rates, e.g. the Tokyo-based Tibor. These rates are collectively referred to as "IBOR" rates and all of them serve the purpose to indicate the interest rate at which large banks borrow from one another by unsecured term deposits. IBOR rates may serve as benchmarks for adjustable-rate loans or as underlyings in derivative contracts, e.g. interest rate swaps. Hence, they are of vital importance for the global financial system. Libor in particular, but also Euribor have attracted widespread attention from the public, policymakers, and academics alike, after it was revealed that these rates had been manipulated. When the scandal was triggered in 2008 and at the time of this writing (2016) still, IBOR rates are determined by conducting surveys among the banks most active in the respective markets. The rates are not based on verified transactions, but on banks' judgmental quotes[1]. This provides panel banks with the opportunity to manipulate IBOR rates by reporting biased estimates. In the aftermath of the scandal, regulatory bodies around the world issued suggestions on how to reform the rate setting process of IBOR rates such as to prevent manipulation in the future[2]. The measures implemented so far encompass tighter governance and regulatory monitoring of the fixing process. In case of the Euribor, the administrator revised its code of conduct for panel banks in 2013, following consultations with its panel banks and recommendations of ESMA and EBA (2013).

In this paper I analyze panel banks' contributions to the Euribor survey and interpret their quotes as forecasts of an ex-ante unobserved "true" interest rate. This is facilitated by the Euribor definition as the lending rate between two hypothetical prime banks[3]. I employ the test developed by Bernhardt, Campello and Kutsoati (2006) for financial analysts' forecasts to investigate whether banks' forecasting errors are independent of any event in their information sets. My results indicate that the Euribor survey contributions exhibit a similar contrarian bias as has been documented among other professional forecasters[4]. The test classifies forecasts according to three categories which the authors refer to as "herding", "anti-herding", or "unbiased". At its core is the question whether the sign of forecasting errors is predictable, given some prior. The test relies on the identifying assumption that forecasters' posterior expectations are symmetric

[1] I provide a detailed description of the rate setting process for the Euribor in Section 3.

[2] See Duffie and Stein (2015) for a discussion of these contributions.

[3] In contrast, the Libor is defined as the rate at which each contributing panel bank can borrow.

[4] Bernhardt, Campello and Kutsoati (2006) document contrarian behavior in company earnings forecasts. Similar behavior by forecasters has been documented e.g. by Pierdzioch, Rülke and Stadtmann (2013) in the case of metal prices or by Pierdzioch, Rülke and Stadtmann (2010) for oil price forecasts.

around the mean given all information at their disposal. The key insight underlying the test is the following. Under the null hypothesis of unbiasedness, the forecast equals the median of posterior beliefs. Hence, it is as likely to exceed the forecasting target as to fall short. This holds true both, unconditionally as well as conditional on any event in the forecaster's information set. However, when a panel bank engages in what Bernhardt, Campello and Kutsoati (2006) call herding, it locates its quote between the prior and the posterior. Consequently, when the quote is larger than the prior it is still smaller than the posterior and the probability to exceed the true interest rate is smaller than one half. Likewise, when the quote is smaller than the prior it is still larger than the posterior. Hence, conditional on this event the quote falls short of the realized interest rate with probability smaller than one half. The opposite outcomes occur when banks engage in anti-herding. In this case the quotes "overshoot" the posterior away from the consensus prior.

The key challenge for the application of the test by Bernhardt, Campello and Kutsoati (2006) is that the true realized interest rate for term deposits is not observable for any party other than the panel banks. This is also what distinguishes this paper from extant applications of the test. As a major contributions I develop a proxy rate based on CDS spreads for the Euribor panel banks. The proxy tracks the Euribor fixing remarkably well until August 2007, see Figure 1.

[Figure 1 about here.]

My central finding is that panel banks engage in the behavior called anti-herding by Bernhardt, Campello and Kutsoati (2006), i.e. bias their quotes away from the prior in the direction of the posterior. Furthermore, there is variation across banks in the extent to which they offset their quotes this way. There are two implications of this result. First, the dispersion of quotes across banks is larger when banks are anti-herding than in the scenario of unbiased reporting. Second, on occasions where all banks obtain a posterior on one side of the prior - e.g. when all banks' posteriors are larger than the prior - the Euribor fixing overshoots the actual interest rate. My results may inform policymakers in their ongoing efforts to reform IBOR rates. The immediate responses to the manipulation scandal have focused on sanctions on misreporting, reforming the agencies administrating the benchmarks, and setting governance standards for contributing panel banks (Wheatley, 2012; ESMA and EBA, 2013). However, the need to base benchmarks on transactions rather than judgmental surveys has also been emphasized (Market Participants Group on Reforming Interest Rate Benchmarks, 2014; Official Sector Steering Group, 2014). My results strengthen the empirical evidence for the latter cause.

The remainder of this paper is organized as follows. I discuss the literature related to my paper in Section 2. Then, I provide a detailed description of the rate setting process of the Euribor and the data on Euribor survey contributions in Section 3. The CDS-based proxy is introduced in Section 4. As non-stationarity and measurement error in the proxy may bias my tests, a formal framework is introduced in Section 5. This allows me to determine the suitable transformation of the data such that the test is consistent and to make the identifying assumptions explicit. In Section 6 I perform the tests and discuss the results. Section 7 concludes.

2 Literature

This paper overlaps with two separate lines of literature. The first is related to the behavior of professional forecasters. The principal reference for my paper is Bernhardt, Campello and Kutsoati (2006) who develop a non-parametric test to detect herding or anti-herding in I/B/E/S analysts' forecasts. The authors' contribution relative to previous attempts to uncover herding or anti-herding is that their test is robust to correlation in information, unforecasted shocks to the target, information arrival, and measurement error. The latter property is of particular importance for my application, as I have to rely on a proxy of the forecasting target. Zitzewitz (2001) is one of the early contributions to report anti-herding in I/B/E/S earnings forecasts, using a regression-based approach. On the theoretical side, Ottaviani and Sorensen (2006) present and discuss two theories of forecasters' strategic behavior. According to the theory of "reputational cheap talk", forecasters seek to foster their reputation for forecasting talent, i.e. for being well informed. The market uses published forecasts and the ex-post observable forecasting target to evaluate forecasting talent. In the alternative theory of a "forecasting contest" the payoff to forecasters depends on the relative ranking of their estimates in terms of distance to the realized target. In this scenario, forecasters trade off the incentive to provide accurate forecasts and to deviate from the consensus prior in order to leave more competitors behind in case of a lucky guess. Ottaviani and Sorensen (2006, p.455) derive that the anti-herding documented by Zitzewitz (2001) and Bernhardt, Campello and Kutsoati (2006) is compatible with the predictions of the forecasting contest model, but not with those of the reputational cheap talk model. As panel banks in the Euribor survey exhibit anti-herding as well, the forecasting contest model may represent a suitable description of the incentives responsible for the observed behavior.

The second line of literature related to my paper is concerned with the manipulation of the financial benchmarks of the IBOR family. Initial suspicions about the reported quotes were raised in the news, but it required regulatory investigations to prove misconduct. This lead academics to develop procedures aimed at detecting manipulation from the submitted quotes alone. Abrantes-Metz, Villas-Boas and Judge (2011) examine the distribution of the second digit of reported Libor quotes to detect manipulation. Snider and Youle (2014) devise a statistical test exploiting the trimming in the rate setting process to test for portfolio-based incentives to manipulate. The authors report that the USD Libor was mostly accurate until August 2007, but was persistently manipulated afterwards. Interestingly, the CDS-based proxy I introduce in Section 4 tracks the 12-month Euribor rate very closely until that time, but not afterwards. A recent contribution that aims to quantify the extent of manipulation in the Euribor is Eisl, Jankowitsch and Subrahmanyam (2016). A second topic discussed in the literature on the IBOR family is the reform to prevent future manipulation. Duffie and Stein (2015) stress the need for transactions-based data input to the benchmarks, and propose to include other money market instruments besides unsecured term deposit rates. Duffie, Dworczak and Zhu (2014) present a mechanism on how to optimally weight trading data for a transactions-based benchmark.

3 Background

3.1 The Euribor and Its Rate Setting Process

The Euribor is a benchmark rate for interest rates paid on unsecured interbank term deposits in the Euro area. The benchmark is used as an underlying for interest rate derivatives, as a reference for adjustable-rate loans, and in risk management[5]. Euribor rates are published for maturities ranging from one week to twelve months and for several currencies, most prominently the Euro. They are determined via a survey among a panel of banks, i.e. they are not based on actual transactions. At the time of this writing (2016), the governing body responsible for the administration of the Euribor is the European Money Markets Institute (EMMI). The EMMI is a non-profit organization formed by European national banking federations. The calculating agent - the institution responsible for conducting the survey and for aggregating the submitted quotes into a single rate, the so-called Euribor fixing - is Global Rate Set Systems (GRSS). The data used in this paper was sampled for the period of July 2005 - July 2007. During that period

[5]In its final report the Market Participants Group on Reforming Interest Rate Benchmarks (2014, p.347-348) estimated the notional volume of outstanding financial contracts indexed to Euribor to be greater than $180TN at the end of 2012. The report determined the market footprint of the 12-month Euribor, which is analyzed in this paper, to be smaller than the footprints of shorter tenors, but it is still classified as “medium” for interest rate swaps and retail mortgages

the Euribor was administered by Euribor-EBF, the precursor organization of EMMI and the calculating agent was Thompson Reuters. The transition from Euribor-EBF to EMMI and the change of the calculating agent came as a to the Euribor manipulation scandal. Despite the institutional changes surrounding the Euribor, the core definition as a benchmark for unsecured interbank term deposit rates has remaind unchanged since its inception in 1999. The central document governing the rate setting process is the Euribor Code of Conduct published by EMMI. According to its current version, *"Panel banks provide daily quotes of the rate, rounded to two decimal places, that each panel bank believes one prime bank is quoting to another prime bank for interbank term deposits within the euro zone."*[6] Two aspects of this definition are of particular importance for my paper.

1. Banks are requested to quote their beliefs, i.e. to disclose their expectations. Therefore, the survey submissions can be interpreted as forecasts.

2. The entity to be forecasted is the rate for interbank term deposits exchanged between two prime banks. Accordingly, banks are requested to forecast the same entity. Unlike in the case of the Libor - where banks are requested to disclose their own borrowing costs - there is no direct link between differences in Euribor quotes and heterogeneous borrowing conditions of contributing panel banks.

These two properties of the Euribor definition allow me to link the submitted quotes with the literature on financial analysts' forecasts. In comparison with other studies of forecasters' behavior there are two important institutional peculiarities when analyzing Euribor submissions. First, banks do not submit their quotes sequentially, but simultaneously. As the Code of Conduct (p.19) specifies, banks are requested to submit their quotes by 10:45 a.m. (CET). At 11:00 a.m. the calculating agent processes the Euribor calculation, i.e. aggregates the individual quotes and publishes the Euribor fixing. Hence, contributing panel banks cannot observe other banks' contributions on a given day prior to submitting their own quotes. This situation differs from other settings of professional forecasting. For instance, equity research analysts who produce company earnings forecasts need not publish their estimates at the same time. In such a situation the econometrician has to account for the fact that analysts update their expectations upon observing other analysts' estimates. The simultaneous submission of Euribor quotes simplifies the analysis. Once a common prior expectation has been determined, there is no need to account for sequential publication of forecasts. The second peculiarity stems from the fact that

[6] See European Money Markets Institute (2013, p.19).

the market for unsecured interbank term deposits is an OTC market that is hard to monitor for outside observers[7]. When two banks agree on a term deposit contract and perform the implied transactions, this remains unobserved by any party other than the two counterparties. Some transactions in the unsecured segment are entered via electronic trading platforms where public bids are made and therefore size, maturity, and interest rates of loans are publicly observable. However, in 2006 56% of transactions were conducted by direct trading and only 27% and 17% by voice broker and electronic trading, respectively. In 2014 the share of direct trading has remained unchanged and the share of electronic trading has decreased[8]. One consequence of this market structure is that current rates, volumes, and maturities are unobservable for market outsiders. Therefore, it is more difficult to analyze banks' forecasts of term deposit rates, as there is no objective measure against which to evaluate their quotes. In other settings, e.g. company earnings forecasts, the forecasted entity becomes publicly observable ex-post: The public can assess how accurate analysts' forecasts were once the company publishes its income statement. One of the major contributions of this paper is that I create a proxy for 12-month term deposit rates based on CDS spreads against which I can evaluate banks' rate submissions. I provide a detailed description in Section 4.

