Anti-herding in the Euribor Survey

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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 orthogonal to banks' forecasts. There is strong empirical evidence against this hypothesis. The forecasts exhibit a similar contrarian bias as has been documented among other professional forecasters, e.g. equity research analysts. My finding provides an argument in favor of a transaction-based fixing mechanism for the Euribor benchmark.

Keywords: Euribor, forecasting, benchmark rates

JEL-Classification: G14, G21, C14, G18

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1 Introduction

Euribor is the "Euro Interbank Offered Rate", the Euro area equivalent to the 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 lend funds to 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 (2018) 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 issued recommendations 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, BCK henceforth) for financial analysts' forecasts to investigate whether banks' forecasting errors are independent of forecasts. 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". A formal definition of these categories is provided in Section 4. They are exhaustive in the sense that any possible forecast belongs to either one of these three categories. At the core of the test is the question whether the sign of forecasting errors is predictable, given the information available at

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

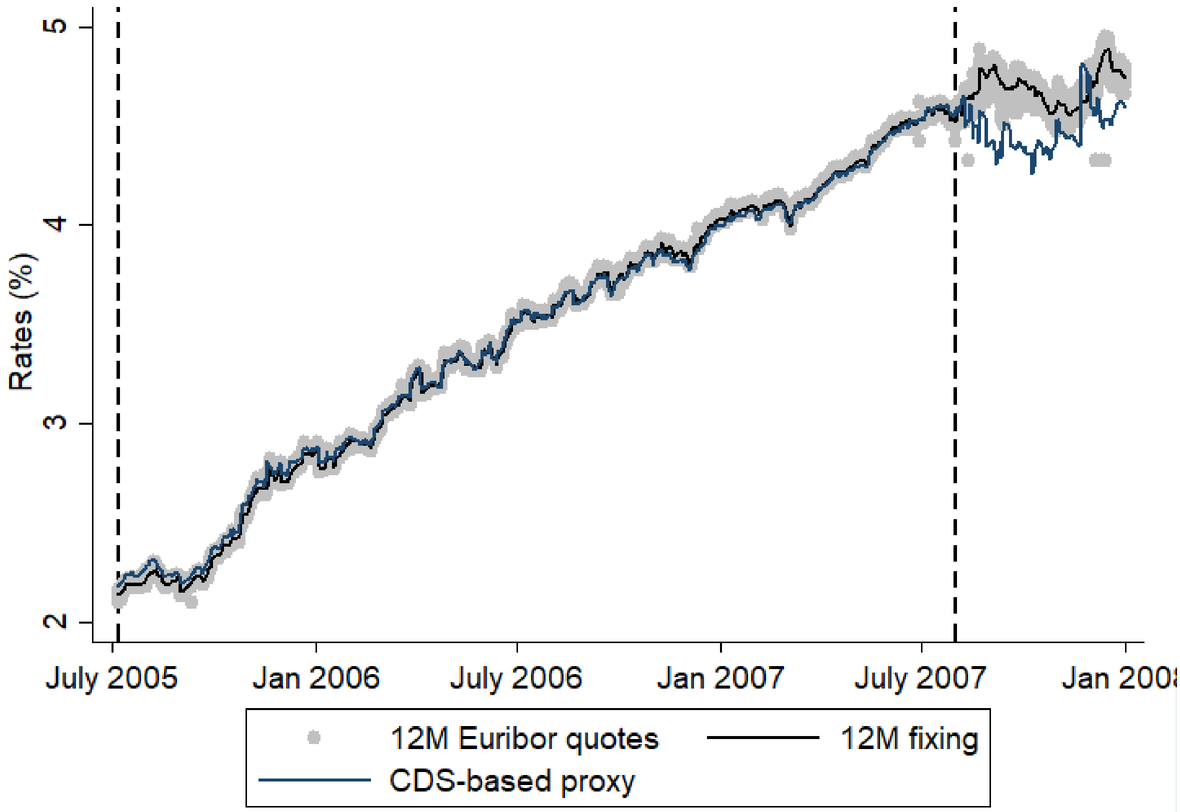
[2] See Duffie and Stein (2015) for a discussion of these contributions.

[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.

the time of the forecast issue. The key challenge for the application of the BCK test is that the true realized interest rate for term deposits is only observable for market participants. As is often the case with OTC markets, the public and hence the econometrician do not observe realized prices. This is also what distinguishes this paper from extant applications of the test. As a major contribution 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: 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. All figures are given in percentage points. The dashed vertical lines indicate the sampling period used in the subsequent analysis - July 2005 until July 2007.

My central finding is that panel banks engage in the behavior called anti-herding by BCK. 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 receive news that go in the same direction - e.g. that the interbank rate has gone up - 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[5]. As a consequence, EMMI - the current administrator of the Euribor benchmark - launched a consultation process on Euribor reform in October 2015. The key component of the suggested reform is a volume-weighted average of those rates prevailing in actual transactions, similar to the EONIA fixing. Further elements of the reform include a broader universe of eligible money market transactions, including transactions with non-banks. In May 2017 EMMI published the results of a pre-live verification program. It found that current trading activity and rates do not allow for a seamless transition to a transaction-based fixing mechanism. As a result a hybrid model of quotes and transactions will be developed, an impact assessment is scheduled for the first half of 2018, and a consultation is scheduled for the second half of 2018. In summary, more than ten years after the outbreak of the financial crisis a transaction-based benchmark fixing mechanism has not yet been adopted. My results provide further evidence in favor of such a transition.

The remainder of this paper is organized as follows. I discuss the literature related to my paper in Section 2. I then provide a detailed description of the rate setting process of the Euribor and the data on Euribor survey contributions in Section 3. In Section 4 I introduce an analytical framework. This allows for a formal definition of herding and anti-herding. The CDS-based proxy is introduced in Section 5. The central finding of this paper is presented in Section 6. Here I perform the BCK test and provide evidence in favor of anti-herding. As the BCK test is not suitable to examine cross-sectional variation in anti-herding, I extend the analytical framework in Section 7. I recast herding and anti-herding in terms of two parameters and estimate these at the bank level. The results suggest that there is heterogeneity in the extent to which individual banks anti-herd. I summarize my findings on anti-herding in Section 8. Section 9 concludes.

[5]The (Financial Stability Board, 2014*a*,*b*) emphasizes the importance of including transactions in the fixing mechanism of financial benchmarks. IOSCO (2013) develops general principles for financial benchmarks and references *"prices, rates, and indices or values that have been formed by the competitive forces of supply and demand"* as preferable data input for benchmark rates where markets are sufficiently active. Following a consultation process the EU has adopted Regulation (EU) 2016/1011 on indices used as benchmarks in financial instruments and financial contracts or to measure the performance of investment funds. Among others this regulation sets out data quality requirements and states that transaction-based data inputs should be used where possible. The regulation came into force on 1 January 2018, but in the case of Euribor a transitional period applies that allows the current regime to remain in operation at least until 31 December 2019.

2 Literature

This paper overlaps with two separate lines of literature. The first is centered around the manipulation of financial benchmarks of the IBOR family. There may be more than one motive to manipulate a benchmark rate. Duffie and Stein (2015) note that during the financial crisis of 2007 to 2009, no bank wished to appear to be less creditworthy than others, as concerns over their creditworthiness might have raised their costs of funding, or in the extreme case, caused a run. In the case of Libor and possibly also in the case of Euribor this situation provided an incentive to report lower rates. Duffie and Stein (2015) identify a second basic motive for manipulating IBOR rates, namely the desire to profit on positions in derivative financial instruments that are contractually linked to the benchmark. Here, there may be an incentive to produce a higher or a lower benchmark fixing, depending on the trading position of the bank or a given trading desk. A further potential motive may arise from a panel bank's business model. If loans constitute a substantial share of a bank's assets and if these are adjustable-rate loans linked to an IBOR benchmark, there may be an incentive to manipulate the benchmark upward to generate higher interest income. The key fact here is that the incentives to manipulate may vary across banks and lead to upwardly or downwardly biased survey contributions.