There are further noteworthy institutional features of the Euribor rate setting process. In order to safeguard the benchmark from outliers and erratic quotes, the calculating agent determines the fixing as a trimmed mean[9]. Specifically, the calculating agent eliminates 15% of the quotes at each, the top and the bottom of the quote range. The remaining 70% of quotes are averaged and rounded to three decimal places. As the quotes at the tails are excluded, the average is less affected by outliers. However, the Euribor manipulation scandal discussed in **??** has brought to light that occasionally banks have strategically submitted high or low quotes in order to manipulate the composition of the center 70% of quotes. A further issue is the definition of a prime bank. In its current version the Euribor Code of Conduct defines a prime bank as *"a credit institution of high creditworthiness for short-term liabilities, which lends at competitive market related interest rates and is recognised as active in euro-denominated money market instruments while having access to the Eurosystem's (open) market operations"*[10]. This definition was adopted after a recommendation of ESMA and EBA (2013) to clarify the term

[7]The ECB aims to elucidate the European money market by its annual Money Market Survey and its biannual Money Market Study. Both publications are based on surveys among those banks who participate in the European money market.

[8]The 2006 figures are relevant for my paper, as I use data from 2005-2007. Figures for both years are published in ECB (2015, p.15).

[9]See European Money Markets Institute (2013, p.19) for a detailed description of the calculation process.

[10]European Money Markets Institute (2013, p.2)

"prime bank" and a less precise definition was in place at the time the data for this paper was sampled. Using data from 2006-2012, Taboga (2014) suggests that at least some of the volatility in the twelve-month Euribor rate after August 2007 may be attributed to survey respondents' diverging perceptions of what a prime bank is. However, the author also emphasizes that before the crisis - i.e. during the sampling period of my paper - "most large and internationally active banks enjoyed high credit ratings, had tiny CDS premia and could, without almost any doubt, be considered 'prime' "[11].

3.2 Data Collection and Cleaning

Raw data on EUR-Euribor submissions as well as the fixing are publicly available at the EMMI website[12]. I collect the bank-specific quotes for the twelve month tenor during the period from July 5, 2005 until July 31, 2007. The choice of this time frame is due to the availability of a workable CDS spread-based proxy for the twelve month Euribor rate. The construction of the proxy - described in detail in Section 4 - requires data on the 12-month EONIA indexed swap, which is not available prior to July 5, 2005. As Taylor and Williams (2009) point out, the emerging financial crisis leads to distortions in the interbank market and potentially also the in CDS market as of August 2007. This is reflected in a sudden and persistent increase in the average deviation of the proxy and the Euribor quotes[13].

I use the following notation throughout this paper. q_{it} denotes the twelve-month Euribor quote of bank i on day t. F_t denotes the twelve-month Euribor fixing on day t as published by the calculating agent. Data cleaning is required before the quotes can be analyzed. First, there is no unique ID for each reporting institution, but panel banks are identified via abbreviations of their names. As some of the panel banks change their name during the sampling period and because of occasional typos, the data contain multiple abbreviations for the same reporting entity. Therefore, the first step is to harmonize the names and to assign a unique ID. Throughout the years of 2005 and 2006 the number of panel banks equals 48. Beginning in December 2006 the number gradually declines to 45 at the end of July 2007, see Figure 2.

[Figure 2 about here]

Second, the quotes contain fat finger errors as has previously been documented by ESMA

[11] Taboga (2014, p.73)
[12] http://www.emmi-benchmarks.eu/euribor-org/euribor-rates.html
[13] This is depicted in Figure 1. The proxy is introduced in detail in Section 4.

and EBA (2013). This leads to occasional extreme outliers[14]. Whereas typos by the submitters can occur on any of the three digits reported, they have the largest impact on the leading digit. I tackle these by the following procedure: I calculate the absolute value of the difference between a given quote and the last submitted quote $|q_{it} - q_{i,t-1}|$, the next submitted quote $|q_{it} - q_{i,t+1}|$, and the contemporaneous fixing $|q_{it} - F_t|$. When all three differences exceed 80bps, the quote q_{it} is labeled as a fat finger error and is replaced by a missing value. Thereby, 11 quotes are set to missing. I identify 7 further outliers by inspection. These are most likely due to fat finger errors on the second digit and I manually set them to missing. I make no attempt to correct for fat finger errors on the last digit. The twelve-month Euribor fixing, the cleaned quotes and those quotes identified as fat finger errors are displayed in Figure 3.

[Figure 3 about here]

After cleaning the data I retain 24,514 observations with 242 missing quotes. The average number of missing quotes per bank is 5, the maximum number per bank is 25. I consider the daily range of quotes $\max_i\{q_{it}\} - \min_i\{q_{it}\}$ to assess the cross-sectional variation. Overall, the quotes are very concentrated at the daily level. The average daily range of quotes is 4.27bps, the 10% quantile is 3bps and the 90% quantile is 6bps. See Table 1 for details.

[Table 1 about here]

Over the course of the sampling period the Euribor fixing gradually rises from around 2% to more than 4%. This increase is driven by a tightening monetary policy, as can be seen form Figure 4. The ECB discount facility - which operates as a lower bound in the Euro-denominated unsecured overnight money market - was raised from 1% to 3% during the sampling period.

[Figure 4 about here]

4 Constructing the Proxy

4.1 Intuition and Data

With regard to the creditor's payoff, term deposits are very similar to bonds. The major difference is that there is a secondary market for bonds such that creditors can liquidate their assets prior to maturity. Therefore, one might suspect that term deposits exhibit a liquidity premium

[14] See - for instance - the example given in ESMA and EBA (2013, p.13) for the 5M tenor. Bank 7 reports a series of 1.87%, 2.87%, and 1.85% on three consecutive days. It is very likely that the submitter intended to report 1.87% on the second instance as well, but mistyped the leading digit on the keyboard.

over bonds emitted by the same borrower and with the same time to maturity. In my present application I cannot account for the liquidity premium in term deposits. I argue that during the sampling period - July 2005 until July 2007 - the key risk factor driving both, bond yields as well as term deposit rates is credit risk, i.e. the risk that the borrower defaults on his debt[15]. Another security that establishes a market for credit risk - or rather protection thereof - is the credit default swap (CDS). The buyer of a CDS pays a periodic premium to the seller. In case the emitter of the underlying security defaults, the buyer of the CDS may sell the underlying at notional value to the seller. In this section I adopt and combine two simple models from Chan-Lau (2006) that link an emitter's default probability with the associated bond yields and CDS spreads. Thereby I obtain an estimate for the bond yield - and as I claim also for the term deposit rate - from CDS spreads. I consider a one-period model. At the beginning of the period the bank issues a bond. With probability $1-p$ the bank does not default and the bond pays one unit of the domestic currency at the end of the period. With probability p the bank defaults and the bond pays the recovery rate $0 \leq RR < 1$. Given the risk-free rate r_f, a risk neutral investor exhibits the willingness to pay B for the bond.

$$B = \frac{(1-p) + pRR}{1+r_f}$$

Hence I obtain a relation between the default probability, the risk-free rate, the recovery rate and the yield of the bond $1+r = 1/B$.

$$1 + r = \frac{1+r_f}{1-p(1-RR)} \tag{4.1}$$

Now I turn to the CDS spread. The CDS requires the protection buyer to pay the premium S_{CDS} at a quarterly frequency. I simplify the analysis and assume $4S_{CDS}$ has to be paid upfront. If the bank does not default, the protection buyer receives nothing at the end of the period. However, if the bank defaults, the protection buyer can buy the bond at the recovery rate RR and exchange it for notional value with the protection seller. Accordingly, a risk neutral investor's willingness to pay for the CDS is given as follows.

$$4S_{CDS} = \frac{p(1-RR)}{1+r_f} \tag{4.2}$$

[15] As of August 2007 my proxy is substantially smaller than the Euribor fixing, see Figure 1. A potential explanation thereof could be that the premium on liquidity risk in term deposit rates has become non-negligible.

I may substitute the term $p(1-RR)$ in Equation (4.1) by $4S_{CDS}(1+r_f)$ to obtain a proxy for the bond yield based on the CDS spread.

$$1+r = \frac{1+r_f}{1-4S_{CDS}(1+r_f)} \tag{4.3}$$

I collect price data on credit default swaps from Markit. More precisely, I collect daily prices quoted in basis points for CDS that meet the following selection criteria: i) The issuer of the underlying debt security is a European credit institution. ii) The time to maturity of the CDS is one year. iii) The underlying seniority tier is senior unsecured debt. iv) The CDS is denominated in EUR. v) The type of restructuring event that triggers the default swap contract is "modified modified restructuring" (MM). The price data is collected for the sampling period of July 5, 2005 until July 31, 2007. 269 European banks are covered. Using the one-year price data allows for a perfect maturity match with the quoted twelve-month Euribor rates. I choose the MM restructuring type because in the Markit database it is the most widely used one for EUR denominated instruments. To obtain an estimate for term deposit rates as defined by Equation (4.3), data on the risk-free rate is required as well. For this purpose I use the twelve-month EONIA indexed swap rate, the data is obtained from the website of the German Bundesbank[16]. In total, I gather 97,943 observations. I exclude 6,148 observations where the default probability as implied by Equation (4.2) exceeds 100%[17]. Each one of the remaining observations represents a candidate proxy for the interest rate paid on a twelve-month unsecured term deposit on a given day, i.e. a candidate for the "true" rate banks are requested to estimate in the Euribor survey.

4.2 Proxy Selection

In this subsection I describe how I construct the time series of proxy interest rates $\tilde{r}_t$ from the large number of candidate proxies obtained from the data on CDS spreads. On any given trading day, each European bank for which one-year CDS price data is available provides a candidate proxy rate. As explained in Section 3.1, the EMMI's Code of Conduct defines the Euribor as

[16] After the financial crisis there has been renewed interest in the question which rates to use as risk-free rates for discounting. The use of overnight indexed swaps (OIS) has been suggested among others by Hull and White (2013). Taboga (2014, p.54-55) explains in detail the definition of the twelve-month EONIA indexed swap and its relation to the twelve-month Euribor. As a robustness check, I use zero-coupon yields on German sovereign debt obtained from Datastream as an alternative risk-free rate. The resulting proxy remains virtually unchanged.

[17] Notice that this is the default probability under the risk-free measure. When the market anticipates an impending credit event, CDS prices may rise so high that the annualized default probability becomes unrealistically high. How to treat these cases has no practical relevance for constructing a proxy for the Euribor rate, as this is supposed to represent the funding conditions of a prime bank, i.e. a bank with outstanding creditworthiness.

the funding costs of a prime bank. Therefore, finding a good proxy essentially boils down to deciding which bank is a prime bank. Since the concept of a prime bank remains elusive, any choice I make in this regard will introduce measurement error in the proxy. I provide a detailed account of how I treat this measurement error in the econometric analyses in Section 6.1 and in more detail in Appendix A.2. After testing several specifications, I settle for the following definition of a prime bank and hence the proxy interest rate $\tilde{r}_t$. I identify those banks for which CDS price data is available and who are also part of the Euribor panel[18]. On any given trading day I consider that member of this group with the lowest CDS spread and define it as the prime bank of the given day. The proxy interest rate $\tilde{r}_t$ is defined as the deposit rate implied by said bank's CDS spread using Equation (4.3). I depict the resulting time series of the proxy and the twelve-month Euribor fixing as well as the associated quotes in Figure 1. The proxy tracks the fixing remarkably closely, in fact the difference between the two rates exceeds five basis points in absolute value only at few occasions, see Figure 5. This suggests that even when the Euribor fixing has been manipulated by reporting panel banks, the deviation from the rate that would have realized under truthful reporting is rather low.

[Figure 5 about here.]

I consider two alternative definitions of the proxy as a robustness check. Under the first alternative I define the proxy rate as the mean of the rates from the five banks in the Euribor panel with the lowest CDS spreads on any given day. The resulting proxy remains virtually the same. Under the second alternative, I use the mean of the ten banks in the universe of all European banks for which CDS data are available, irrespective of membership in the Euribor panel. Under this definition the resulting proxy is smaller on average. I suspect that this may be caused by the inclusion of some government sponsored development banks which enjoy explicit government guarantees and therefore have lower CDS spreads and hence lower implied term deposit rates than usual corporate banks. I disregard this alternative proxy, as it does not resemble the intention of the prime bank notion. For the sake of completeness, I highlight the divergence between the CDS-based proxy and the Euribor quotes as of August 2007 in Figure 6.

[Figure 6 about here.]

[18]As reporting banks in the Euribor survey are merely identified via abbreviations of their names (see Section 3.2), no matching table to the Markit database is available. I manage to match 40 out of 48 banks by hand.

4.3 Empirical Properties of the Proxy

In this subsection I conduct a time series analysis of the proxy rate $\tilde{r}_t$. I provide evidence in favor of the claim that $\tilde{r}_t$ is best described by a random walk with drift and - most importantly - that the first differences of $\tilde{r}_t$ exhibit no ARMA components. This property is of vital importance for the consistency of the econometric analyses conducted in Section 6.

The time series $\tilde{r}_t, \quad t = 1, \ldots, T$ is observed for $T = 516$ business days. Its depiction in Figure 1 strongly suggests that the series is non-stationary. Despite the graphical evidence I perform the stationarity test of Kwiatkowski et al. (1992) and the unit-root tests of Dickey and Fuller (1979) and Elliott, Rothenberg and Stock (1996) for the sake of completeness. The null hypotheses, test statistics, and critical values are presented in Table 3. All three tests support the hypothesis that $\tilde{r}_t$ is non-stationary. I perform the same two unit root tests on the differenced series $\Delta\tilde{r}_t = \tilde{r}_t - \tilde{r}_{t-1}$ and reject the null hypothesis of a unit root.

[Table 3 about here.]

Having established that the proxy is $I(1)$, I proceed to analyze the time series properties of the differenced series $\Delta\tilde{r}_t$. These are important, because they are informative about the measurement error originating from the proxy definition. To make this point clear I will introduce a formal framework. Assume there is an unobserved "true" rate r_t, yet the econometrician observes the proxy $\tilde{r}_t$. I define the measurement error ζ_t as the difference between the actual interest rate and the proxy.

$$\tilde{r}_t = r_t - \zeta_t \tag{4.4}$$

I will furthermore assume that the actual interest rate follows a random walk with drift[19].

$$\begin{aligned} \Delta r_t &= \mu + \epsilon_t \\ \epsilon_t &\overset{iid}{\sim} N(0, \sigma_\epsilon^2) \end{aligned} \tag{4.5}$$

The differenced series of the proxy is given by $\Delta\tilde{r}_t = \Delta r_t - \Delta\zeta_t$ and its autocorrelation structure depends on the stationarity of the measurement error ζ_t. Consider two alternative hypotheses. Under H_0 the measurement error is stationary and under H_1 it follows a random walk, possibly

[19] Given the steady and comparably smooth development of interest rates during the sampling period, a simple model as the random walk with drift may be suitable to provide a tight fit to interest rates, see Figure 1.

with drift.

$$H_0: \quad \zeta_t \overset{iid}{\sim} N(0, \theta\sigma_\epsilon^2), \quad \theta > 0$$
$$H_1: \quad \Delta\zeta_t = \alpha + \omega_t, \quad \omega_t \overset{iid}{\sim} N(0, \theta\sigma_\epsilon^2), \quad \theta > 0$$

Under the null hypothesis of a stationary measurement error the differenced series $\Delta\tilde{r}_t$ is positively correlated with its first lag and lead: $E[\Delta\tilde{r}_t \cdot \Delta\tilde{r}_{t-1}] = [-\zeta_{t-1}^2] = \theta\sigma_\epsilon^2$. Conversely, the differenced series $\Delta\tilde{r}_t$ exhibits no autocorrelation under the alternative hypothesis. A similar argument can be made for autoregressive terms in the actual interest rate r_t. If these are present, i.e. if r_t follows some ARIMA(p,1,q) process, the differenced series $\Delta\tilde{r}_t$ exhibits a non-zero autocorrelation structure. In the remainder of this subsection I provide evidence for the hypothesis that the CDS-based proxy introduced in the previous subsection is best described by an ARIMA(0,1,0) process. This implies that both, the true rate r_t as well as the measurement error ζ_t follow ARIMA(0,1,0) processes as well. This is an important finding, because the consistency of the test statistic applied in Section 6 depends on the assumption that the increments in the measurement error $\Delta\zeta_t$ are independently distributed.

To begin the analysis I provide graphs of the autocorrelation and of the partial autocorrelation function of $\Delta\tilde{r}_t$ in Figures 7 and 8, respectively. Neither the autocorrelation coefficients, nor the partial autocorrelation coefficients exceed the 99% confidence interval at any one of the first 20 lags. This is supportive of the claim that both, the actual rate as well as the measurement error follows an ARIMA(0,1,0) process. Next, I specify four different models of the ARIMA(p,1,q)-type for the differenced proxy series $\Delta\tilde{r}_t$, where $p, q \in \{0, 1\}$.

$$\begin{aligned} \Delta\tilde{r}_t =& \gamma + \phi\Delta\tilde{r}_{t-1} + u_t - \psi u_{t-1} \\ & u_t \overset{iid}{\sim} N(0, \sigma_u^2) \\ & 0 \leq |\phi| < 1, \quad 0 \leq |\psi| < 1 \end{aligned} \tag{4.6}$$

Coefficient estimates and model selection criteria are presented in Table 4.

[Table 4 about here.]

Whereas the coefficients ϕ in the ARIMA(1,1,0) and ψ the ARIMA(0,1,1) specification are greater than zero at the 5% significance level, the Bayesian Information Criterion favors the more parsimonious ARIMA(0,1,0) model. Both coefficients are insignificant in the ARIMA(1,1,1) specification. Therefore, I conclude that it is empirically justified to assume that both, the actual rate r_t as well as the measurement error ζ_t follow a random walk with no ARMA terms, but possibly with a drift. I propose a model of the unobserved interest rate, the measurement error and banks' expectations in Section 5. Building on this model I analyze banks' forecasting behavior in Section 6.

5 A Framework for Expectations and Measurement Error

5.1 Expectation Formation

There are N banks who provide daily quotes for their supposed best estimate of the interest rate r_t, where time is indexed as $t = 1, \ldots, T$. The interest rate r_t is ex-post observable for banks, but not for market outsiders. At the beginning of each period t banks have homogeneous expectations about the realization of r_t at the end of the period. I call this expectation the *common prior*. Throughout the period (trading day), banks engage in money market operations. Thereby each bank $i \in \{1, \ldots, N\}$ generates a privately observed signal s_{it} that is informative about the interest rate r_t. After observing the signal banks update their expectations and form heterogeneous posterior beliefs[20]. Next, banks publicly report their quotes q_{it}, which may or may not reflect their private beliefs. The calculating agent determines and publishes the fixing F_t. At the end of the period, banks observe the realization of r_t. Based on said observation they obtain the common prior belief for next period's interest rate r_{t+1}. In this framework banks' quotes in the Euribor survey do not affect the realized interest rate in the market for term deposit rates.

A key challenge for the econometric analysis of the quotes is that the series $\{r_t\}_{t=1}^{T}$ is unobservable for any market outsider including the econometrician. Instead, I generate a proxy $\tilde{r}_t$ from publicly observable CDS spreads as described in Section 4. The proxy includes a measurement error ζ_t. Accounting for this measurement error requires to distinguish two types of information sets, the information $\mathcal{B}_{it}$ of bank i and the information set $\mathcal{E}_t$ of the public (and the econometrician). Each information set contains the realized variables that are observable for the respective party at the end of period t. The public observes the proxy $\tilde{r}_t$, the quotes q_{it} and the

[20]Using data from the Italian electronic trading platform e-MID, Gabrieli (2011, p.10, Figure 4) reports that the intra-day distribution of trading activity is bi-modal. Most of the volume is traded in the morning, i.e. before the Euribor quote is due at 11:00 am. The other spike in trading activity is in the late afternoon. This anecdotal evidence is consistent with the modeling approach described.

fixing F_t. Bank i observes the actual interest rate r_t and its private signal s_{it} on top of that.

$$\mathcal{E}_t = \left\{\tilde{r}_1, \ldots, \tilde{r}_t, q_{1,1}, \ldots, q_{1,t}, q_{2,1}, \ldots, q_{N,t}, F_1, \ldots, F_t\right\} \tag{5.1}$$

$$\mathcal{B}_{it} = \Big\{\mathcal{E}_t \cup \left\{r_1, \ldots, r_t, s_{i,1}, \ldots, s_{i,t}\right\}\Big\} \tag{5.2}$$

For convenience, I reproduce Equation (4.4), i.e. the definition of the measurement error as the difference between the actual interest rate and the proxy.

$$\tilde{r}_t = r_t - \zeta_t$$

As I have shown in Section 4.3, the dynamics of $\tilde{r}_t$ are well described by a random walk with drift and there is no evidence for any AR($\cdot$) or MA($\cdot$) parts in $\Delta\tilde{r}_t$. As explained before, this justifies the assumption that during the sampling period the dynamics of both, r_t as well as ζ_t are governed by random walks with drift. I reproduce Equation (4.5) for convenience.

$$\begin{aligned} \Delta r_t &= \mu + \epsilon_t \\ \epsilon_t &\overset{iid}{\sim} N(0, \sigma_\epsilon^2) \end{aligned}$$

The dynamics of the measurement error are given below.

$$\begin{aligned} \Delta\zeta_t &= \alpha + \omega_t \\ \omega_t &\overset{iid}{\sim} N(0, \theta\sigma_\epsilon^2), \quad \theta > 0 \end{aligned} \tag{5.3}$$

Notice that for the purpose of analytical tractability I have scaled the variance of the innovations in the measurement error process by the variance of the innovations in the interest rate dynamics using the factor $\theta = E[\omega_t^2]/E[\epsilon_t^2]$. Furthermore, I assume that ϵ_t and ω_t are independent at all leads and lags.

$$E[\epsilon_t \omega_{t+k}] = 0 \tag{5.4}$$

Thereby, I follow the convention of the classical error-in-variables (CEV) problem where the measurement error is independent of the unobserved variable, but correlated with the observed proxy. Equation (4.5) allows me to derive the common prior expected value c_t.

$$\begin{aligned} r_t =& \mu + r_{t-1} + \epsilon_t \\ c_t = E\left[r_t | \mathcal{B}_{i,t-1}\right] =& \mu + r_{t-1} \end{aligned} \tag{5.5}$$

Let me now derive the uncertainty of the prior expectation, i.e. the variance of banks' prior expectational error.

$$E\left[(r_t - c_t)^2 | \mathcal{B}_{i,t-1}\right] = \sigma_\epsilon^2$$

As stated earlier, banks privately observe the signal s_{it} based on their money market operations, which I assume to be informative about r_t.

$$s_{it} = r_t + z_{it} \tag{5.6}$$

$$z_{it} \sim N(0, \kappa_i \sigma_\epsilon^2), \quad \kappa_i > 0$$

The parameter κ_i captures the inverse precision of bank i's signal relative to the prior uncertainty. The larger κ_i, the less precise is bank i's private information. I assume the noise z_{it} to be independent of its own leads and lags for a given bank and to be independent of ϵ_t as well as ω_t.

$$E[z_{it} z_{i,t+k}] = 0, \quad k \neq 0 \tag{5.7}$$

$$E[z_{it} \epsilon_{t+k}] = 0 \tag{5.8}$$

$$E[z_{it} \omega_{t+k}] = 0 \tag{5.9}$$

After privately observing the signal, banks form posterior beliefs by Bayesian updating. The bank-specific posterior mean is denoted x_{it}.

$$x_{it} = E\left[r_t | \mathcal{B}_{i,t-1}, s_{it}\right] = \frac{\kappa_i}{1+\kappa_i} c_t + \frac{1}{1+\kappa_i} s_{it} \tag{5.10}$$

Notice that despite the dispersion of posterior beliefs each bank's best estimate x_{it} is unbiased.

5.2 Reporting Quotes

Banks are requested to simultaneously publish their best estimate of r_t. The published forecast q_{it} may or may not equal a bank's actual belief. I use a framework that allows for two types of deviations from reporting truthfully. First, as the Euribor manipulation scandal has highlighted, banks may face incentives to manipulate the fixing F_t due to positions in their trading books or due to their business model. I call this type of deviation *level deviation* henceforth. Second, banks may offset their quotes towards the common prior (herding) or towards their private signal (anti-herding). This is the type of deviation from truthful reporting Bernhardt, Campello and Kutsoati (2006) uncover with their test. I call it *directional deviation* to distinguish it from level deviation. To clarify the concept, I show in Table 2 how herding and anti-herding affect the deviation of quotes from the posterior mean x_{it}. I also graphically illustrate anti-herding in Figure 9. I assume that level deviation does not change over time, i.e. a bank that is trying to move the fixing upwards is doing so all the time. In contrast, the bias introduced through directional deviation may change its sign on a daily basis, because it is determined by the signal being smaller or greater than the prior mean. However, I assume that in case a bank engages in directional deviation, it is either anti-herding everyday or herding everyday, i.e. the type of directional deviation does not change over time.