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 5 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 (2017). The authors find limited potential for manipulation in the Euribor pre June 2007, because of the small cross-sectional range of quotes[6]. A second topic discussed in the context of manipulation 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 (2017) present a

[6] Eisl, Jankowitsch and Subrahmanyam (2017, p. 22)

mechanism on how to optimally weight trading data for a transactions-based benchmark.

The second line of literature related to my paper is concerned with 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, unforecast 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 Sørensen (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 forecasting precision, but also on the number of competitors who submitted the winning guess. 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 winning guess. Ottaviani and Sørensen (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, reputational cheap talk can be ruled out as a valid description of the incentives leading to the observed behavior. However, it is not immediately apparent that the forecasting contest model provides a plausible alternative and. I elaborate on this in Section 8.

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[7]. Euribor rates are published for

[7] In its final report the Financial Stability Board (2014*a*, 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

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 (2018), 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 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 response 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."*[8] 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.

of shorter tenors, but it is still classified as "medium" for interest rate swaps and retail mortgages

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

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 the market for unsecured interbank term deposits is an OTC market that is hard to monitor for outside observers[9]. 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[10]. 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 forecast 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 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 5.

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[11]. 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

[9]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.

[10]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).

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

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 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"*[12]. This definition was adopted after a recommendation of ESMA and EBA (2013) to clarify the term "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' "[13].