6 Testing for Directional Deviation

In this section I employ the test for analyst forecasting behavior developed by Bernhardt, Campello and Kutsoati (2006) to provide evidence for directional deviation in the Euribor quotes. The key challenge is to account for the fact that I do not directly observe the forecasted entity r_t, but rely on the proxy $\tilde{r}_t$ instead. I address the resulting problem of measurement error within the structural framework laid out in Section 5. I propose an ad-hoc function of the submitted quotes that incorporates both, level as well as directional deviation.

$$\text{when bank } i \text{ is herding} \quad q_{it} = \frac{1}{1+\lambda_i} x_{it} + \frac{\lambda_i}{1+\lambda_i} c_t + \nu_i \tag{6.1}$$

$$\text{when bank } i \text{ is anti-herding} \quad q_{it} = \frac{1}{1+\lambda_i} x_{it} + \frac{\lambda_i}{1+\lambda_i} s_{it} + \nu_i \tag{6.2}$$

Recall that x_{it} is the posterior expected value of r_t. There are three bank-specific parameters, λ_i, ν_i, and κ_i. The larger λ_i, the more bank i engages in directional deviation. The larger κ_i, the noisier is the signal bank i observes and the closer lies the posterior x_{it} to the prior c_t, all else equal. The larger ν_i in absolute value, the more bank i engages in level deviation. I consider three hypotheses. As my primary interest is in directional deviation, I make no assumptions about level deviation in any one of them. I assume that under H_0 panel bank i does not engage in directional deviation. Under H_1, panel bank i is herding and under H_2 the bank is anti-herding.

$$\begin{aligned}
&H_0: && \lambda_i = 0 && \Rightarrow q_{it} = x_{it} + \nu_i \\
&H_1: && \lambda_i > 0, \text{bank } i \text{ herding} && \Rightarrow q_{it} = \tfrac{1}{1+\lambda_i} x_{it} + \tfrac{\lambda_i}{1+\lambda_i} c_t + \nu_i \\
&H_2: && \lambda_i > 0, \text{bank } i \text{ anti-herding} && \Rightarrow q_{it} = \tfrac{1}{1+\lambda_i} x_{it} + \tfrac{\lambda_i}{1+\lambda_i} s_{it} + \nu_i
\end{aligned} \tag{6.3}$$

6.1 Construction and Estimation of the Test Statistic

I suggest a transformation of the quotes that will allow me to perform the test of Bernhardt, Campello and Kutsoati (2006) despite the presence of non-stationary measurement error. My general approach to investigating directional deviation is to calculate the BCK statistic S for distinct groups and then to perform a cross-group comparison. As an example, I ask whether banks with a higher balance sheet volume engage more in directional deviation than banks with a smaller balance sheet volume. To answer the question, I assign each bank either to the large volume group or to the small volume group, calculate the S statistic for each group and then test the null hypothesis that S is equal in both groups. More formally, I define M disjunct groups $\mathcal{G}_m, m = 1, \ldots, M$ whose elements are banks i. To calculate the test statistic S_m for each group, I follow Bernhardt, Campello and Kutsoati (2006, p.663) and determine two conditioning indicators $\gamma_{it}^+, \gamma_{it}^-$ as well as two overshooting indicators $\delta_{it}^+, \delta_{it}^-$.

$$\begin{aligned}
\gamma_{it}^+ &= 1 && \Leftrightarrow \Delta\tilde{r}_{t-1} - \Delta q_{it} > 0, && \gamma_{it}^+ = 0 \quad \text{otherwise} \\
\gamma_{it}^- &= 1 && \Leftrightarrow \Delta\tilde{r}_{t-1} - \Delta q_{it} < 0, && \gamma_{it}^- = 0 \quad \text{otherwise} \\
\delta_{it}^+ &= 1 && \Leftrightarrow \gamma_{it}^+ = 1, \Delta\tilde{r}_t - \Delta q_{it} > 0, && \delta_{it}^+ = 0 \quad \text{otherwise} \\
\delta_{it}^- &= 1 && \Leftrightarrow \gamma_{it}^- = 1, \Delta\tilde{r}_t - \Delta q_{it} < 0, && \delta_{it}^- = 0 \quad \text{otherwise}
\end{aligned} \tag{6.4}$$

The sample estimate of S_m is defined as follows.

$$\hat{S}_m = \frac{1}{2}\left(\frac{\sum_{(i,t)\in\mathcal{G}_m} \delta_{it}^-}{\sum_{(i,t)\in\mathcal{G}_m} \gamma_{it}^-} + \frac{\sum_{(i,t)\in\mathcal{G}_m} \delta_{it}^+}{\sum_{(i,t)\in\mathcal{G}_m} \gamma_{it}^+}\right) \tag{6.5}$$

When there is no directional deviation, i.e. H_0 holds true, $S_m = \frac{1}{2}$. When banks are herding $S_m < \frac{1}{2}$ and when banks are anti-herding $S_m > \frac{1}{2}$. I summarize the intuition behind the test statistic in Appendix A.1 and in Appendix A.2 I present a formal proof that using the transformations given in Equation (6.4) S_m is unbiased despite the presence of measurement error. Under the null hypothesis of no directional deviation S_m is asymptotically normal with mean $\frac{1}{2}$. Therefore, a standard mean comparison test can be used to test the null hypothesis of equal directional deviation in two groups. The variance of S_m is bounded from above by the following term.

$$Var(S_m) \leq \frac{1}{16}\left(\frac{1}{\sum_{(i,t)\in\mathcal{G}_m}\gamma_{it}^{-}} + \frac{1}{\sum_{(i,t)\in\mathcal{G}_m}\gamma_{it}^{+}}\right) \tag{6.6}$$

As Bernhardt, Campello and Kutsoati (2006, p.664) point out, the key feature driving the robustness of the test statistic is that the variance of S_m is maximized *when measurement error is not present.* Therefore, using Equation (6.6) for testing the null hypothesis of no directional deviation may increase the probability of Type II error. Falsely failing to reject the null hypothesis is more likely when measurement error is present. However, this is a minor concern in comparison with Type I errors, i.e. falsely rejecting the null hypothesis. As I compute the conditioning and overshooting indicators in Equation (6.4) based on first differences of $\tilde{r}_t$ and q_{it}, the two series $\{\delta_{i,1}^{+}, \ldots, \delta_{i,T}^{+}\}$ and $\{\delta_{i,1}^{-}, \ldots, \delta_{i,T}^{-}\}$ do not fulfill the *iid* property. Observations are autocorrelated with their first leads and lags by construction. I elaborate on this issue in the last paragraph of Appendix A.2 and I address it by selecting a random subsample, where no adjacent observations are present. Thereby, I retain an estimation sample of $10,092$ observations with a gap of at least one business day for a given bank.

Next, I discuss the choice of groups $\mathcal{G}_m$. I collect balance sheet information on the banks in the Euribor panel from the SNL Financial database. As no matching table is available, I hand-match the data. The reporting frequency is annual. I collect data on net net interest income, net fee and commission income, total assets, total liabilities, total equity, central bank reserves, and on long-term credit ratings of the three major credit rating agencies. Furthermore, I collect the country where the bank is headquartered and whether it is listed or not. From these raw data I construct the following characteristics. Fee income share, balance sheet volume measured by total assets, leverage ratio, reserve ratio as measured by central bank reserves to total assets, location in the European periphery, and average creditworthiness. As I noted in Section 2, Ottaviani and Sorensen (2006) present a model of a forecasting contest that leads to predictions compatible with anti-herding. The test based on the whole sample provides evidence in favor of this behavior. When banks differ in the extent of anti-herding along anyone of the groups implied by a median-split of the characteristics listed, this may provide further evidence of the precise nature of such a contest.

6.2 Results of S tests

In this subsection I present and discuss the estimation results for S_m. Throughout this section I calculate the S statistic as defined by Equation (6.5) and I use the asymptotic variance from Equation (6.6) for confidence intervals and mean comparison tests. The estimation results are presented in Table 5. I begin with a test for directional deviation based on the whole sample. Overall, banks engage in anti-herding. The point estimate of the probability of $\gamma_{it}^{-} = 1$, i.e. the quote falling short of the prior, is 50%. However, conditional on that event the probability of the quote falling short of the proxy, i.e. $\delta_{it}^{-} = 1$, is 57%. Likewise, the conditional probability of the quote exceeding the proxy is 61%. This gives a point estimate for the S statistic of 59%. The null hypothesis of no directional deviation, i.e. $S = 50\%$, is rejected at the 1% significance level in favor of anti-herding.

[Table 5 about here.]

The two-sample comparisons of the group-based S-statistic reveal that anti-herding is more pronounced at larger banks in terms of total assets and at banks with a higher fee income share. For balance sheet volume the difference in the test statistic over the two groups is 2 percentage points and this difference is statistically significant at the 5% level. For fee income share, the difference between the two groups is 1.75 percentage points and the difference is statistically significant at the 10% level. For all other tested groups the point estimate of S is close to the sample mean of 59% and the difference is statistically insignificant.

Next, I perform the test for directional deviation at the bank level. The results are presented in Table 6.

[Table 6 about here.]

The point estimate of the test statistic is larger than 50% for all the banks. However, it is statistically significantly different thereof in only 21 out of 45 cases at the 1% level. The range of the test statistic is 14 percentage points and the standard deviation across banks is 3.1 percent. See Table 7 for summary statistics on the distribution of S_i at the bank level.

[Table 7 about here.]

7 Conclusion

In this paper I analyze panel banks' submission to the Euribor survey. Exploiting the definition of the Euribor as the rate at which two abstract prime banks lend to each other, I interpret survey contributions as forecasts of the true rate. The major contribution of this paper is the development of a proxy for said rate based on CDS spreads. This allows me to employ the test by Bernhardt, Campello and Kutsoati (2006) for (anti-)herding in analysts' forecasts. Using data on the period leading up to the August 2007 financial crisis, I find evidence in favor of anti-herding. This evidence prevails both, based on the whole sample as well as at the individual bank level. Ottaviani and Sorensen (2006) develop a model of a financial contest that is consistent with anti-herding among forecasters. One of their model implications is that forecasts are more dispersed than under truthful reporting when agents are anti-herding. Furthermore, a benchmark's fixing may become more volatile than the underlying rate it is supposed to track when panelists anti-herd. With regard to the ongoing debate on how to reform the family of IBOR benchmark rates, my results strengthen the cause for transactions-based rate setting processes.

A Keep in Final Version: Adjusted Quotes for the BCK-statistic

A.1 The Intuition behind the BCK Statistic

In this subsection I briefly summarize the intuition behind the herding test developed by Bernhardt, Campello and Kutsoati (2006). I establish the necessary conditions for the consistency of the test. Subsequently, I demonstrate that when using the adjusted quotes as stated in Equation (6.4) these conditions are met in the application to the EURIBOR quotes.

Let me begin with a simplified model where I ignore the lack of observability and the resulting measurement error. Assume the series r_t, c_t, q_{it} are observable. The bank-specific posterior mean x_{it} is unobservable.

$$r_t = x_{it} + \eta_{it}$$

The bank-specific forecasting error η_{it} has a zero mean, both unconditionally as well as conditional on any entity in the bank's information set.

$$E[\eta_{it}|\mathcal{B}_{i,t-1}, s_{it}] = 0$$
$$\Rightarrow E[\eta_{it}] = 0$$

Moreover, η_{it} is distributed symmetrically such that its mean equals its median. For this subsection I ignore level deviation. As before, I consider the null hypothesis that banks report without bias, the first alternative hypothesis that banks are herding and the second alternative hypothesis that banks are anti-herding.

$$H_0: \quad q_{it} = x_{it}$$
$$H_1: \quad q_{it} = \frac{1}{1+\lambda_i} x_{it} + \frac{\lambda_i}{1+\lambda_i} c_t$$
$$H_2: \quad q_{it} = \frac{1}{1+\lambda_i} x_{it} + \frac{\lambda_i}{1+\lambda_i} s_{it}$$

This resembles the standard case considered by Bernhardt, Campello and Kutsoati (2006). The appropriate test statistic in terms of population moments is given as follows.

$$S = \frac{1}{2} \left(Pr[r_t < q_{it} | c_t < q_{it}] + Pr[r_t > q_{it} | c_t > q_{it}] \right)$$

When banks report truthfully $S = \frac{1}{2}$, when banks are herding $S < \frac{1}{2}$, and when banks are anti-herding $S > \frac{1}{2}$. To see why that is, I consider the summand $Pr[r_t < q_{it}|c_t < q_{it}]$ in isolation. Under the null hypothesis I find the following.

$$r_t < q_{it} \Leftrightarrow \eta_{it} < 0$$

As stated before, η_{it} is symmetrically distributed around zero, both conditionally as well as unconditionally. Hence, $Pr[r_t < q_{it}|c_t < q_{it}] = \frac{1}{2}$ when banks report truthfully. Now I consider the same term under the alternative hypothesis that banks are herding.

$$r_t < q_{it} \Leftrightarrow \eta_{it} < \frac{\lambda_i}{1+\lambda_i}(c_t - x_{it})$$

Notice the relation of the term $\frac{\lambda_i}{1+\lambda_i}(c_t - x_{it})$ with the conditioning event under the assumption of herding.

$$c_t < q_{it} \Leftrightarrow \frac{\lambda_i}{1+\lambda_i}(c_t - x_{it}) < 0$$

Hence, under herding $Pr[r_t < q_{it}|c_t < q_{it}] < \frac{1}{2}$ and likewise $Pr[r_t > q_{it}|c_t > q_{it}] < \frac{1}{2}$. One of the major advantages of the herding test developed by Bernhardt, Campello and Kutsoati (2006) is its robustness towards several disruptive factors, among them measurement error as well as cross-sectional correlation of forecasting errors. In the remainder of this subsection I demonstrate this robustness using a simplified example. As in the main text, I assume the observed interest rate is prone to measurement error ζ_t. However, for the moment I maintain the assumption that c_t is observable. Hence, $\tilde{r}_t = x_{it} + \eta_{it} - \zeta_t$. Let $H(\cdot)$ denote the cdf of η_{it}. Under the null hypothesis of truthful reporting I find $\tilde{r}_t < q_{it} \Leftrightarrow \eta_{it} < \zeta_t$. Provided that $p(\zeta_t|c_t < q_{it}) = p(\zeta_t|c_t > q_{it})$, the two summands in the test statistic cancel out the disturbance through the measurement error.

$$\begin{aligned} S =& \frac{1}{2}\left(Pr[\tilde{r}_t < q_{it}|c_t < q_{it}] + Pr[\tilde{r}_t > q_{it}|c_t > q_{it}]\right) \\ =& \frac{1}{2}\left(H(\zeta_t) + 1 - H(\zeta_t)\right) = \frac{1}{2} \end{aligned}$$

The simplified examples presented above demonstrate the two necessary conditions for the test statistic to robustly detect directional deviation despite the presence of measurement error. Using the generic events A and B for the first summand $Pr(A|B)$, these two conditions are the following.

1. Under the null hypothesis of truthful reporting the event A must occur with probability $\frac{1}{2}$ conditional on any event B in the bank's information set.

2. When the forecasted entity is observed with error, the measurement error must have the same conditional distribution given any observable event B.

(Bernhardt, Campello and Kutsoati, 2006, p.664) demonstrate that if these conditions are fulfilled, the presence of measurement error reduces the variance of S. Therefore, measurement error may increase the probability of Type II errors, i.e. I may falsely fail to reject the null hypothesis. In the next subsection I demonstrate that my choice for A and B meet the two requirements above in the face of measurement error as introduced in Section 5.

A.2 Accounting for Measurement Error

I reproduce those features of the framework laid out in Section 5.1 that are essential for my proof. The common prior mean is given by $c_t = \mu + r_{t-1} = r_t - \epsilon_t$ and the private signal is defined as $s_{it} = r_t + z_{it}$. The posterior mean is given by $x_{it} = \frac{\kappa_i}{1+\kappa_i} c_t + \frac{1}{1+\kappa_i} s_{it}$. The following two equations are easily verified: $\Delta c_t - \Delta x_{it} = \frac{1}{1+\kappa_i}(\Delta c_t - \Delta s_{it})$ and $\Delta s_{it} - \Delta x_{it} = \frac{\kappa_i}{1+\kappa_i}(\Delta s_{it} - \Delta c_t)$. I find the following expression for the posterior expectational error $\eta_{it} = x_{it} - r_t$.

$$\eta_{it} = \frac{\kappa_i}{1+\kappa_i}\epsilon_t - \frac{1}{1+\kappa_i} z_{it} \tag{A.1}$$

As ϵ_t and z_{it} are assumed to be normally distributed and independent of each other at all leads and lags, the first differences of η_{it} follow a normal distribution as well.

$$\Delta\eta_{it} \sim N\left(0, \quad 2\frac{\kappa_i}{1+\kappa_i}\sigma_\epsilon^2\right)$$

Let me now show that the two requirements listed in Appendix A.1 are indeed fulfilled by my choice of events given in Equation (6.4). I begin with the first requirement. Recall the general definition of quotes under level and directional deviation given in Equation (6.3) and consider the null hypothesis (no directional deviation, arbitrary level deviation).

$$\Delta\tilde{r}_t - \Delta q_{it} < 0 \Leftrightarrow \Delta r_t - \Delta x_{it} < \Delta\zeta_t \tag{A.2}$$

I have assumed that $\Delta\zeta_t = \alpha + \omega_t$ and presented empirical evidence in favor of that assumption in Section 4.3. As $\Delta r_t - \Delta x_{it} = \Delta\eta_{it}$, the LHS of the above inequality is symmetrically distributed around zero conditional on any event in the information set of bank i. Let $G(\cdot)$ denote the cdf of $\Delta\eta_{it}$. For the first requirement to be fulfilled the following expression needs to hold true under H_0.

$$\begin{aligned}&\frac{1}{2}\left(Pr\left[\Delta\eta_{it} < \alpha + \omega_t \middle| \Delta\tilde{r}_{t-1} - \Delta q_{it} < 0\right] + Pr\left[\Delta\eta_{it} > \alpha + \omega_t \middle| \Delta\tilde{r}_{t-1} - \Delta q_{it} > 0\right]\right)\\ =&\frac{1}{2}\left[G(\alpha + \omega_t) + 1 - G(\alpha + \omega_t)\right] = \frac{1}{2}\end{aligned}$$

The test statistic is robust to measurement error when the distribution of ω_t is the same under both conditioning events. To see that this is indeed the case consider the conditioning event in the first summand and note that $\Delta r_{t-1} = \Delta c_t$.

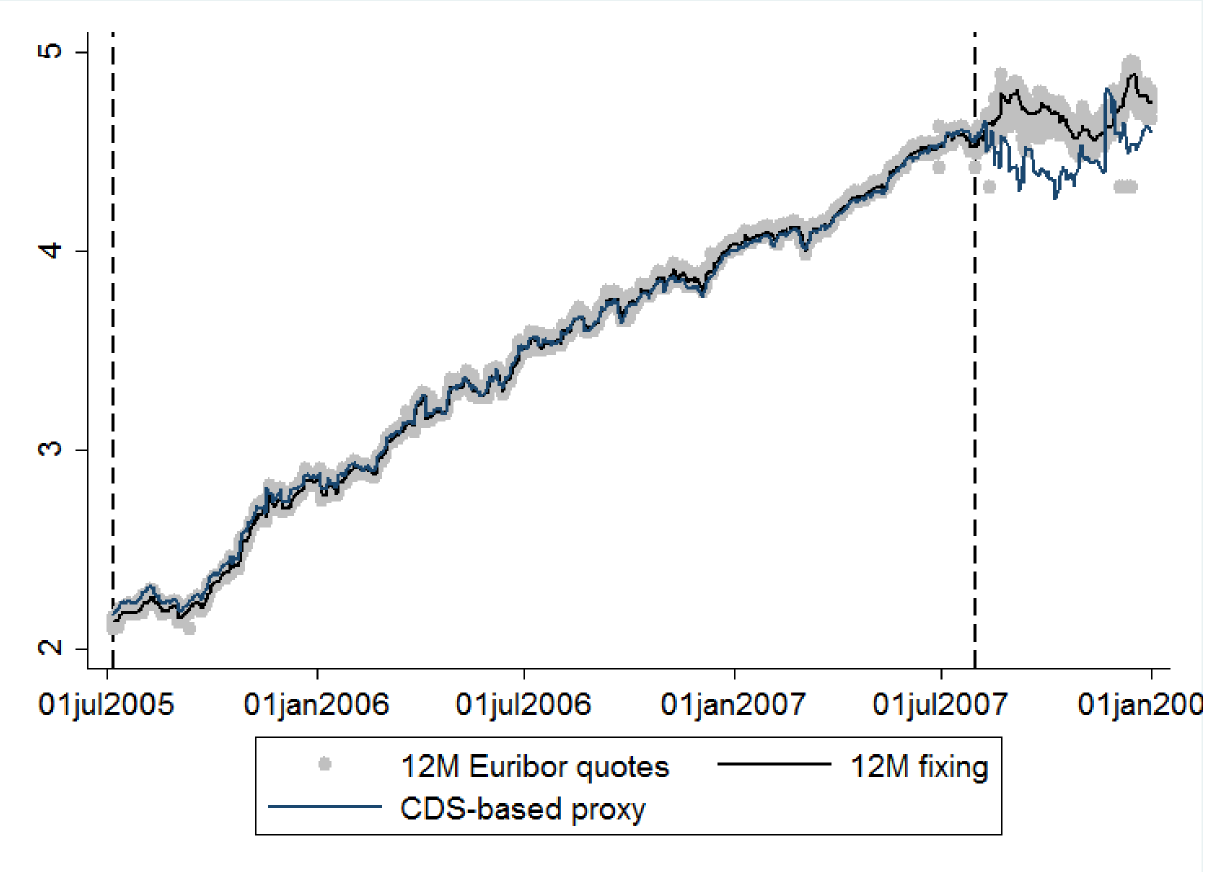
$$\begin{aligned} \Delta \tilde{r}_{t-1} - \Delta q_{it} &< 0 \\ \Leftrightarrow \Delta c_t - \Delta x_{it} &< \Delta \zeta_{t-1} \\ \Leftrightarrow \frac{1}{1+\kappa_i} \left[\Delta c_t - \Delta s_{it} \right] &< \alpha + \omega_{t-1} \\ \Leftrightarrow \frac{1}{1+\kappa_i} \left[\Delta z_{it} - \Delta \epsilon_t \right] &< \alpha + \omega_{t-1} \end{aligned}$$

This shows that the distribution of ω_t is indeed the same under both conditioning events, because ω_t - the innovation process in the measurement error - is independent of ϵ_t, z_{it}, and of its own leads and lags. The latter property is a direct consequence of the ARIMA(0,1,0) structure of ζ_t established in Section 4.3. Hence, both requirements listed in Appendix A.1 are met. Accordingly, under the null hypothesis of no directional deviation, $S = \frac{1}{2}$ despite the presence of measurement error.

Another issue for the estimation of S arises from the fact that I use first differences to account for non-stationarity. Provided there is an *iid* sample, the cdf of $\Delta \eta_{it}$, $G(\cdot)$, can be estimated using arithmetic averages of indicator functions as in Equation (6.4). However, $\Delta \eta_{it}$ is correlated with its first lead and lag by construction: $E[\Delta \eta_{it} \Delta \eta_{i,t+1}] = -\frac{\kappa_i}{1+\kappa_i} \sigma_\epsilon^2$. Therefore, estimating $G(\cdot)$ based on the whole sample does not fulfill the *iid* requirement. I address this issue by restricting the estimation sample to a random subsample where no two adjacent trading days are present. Specifically, I devise an algorithm that starts with the whole sample and picks a random day drawing from the uniform distribution. This day is marked as admissible for the estimation sample and the previous and the next day are marked as not admissible. The remaining days are passed to the next iteration and another day is picked at random for the estimation sample, etc.

B Figures and Tables for the Main Text

Figure 1: Quotes, Euribor Fixing, and the CDS-based Proxy



This figure shows the quotes and the fixing of the 12-month EUR Euribor rate as well as the proxy based on CDS contracts with one year to maturity. The grey area represents the range of submitted quotes on a given day, the solid black line is the Euribor fixing and the solid blue line is the proxy. The dashed vertical lines indicate the sampling period used in the subsequent analysis - July 2005 until July 2007.

Table 1: Descriptive Statistics on Raw Quotes

total observations	24,514
missing quotes	
– total	242
– average per bank	5
– max. per bank	25
daily range[1] (in bps)	
– average	4.27
– min.	2
– max.	20
– bottom 10% $\leq$	3
– top 10% $>$	6
deviation from fixing[2]	
– within standard deviation (bps)	0.79
– between standard deviation (bps)	0.47
– share of variance due to between variation (%)	26.40

[1] The daily range is defined as $\max_i\{q_{it}\} - \min_i\{q_{it}\}$.
[2] The deviation from fixing is defined as $d_{it} = q_{it} - F_t$.