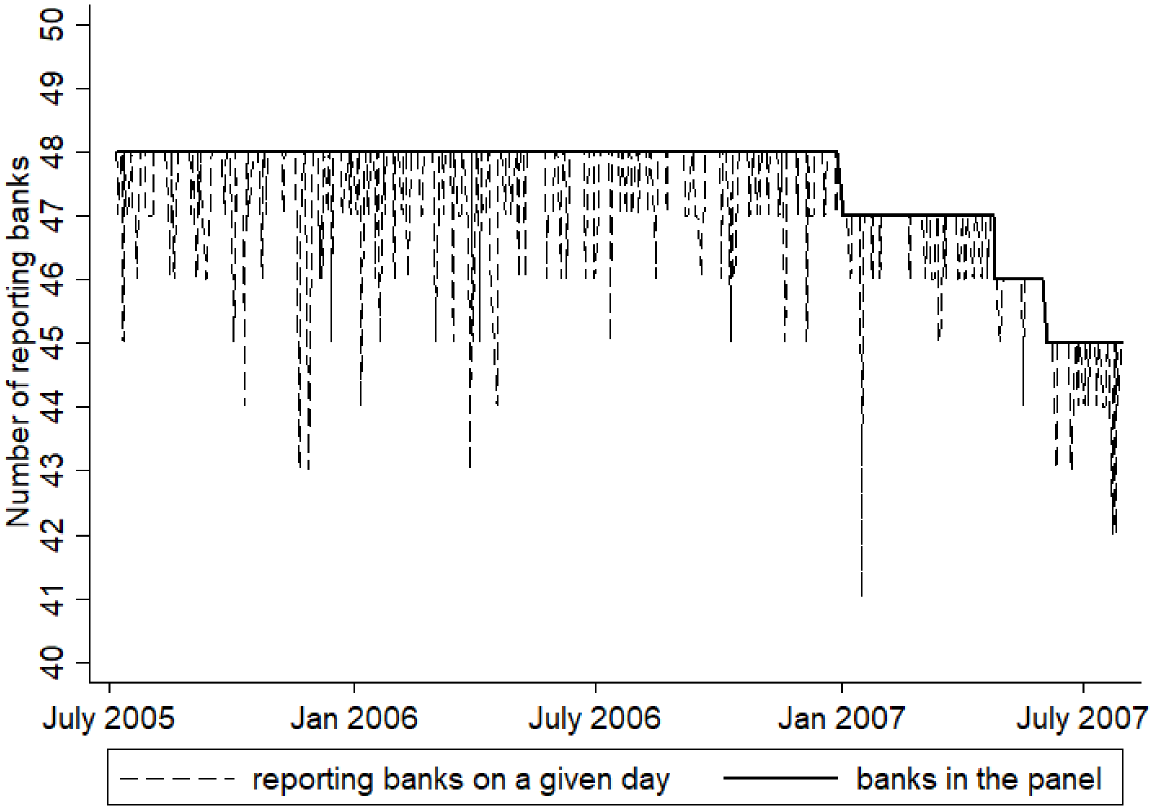
3.2 Data Collection and Cleaning

Raw data on EUR-Euribor submissions as well as the fixing are publicly available at the EMMI website[14]. 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 5 - 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 in the 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[15].

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

[12] European Money Markets Institute (2013, p.2)
[13] Taboga (2014, p.73)
[14] http://www.emmi-benchmarks.eu/euribor-org/euribor-rates.html
[15] This is depicted in Figure 1. The proxy is introduced in detail in Section 5.

Figure 2: Number of Reporting Banks



This figure shows participation in the Euribor panel during the sampling period. The solid line indicates number of members in the Euribor panel, the dashed line indicates the number of submitted quotes on any given day. For most of the sampling period the Euribor panel was composed of 48 banks. Starting in December 2006 three banks subsequently left the panel. The number of submitted quotes does not drop below 40 on any given day during the sampling period.

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. Throughout this paper I restrict the analysis to those 45 banks that submit quotes during the whole sampling period.

Second, the quotes contain fat finger errors as has previously been documented by ESMA and EBA (2013). This leads to occasional extreme outliers[16]. Whereas typos by the submitters can occur on any of the three digits reported, they have the largest impact on the leading digit.

[16]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.

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 11. 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.

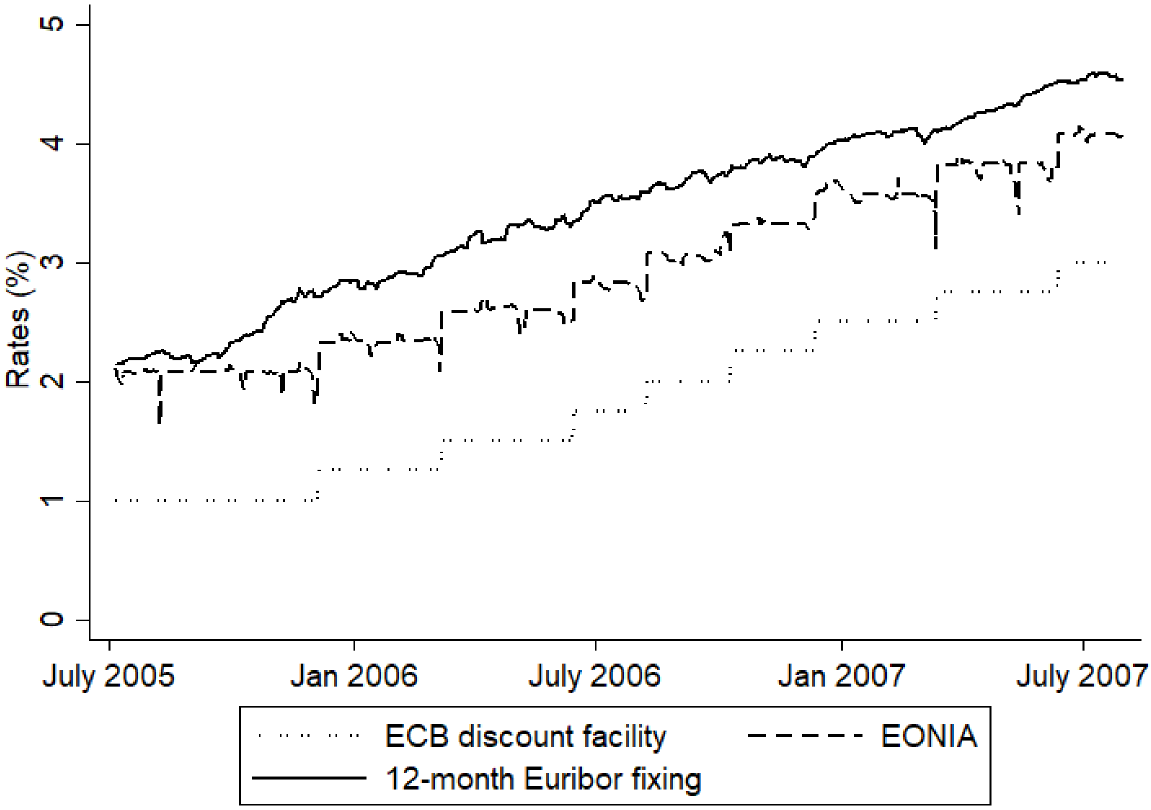
Table 1: Descriptive Statistics on Raw Quotes