Figure 2: Number of Reporting Banks

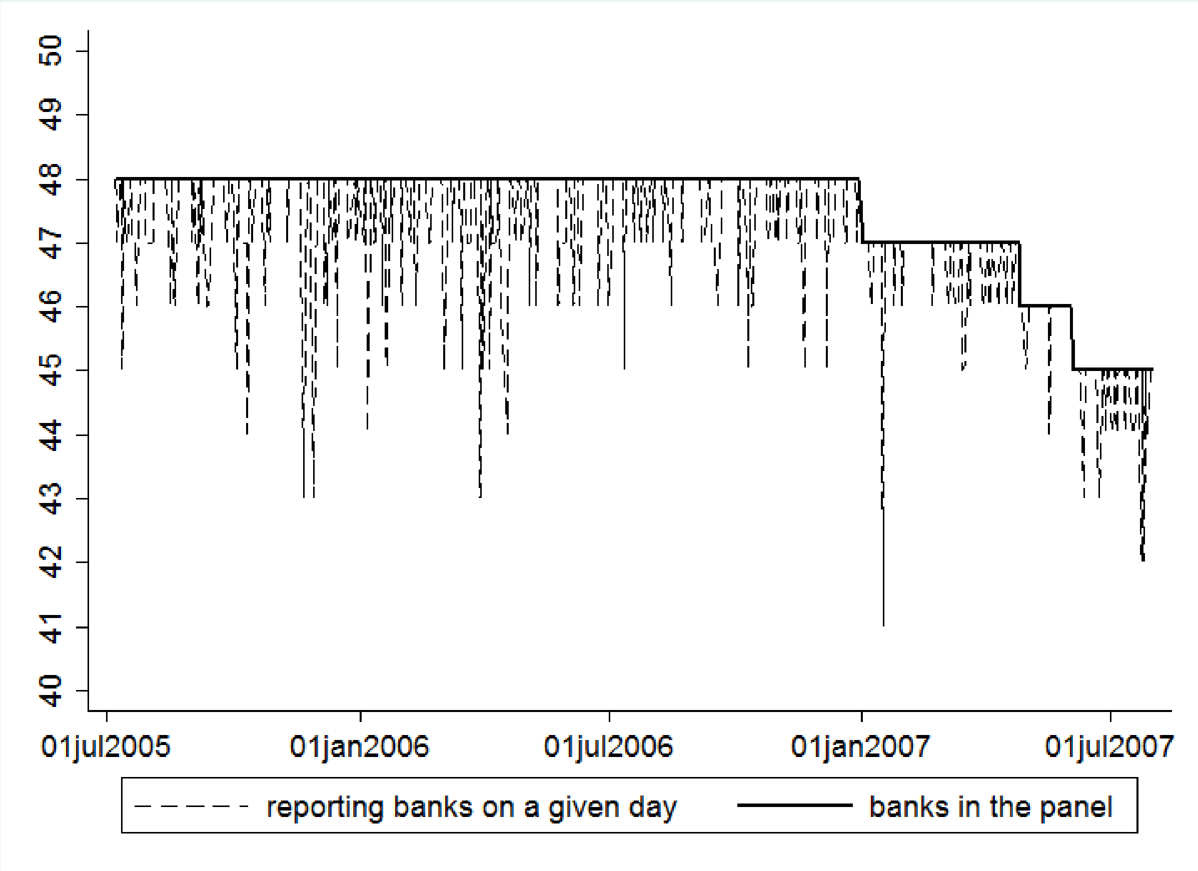


Table 2: Herding and Anti-herding

	$x_{it} < c_t$	$x_{it} > c_t$
Herding	$q_{it} > x_{it}$	$q_{it} < x_{it}$
Anti-herding	$q_{it} < x_{it}$	$q_{it} > x_{it}$

Figure 3: Quotes, Fixing and Fat Finger Errors

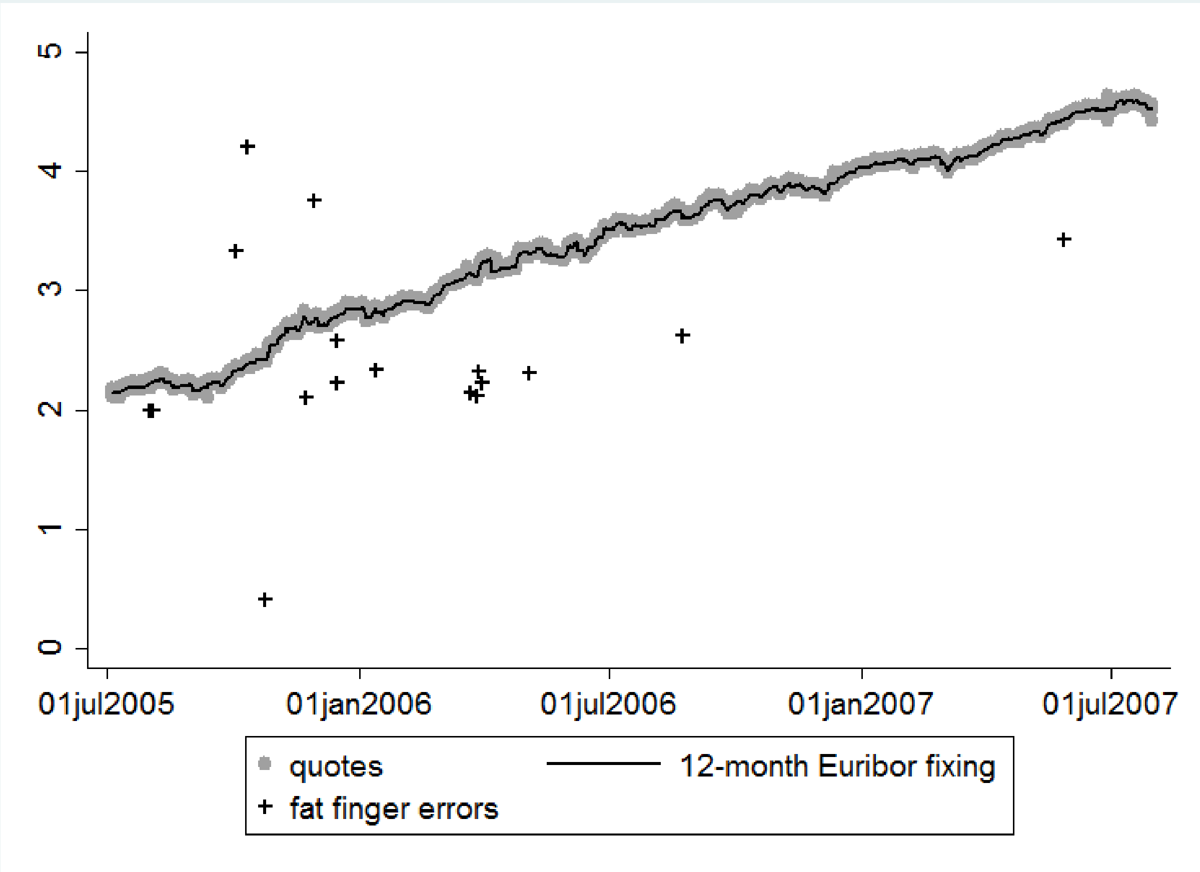
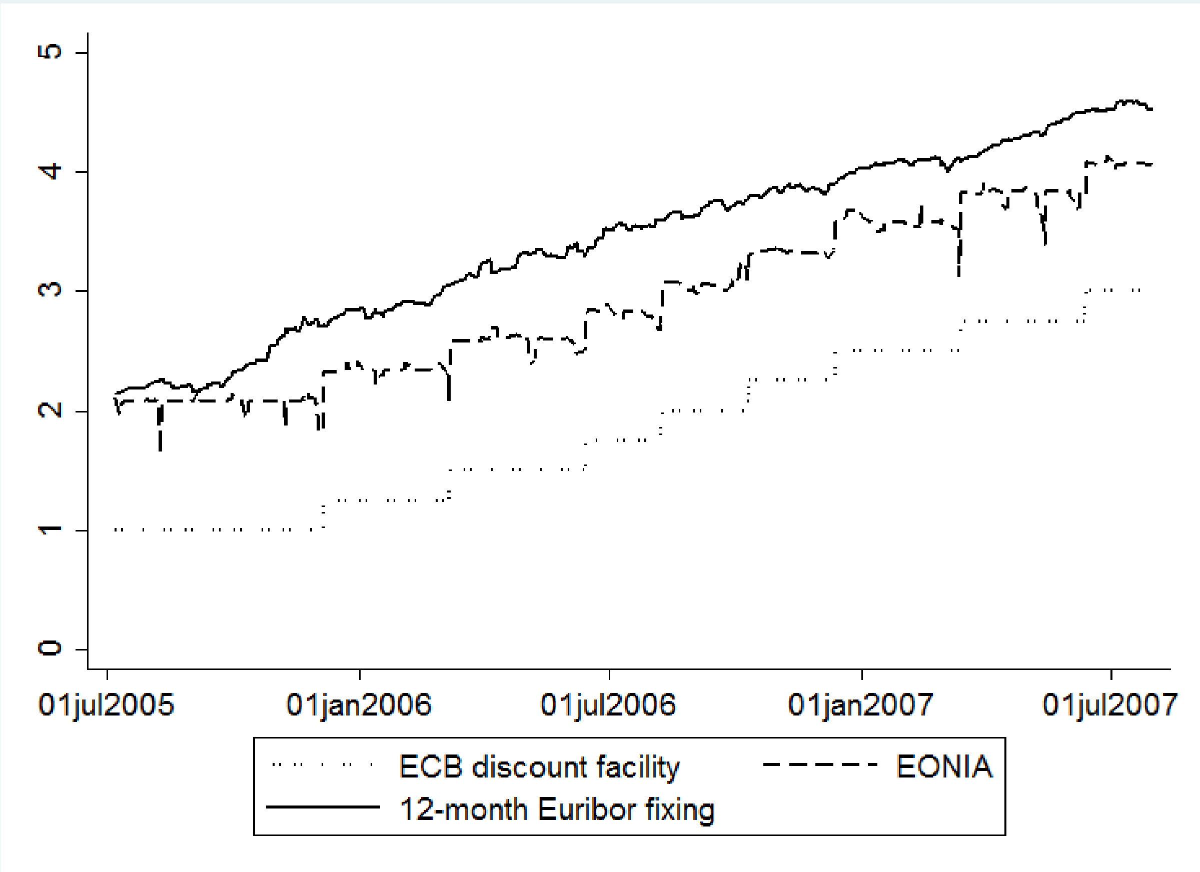


Figure 4: ECB monetary policy and the Euribor fixing



ECB Discount Facility, EONIA, and twelve-month Euribor fixing.

Figure 5: Difference between Fixing and Proxy

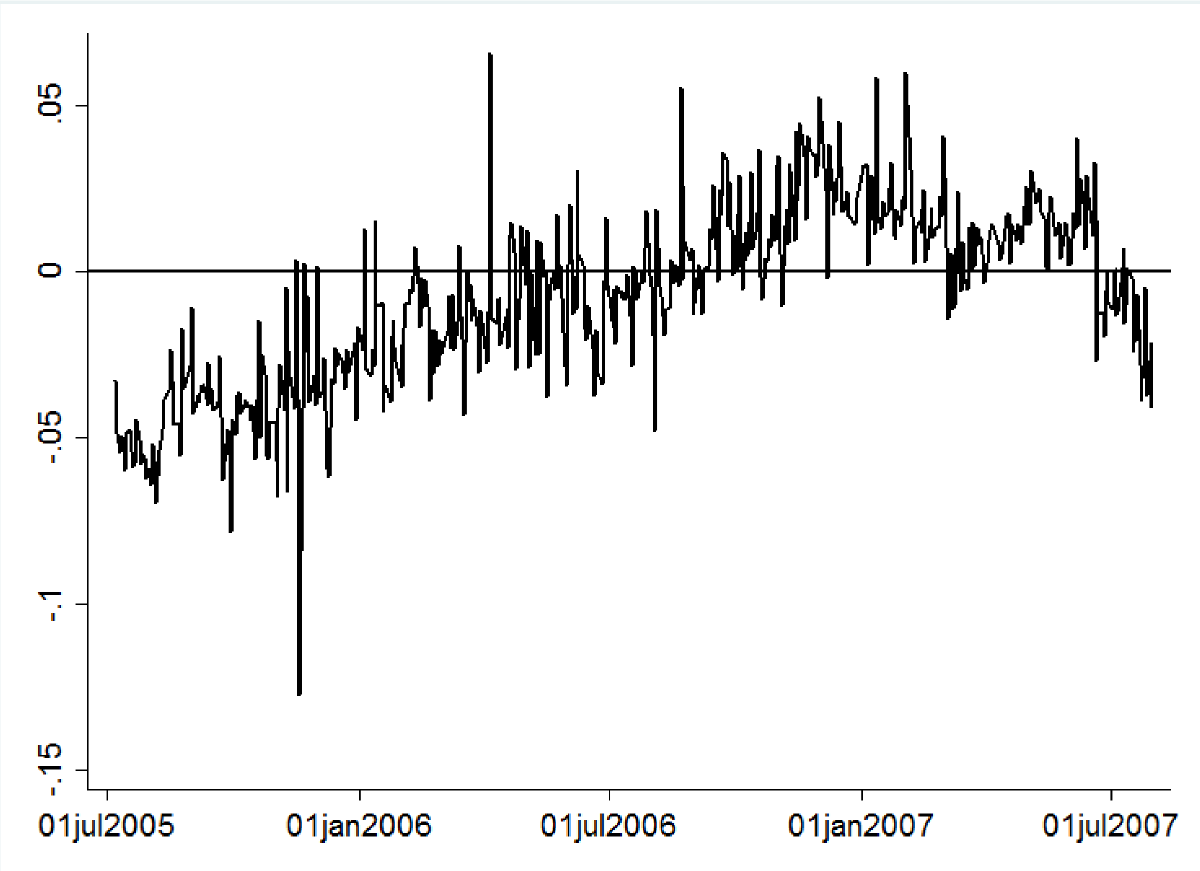


Figure 6: Difference between Fixing and Proxy as of August 2007

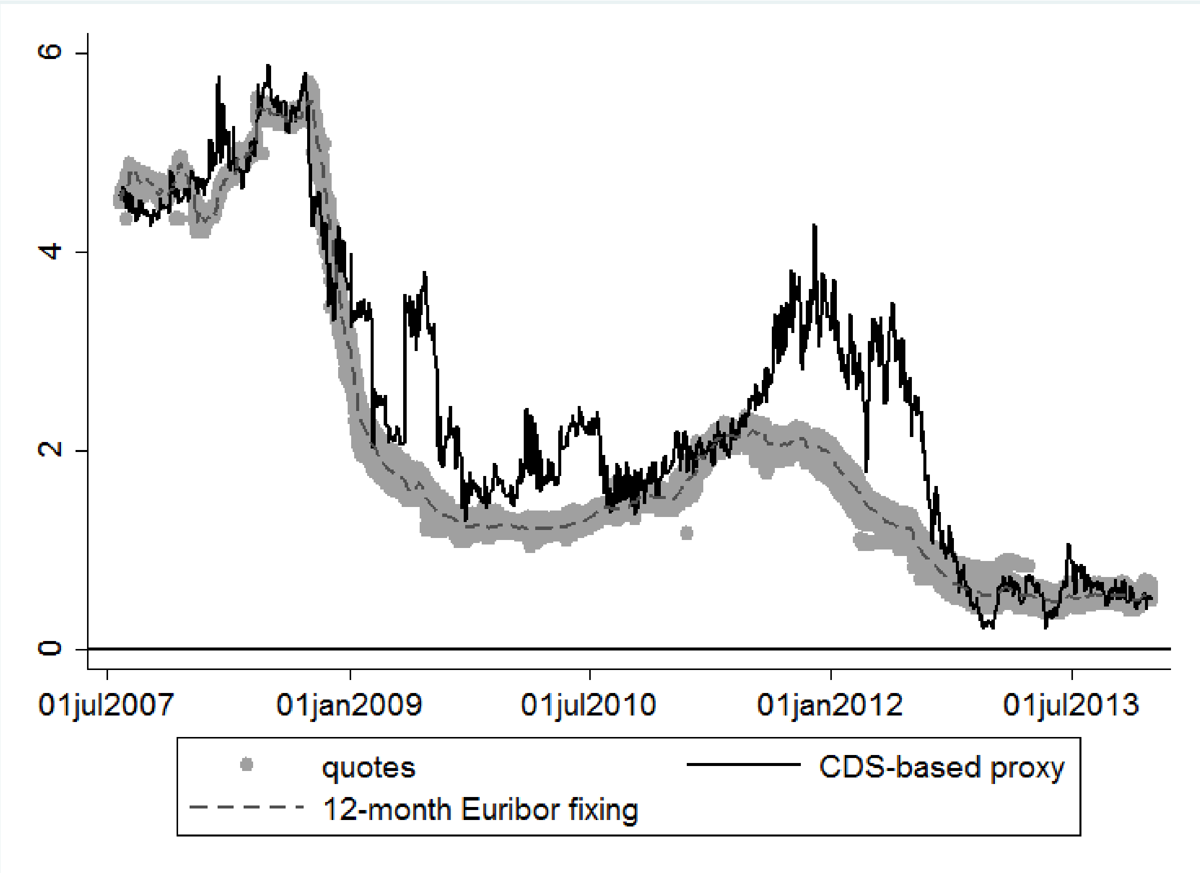


Figure 7: Autocorrelation Function of the Proxy

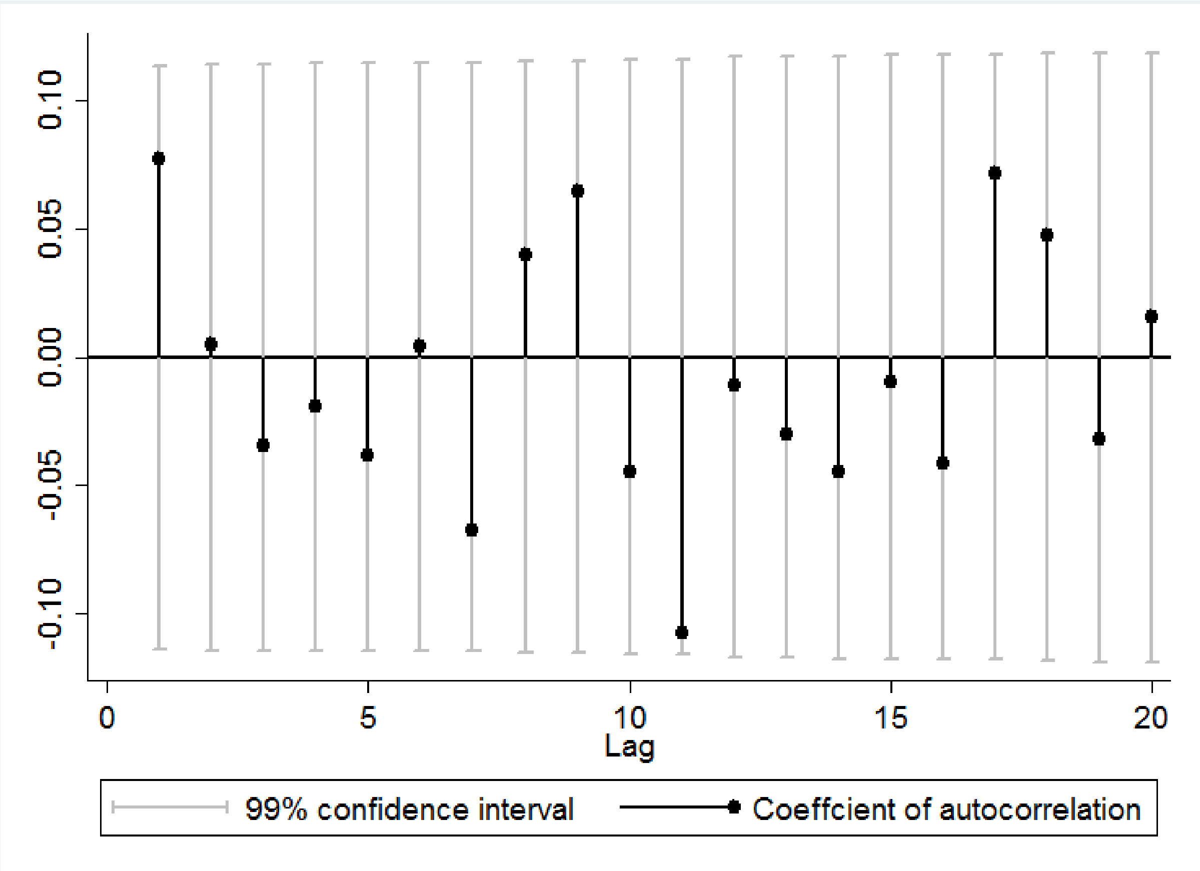


Figure 8: Partial Autocorrelation Function of the Proxy

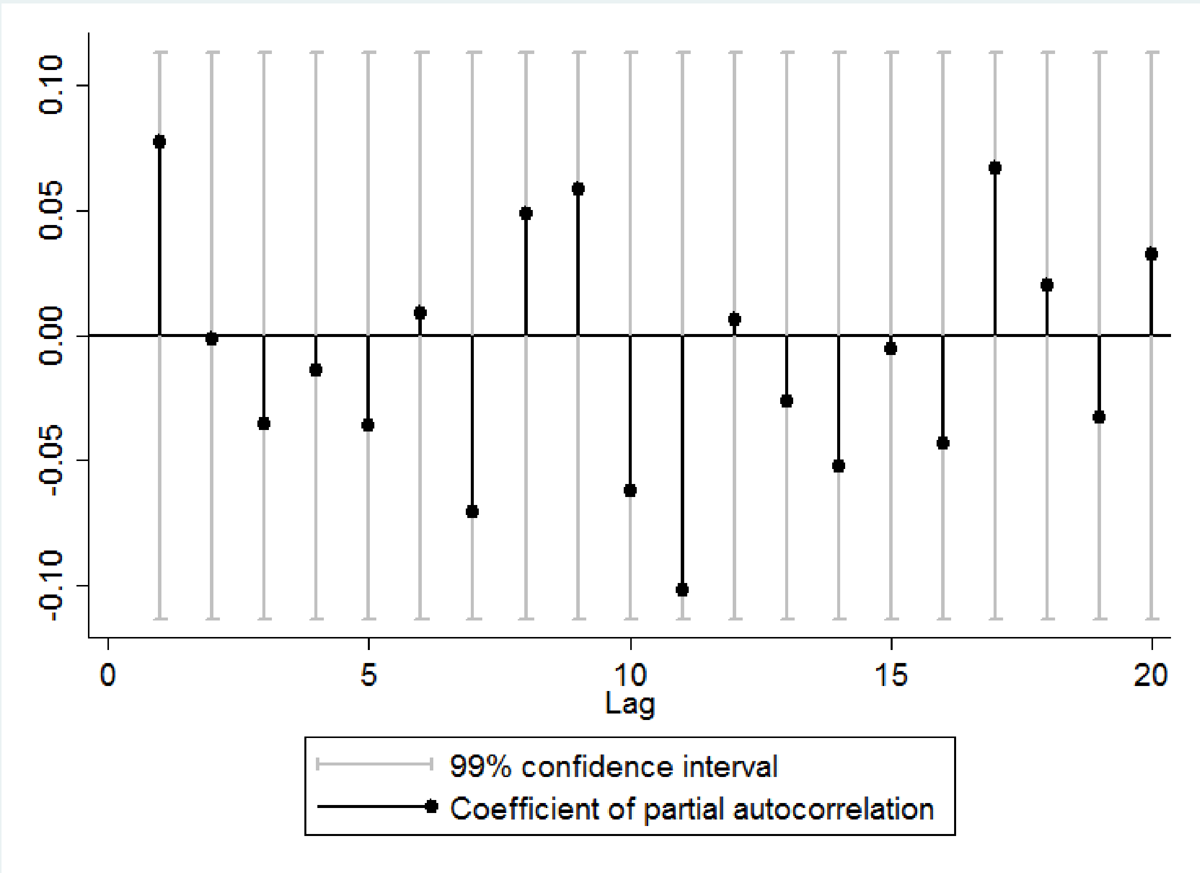
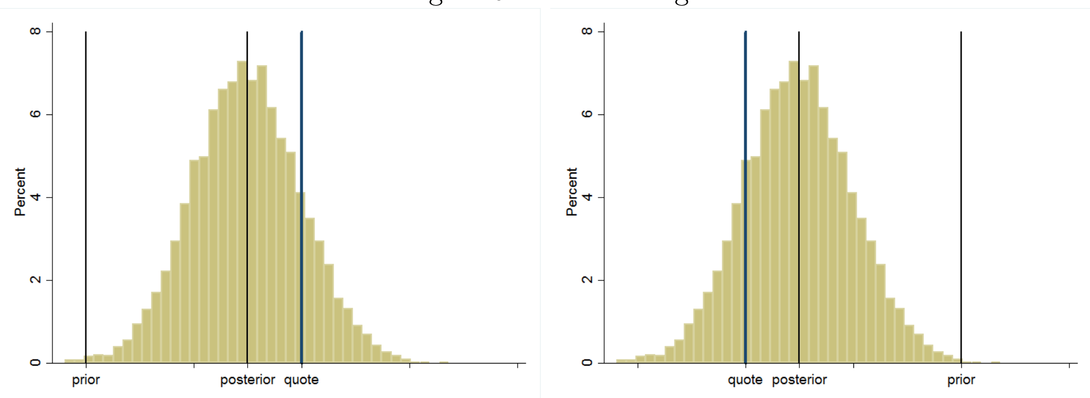


Figure 9: Anti-herding



Posterior distribution of the forecasting target - the interest rate r_t. Both panels illustrate anti-herding as defined by Bernhardt, Campello and Kutsoati (2006). Below, the prior is denoted by c_t, the posterior by x_{it}, and the quote by q_{it}.