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 $d_{it} = q_{it} - F_t$.

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 3. 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 3: ECB monetary policy and the Euribor fixing



This figure shows the gradual increase of key interest rates during the sampling period. The dotted line indicates the ECB discount facility, i.e. the rate at which the ECB accepts overnight funds. This rate is part of the ECB's traditional monetary policy toolbox and operates as the lower bound for rates in the overnight interbank market. The dashed line indicates the EONIA rate, i.e. the volume-weighted average rate in the overnight interbank market. The solid line indicates the twelve-month Euribor fixing. All figures are percentage points.

4 The Analytical Framework

In this section I introduce a simple framework for the unobserved interest rate and banks' expectations. This allows for a formal definition of "herding" and "anti-herding", i.e. the type of misreporting the BCK test is designed to uncover. The premise of the test is that forecasters combine public and private information by Bayesian updating. The public information represents prior beliefs and after observing a private signal forecasters update these to form posterior beliefs. The BCK test relies on non-parametric identifying assumptions which are formally stated below. The most important one of them is that posterior beliefs are symmetrically distributed around their mean, hence posterior expectational errors are symmetrically distributed around zero. Then, the key insight underlying the BCK test is the following. Under the null hypothesis of unbiasedness, panel banks issue the median (mean) of posterior beliefs as forecasts. Therefore, the forecast 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 BCK call herding, it locates its quote between the prior and the posterior mean. 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 as well. The opposite outcomes occur when banks engage in anti-herding. In this case the quotes "overshoot" the posterior away from the consensus prior. The BCK test exploits these properties by estimating overshooting probabilities given certain conditioning events. I illustrate herding, anti-herding, and unbiased reporting in Table 2 and in Figure 4. See Bernhardt, Campello and Kutsoati (2006) for further details.

In order to ensure consistency of the BCK test, two issues have to be addressed. These are the lack of observability of the forecasting target and the potential systematic manipulation as highlighted in the Libor/Euribor scandal. The former issue requires to impose distributional assumptions on the proxy and these are formally stated and discussed in the next section. The latter issue requires to impose certain assumptions on the quotes and on banks' expectations and I present these assumptions in this section. The test results follow in Section 6. The BCK test is robust to a variety of potentially interfering factors such as cross-sectionally correlated private signals. However, it merely classifies bank's quoting behavior on a nominal scale. Therefore, it is not suitable to investigate whether one bank engages to a greater extent in anti-herding than another. In Section 7 I introduce a parametric model of banks' quotes and discuss which further assumptions are required to allow for identification of these parameters. The parameter estimates allow to investigate the cross-sectional heterogeneity of herding and anti-herding.