Left panel: "up-signal": $c_t < x_{it}$, $\quad Pr[r_t < q_{it} | c_t < q_{it}] > 1/2$

Right panel: "down-signal": $c_t > x_{it}$, $\quad Pr[r_t > q_{it} | c_t > q_{it}] > 1/2$

Table 3: Unit-root and Stationarity Tests on the CDS-based Proxy

	Stationarity Test	Augmented Dickey-Fuller Test	Modified Dickey-Fuller Test	
Lags included	Test Statistic	Test Statistic	Test Statistic	10% critical value
18	0.447	-0.762	-1.957	-2.537
17	0.469	-0.759	-1.911	-2.541
16	0.492	-0.834	-1.780	-2.544
15	0.519	-0.848	-1.857	-2.547
14	0.549	-0.868	-1.866	-2.551
13	0.583	-0.825	-1.966	-2.554
12	0.623	-0.847	-2.014	-2.557
11	0.669	-0.845	-1.995	-2.560
10	0.724	-0.772	-2.211	-2.563
9	0.790	-0.713	-2.340	-2.566
8	0.870	-0.711	-2.190	-2.569
7	0.970	-0.759	-2.072	-2.572
6	1.100	-0.701	-2.221	-2.575
5	1.270	-0.699	-2.183	-2.578
4	1.510	-0.72	-2.253	-2.580
3	1.870	-0.751	-2.281	-2.583
2	2.470	-0.750	-2.359	-2.585
1	3.670	-0.804	-2.349	-2.588
0	7.250	-0.867		

This table presents the test statistics from one stationarity test and two unit root tests on the CDS-based proxy $\tilde{r}_t$ introduced in Section 4. The maximum lag length is chosen according to the criterion proposed by Schwert (1989). The stationarity test conducted is the test by Kwiatkowski et al. (1992). The test is performed using the *kpss* Stata package courtesy of Baum (2000). The null hypothesis for the stationarity test is that $\tilde{r}_t$ is trend stationary. The 1% critical value for the test is 0.216. The table makes evident that the null hypothesis is rejected at the 1% level of significance in all specifications. The unit root test labeled "augmented Dickey-Fuller test" is the test by Dickey and Fuller (1979). The null hypothesis of the test is that $\tilde{r}_t$ has a unit root and the 10% critical value is -1.283 for all specifications. The unit root test labeled "modified Dickey-Fuller test" is the test by Elliott, Rothenberg and Stock (1996). The null hypothesis is the same as in the augmented Dickey-Fuller test and the 10% critical value is displayed in a separate column. For both unit root tests the null hypothesis cannot be rejected at the 10% level of significance in any one of the 18 specifications. Together the three tests present strong evidence in favor of the hypothesis that $\tilde{r}_t$ is $I(1)$.

Table 4: ARIMA(p,1,q) Model Comparison for the Proxy

	I	II	III	IV
Model type	ARIMA(0,1,0)	ARIMA(0,1,1)	ARIMA(1,1,0)	ARIMA(1,1,1)
γ	0.005***	0.005***	0.005***	0.005***
	(0.0008)	(0.0009)	(0.0009)	(0.0009)
ϕ			0.078**	0.067
			(0.0380)	(0.5834)
ψ		0.077**		0.010
		(0.0380)		(0.5836)
σ_u	0.018***	0.018***	0.018***	0.018***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
$\ln(\hat{L})$	1,327.535	1,329.069	1,329.082	1,329.082
df	2	3	3	4
BIC	-2,642.582	-2,639.406	-2,639.432	-2,633.188

This table presents regression results for four ARIMA(p,1,q) models of the proxy rate $\tilde{r}_t$. The sample size equals $T = 515$ for all four models. The unrestricted regression equation is given by Equation (4.6) in the main text. Standard errors are given in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Whereas the MA(1) and AR(1) coefficients in columns II and III, respectively, are significantly greater than zero, the Bayesian Information Criterion favors the more parsimonious ARIMA(0,1,0) model of column I.

Table 5: Estimation Results for S_m

	N	$\Pr(\gamma_{it}^{-} = 1)$	$\Pr(\delta_{it}^{-} = 1)$	$\Pr(\delta_{it}^{+} = 1)$	S_m	99% CI	z	p-value
Whole sample	10,092	50.18	57.03	60.80	**58.91**	[57.94, 59.89]		
Balance sheet								
small	4,052	49.80	55.85	60.42	**58.14**	[56.60, 59.67]	-2.076	3.79
large	4,174	50.12	59.13	61.72	**60.42**	[58.91, 61.94]		
Fee income share								
low	3,923	49.78	56.12	60.56	**58.34**	[56.77, 59.90]	-1.746	8.09
high	3,832	50.55	59.11	61.53	**60.32**	[58.74, 61.90]		
Leverage								
low	4,025	50.10	57.43	60.93	**59.18**	[57.64, 60.73]	-0.330	74.15
high	4,151	49.82	57.74	61.35	**59.55**	[58.20, 61.70]		
Creditworthiness								
low	3,058	49.48	57.70	60.32	**59.10**	[57.24, 60.78]	-0.455	64.89
high	3,508	49.91	57.74	61.41	**59.57**	[57.92, 61.23]		
Reserve ratio								
low	3,916	50.89	57.85	60.58	**59.22**	[57.65, 60.78]	-0.151	88.03
high	3,893	49.34	57.37	61.41	**59.39**	[57.82, 60.96]		
European Periphery								
no	7,401	49.79	56.88	61.14	**59.10**	[57.87, 60.15]	-0.203	83.89
yes	2,147	51.14	58.65	59.87	**59.26**	[57.14, 61.37]		
Listed								
no	4,153	50.40	55.71	60.78	**58.24**	[56.72, 59.76]	-1.339	18.06
yes	5,510	50.00	58.11	61.13	**59.62**	[58.30, 60.94]		

This table shows the S statistic for different groups as defined by Equation (6.5).

Table 6: Ranking of Banks by S_i

Rank	ID	N	S_i	99% CI		se	at most equal to this rank given a significance level of 10%	5%	1%
1	46	214	**53.44**	[44.61	62.27]	3.43	29	39	46
2	32	214	**53.83**	[45.02	62.64]	3.42	33	39	46
3	8	216	**53.86**	[45.09	62.63]	3.41	33	39	46
4	16	212	**54.27**	[45.43	63.12]	3.43	36	41	46
5	39	217	**54.96**	[46.22	63.71]	3.40	38	43	47
6	15	213	**55.46**	[46.63	64.29]	3.43	39	44	47
7	30	213	**56.11**	[47.25	64.97]	3.44	42	45	48
8	19	215	**56.19**	[47.40	64.98]	3.41	42	45	48
9	38	217	**56.74**	[48.00	65.49]	3.40	43	46	48
10	54	206	**56.81**	[47.80	65.83]	3.50	44	46	48
11	35	213	**56.82**	[47.98	65.66]	3.43	43	46	48
12	20	207	**56.99**	[48.04	65.95]	3.48	44	46	48
13	58	208	**57.06**	[48.12	65.99]	3.47	44	46	48
14	42	216	**57.07**	[48.28	65.86]	3.41	44	46	48
15	18	216	**57.53**	[48.75	66.31]	3.41	44	46	48
16	9	214	**57.57**	[48.76	66.38]	3.42	44	46	48
17	22	214	**58.20**	[49.38	67.02]	3.42	46	47	48
18	28	216	**58.30**	[49.53	67.06]	3.40	46	47	48
19	47	216	**58.33**	[49.57	67.10]	3.40	46	47	48
20	37	207	**58.38**	[49.42	67.34]	3.48	46	47	48
21	10	215	**58.55**	[49.76	67.34]	3.41	46	47	48
22	29	217	**58.60**	[49.85	67.35]	3.40	46	47	48
23	7	215	**58.61**	[49.82	67.39]	3.41	46	47	48
24	51	202	**58.92**	[49.86	67.98]	3.52	46	48	48
25	24	215	**59.05**	[50.26	67.83]	3.41	46	48	48
26	57	214	**59.26**	[50.44	68.09]	3.43	46	48	48
27	23	210	**59.62**	[50.71	68.53]	3.46	47	48	48
28	40	213	**59.74**	[50.89	68.60]	3.44	47	48	48
29	1	210	**59.96**	[51.07	68.85]	3.45	47	48	48
30	3	215	**59.98**	[51.19	68.76]	3.41	47	48	48
31	31	213	**60.13**	[51.31	68.96]	3.43	47	48	48
32	4	216	**60.19**	[51.42	68.95]	3.40	47	48	48
33	33	203	**60.49**	[51.45	69.54]	3.51	47	48	48
34	53	208	**61.02**	[52.08	69.96]	3.47	48	48	48
35	25	216	**61.08**	[52.32	69.85]	3.40	48	48	48
36	56	211	**61.23**	[52.35	70.10]	3.45	48	48	48
37	44	214	**62.04**	[53.21	70.87]	3.43	48	48	48
38	45	212	**62.18**	[53.32	71.04]	3.44	48	48	48
39	26	194	**62.45**	[53.20	71.70]	3.59	48	48	48
40	50	215	**62.55**	[53.75	71.34]	3.41	48	48	48
41	43	201	**63.15**	[54.06	72.25]	3.53	48	48	48
42	13	214	**64.01**	[55.21	72.82]	3.42	48	48	48
43	14	213	**64.31**	[55.48	73.13]	3.43	48	48	48
44	2	213	**65.71**	[56.88	74.54]	3.43	48	48	48
45	6	215	**66.98**	[58.19	75.76]	3.41	48	48	48

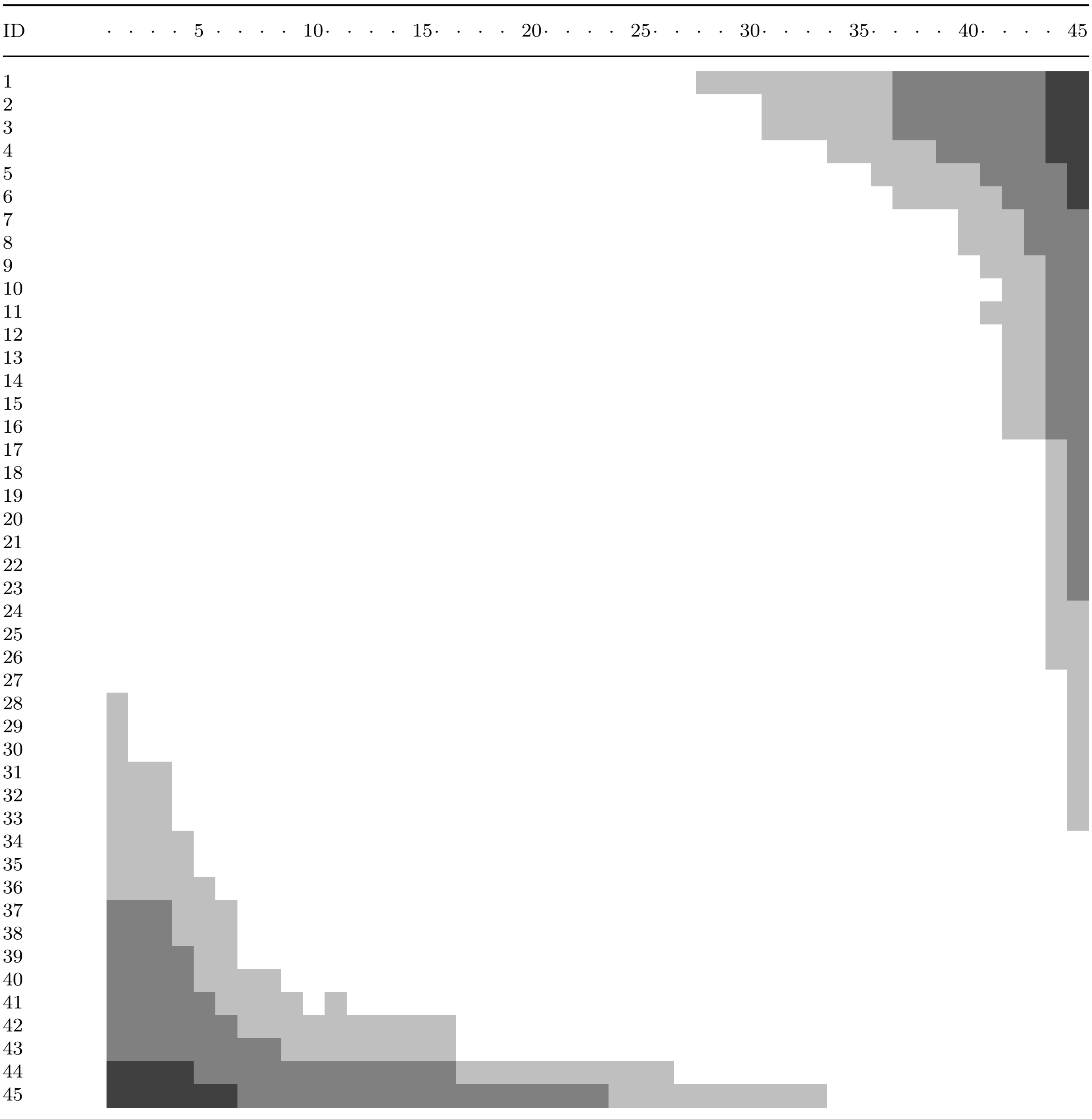
This table shows the S statistic for different groups as defined by Equation (6.5).

Table 7: Distribution of $\hat{S}_i$ (%)

min	53.4
1st quartile	57.0
median	58.6
3rd quartile	61.0
max	67.0
st. dev.	3.1

$N = 45, \bar{T} = 212$

Table 8: Cross-bank significance tests for heterogeneity in anti-herding



Matrix of one-sided tests of equality for the test statistic S as listed in Table 6. Row i, column j of the above matrix represents the p-value of the z-test for equality of S_i and S_j. Bank indices are assigned based on the ranking of S, i.e. $i > j$ implies for the point estimates $S_i > S_j$. The null hypothesis of the z-test is $S_i = S_j$ and the alternative hypothesis is $S_i < S_j$ when $i < j$ and vice versa when $i > j$.

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