4.1 Timing and 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[17]. Next, banks report their quotes q_{it} simultaneously and publicly. The quotes may or may not reflect bank's 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 that 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 r_t.

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 5. The proxy includes a measurement error. Accounting for it 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 fixing F_t. Bank i observes the actual interest rate r_t and its private signal s_{it} on top of that.

$$\mathcal{E}_t = \left\{\tilde{r}_1, \ldots, \tilde{r}_t, q_{1,1}, \ldots, q_{1,t}, q_{2,1}, \ldots, q_{N,t}, F_1, \ldots, F_t\right\} \tag{4.1}$$

$$\mathcal{B}_{it} = \left\{\mathcal{E}_t \cup \left\{r_1, \ldots, r_t, s_{i,1}, \ldots, s_{i,t}\right\}\right\} \tag{4.2}$$

The first identifying assumption I have to impose is that during the sampling period - July 2005

[17] 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 evidence is consistent with the modeling approach described.

until July 2007 - the data generating process of the actual interest rate r_t is a random walk with drift. I present empirical evidence supporting this assumption in Section 5.3.

$$\Delta r_t = \mu + \epsilon_t \tag{4.3}$$

Prior uncertainty is determined by the series ϵ_t which is assumed to be stationary. Let c_t denote the common prior expected value of the interest rate.

$$c_t = E\left[r_t | \mathcal{B}_{i,t-1}\right] = \mu + r_{t-1} \tag{4.4}$$

Banks privately observe the signal s_{it}.

$$s_{it} = r_t + z_{it} \tag{4.5}$$

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

$$x_{it} = E\left[r_t | \mathcal{B}_{i,t-1}, s_{it}\right] \tag{4.6}$$

The posterior expectational error is denoted by η_{it}.

$$\eta_{it} = r_t - x_{it} \tag{4.7}$$

The BCK test makes two identifying assumptions. The first is that the posterior mean must lie between the prior mean and the signal.

$$c_t < s_{it} \Leftrightarrow c_t < x_{it} < s_{it} \tag{4.8}$$

$$s_{it} < c_t \Leftrightarrow s_{it} < x_{it} < c_t \tag{4.9}$$

The second, more important restriction is that the posterior expectational error η_{it} be distributed symmetrically around a zero mean.

$$E[\eta_{it}] = 0 \tag{4.10}$$

$$Pr[\eta_{it} \leq 0] = \frac{1}{2} \tag{4.11}$$

Whereas no explicit assumptions are made about prior uncertainty ϵ_t and signal noise z_{it} it is noteworthy that the posterior uncertainty η_{it} is a function of the former two. Notice that the identifying assumptions imposed so far allow for cross-sectional correlation of signals s_{it}, which is one of the major advantages of the BCK test. In the present application this is particularly convenient, as the signals are interpreted to come from money market operations between two banks. One may argue that each money market transaction generates similar information for both parties involved and hence it is natural to assume that the signals for two banks who entered a trade are correlated. The BCK test is robust to this type of signal correlation.

4.2 Classifying the 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 x_{it}. 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 systematically bias the fixing F_t up or down. 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 BCK uncover with their test. I call it *directional deviation* to distinguish it from level deviation. Ottaviani and Sørensen (2006) explain how reputation and competition may affect the reporting incentives such that directional deviation may arise. 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 4.

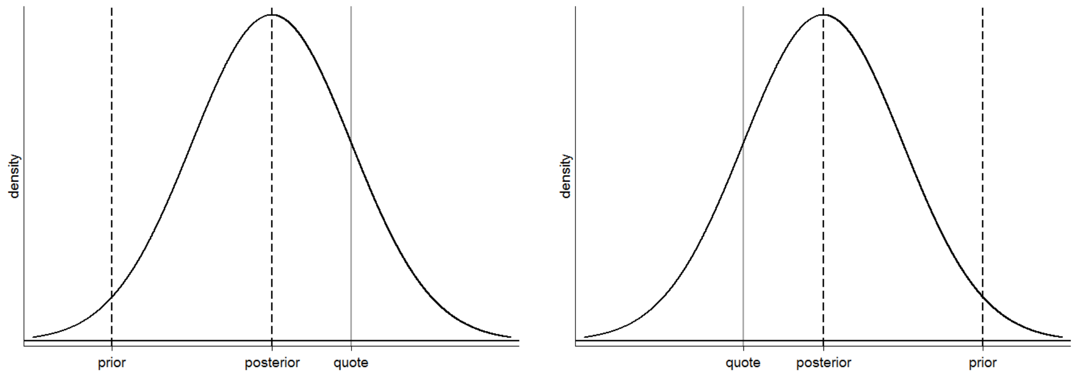
Table 2: Herding and Anti-herding

Prior and signal	Herding	No directional deviation	Anti-herding
$c_t < s_{it}$	$c_t < q_{it} < x_{it} < s_{it}$	$c_t < q_{it} = x_{it} < s_{it}$	$c_t < x_{it} < q_{it} < s_{it}$
$s_{it} < c_t$	$s_{it} < x_{it} < q_{it} < c_t$	$s_{it} < q_{it} = x_{it} < c_t$	$s_{it} < q_{it} < x_{it} < c_t$

This table illustrates "herding", unbiased reporting, and "anti-herding" as defined by Bernhardt, Campello and Kutsoati (2006). The notation is as follows: c_t denotes the common prior mean, s_{it} denotes the bank-specific private signal, x_{it} denotes the posterior mean, and q_{it} denotes the quote, i.e. the issued forecast. The top row illustrates the situation where the signal - and by consequence the posterior and the quote - is larger than the prior. In all three regimes the quote and the posterior lie between the prior and the signal. In the case of herding (left column) the quote is closer to the prior than the posterior. In the case of unbiased reporting (middle column) the two are equal. In the case of anti-herding (right column) the quote is closer to the signal than the posterior. The bottom row illustrates the three categories of reporting in the case where the signal is smaller than the prior.

The cornerstone of the BCK test is the S statistic which would be calculated based on the quotes q_{it}, the prior c_t, and the realization r_t if the latter two were observable for the

Figure 4: 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": $c_t < s_{it} \Leftrightarrow c_t < q_{it}$, $\quad Pr[r_t < q_{it}|c_t < q_{it}] > 1/2$
Right panel: "down-signal": $c_t > s_{it} \Leftrightarrow c_t > q_{it}$, $\quad Pr[r_t > q_{it}|c_t > q_{it}] > 1/2$

econometrician. Under the null hypothesis of no directional deviation $S = \frac{1}{2}$, under the first alternative of herding S is smaller than one half and under the second alternative of anti-herding it is larger.

$$
\begin{aligned}
&H_0: \quad \text{No directional deviation} && S = \frac{1}{2} \\
&H_1: \quad \text{Herding} && S < \frac{1}{2} \\
&H_2: \quad \text{Anti-herding} && S > \frac{1}{2}
\end{aligned}
$$

The underlying intuition for the BCK test is relegated to Appendix A.1. I assume that in case a bank engages in directional deviation, it is either anti-herding every period or herding every period, i.e. the type of directional deviation does not change over time[18]. One of the two key challenges when implementing the BCK test in the Euribor context is the presence of level deviation. Dealing with it requires to impose restrictions on banks' quoting behavior. I present and discuss these here.

[18]This assumption could be relaxed by calculating the S statistic for selected subperiods such as quarters, weekdays, or specific events in the money markets such as IMM dates or central bank operations. However, the potential time-variation of directional deviation is outside of the scope of this paper.

4.3 Restrictions on Level Deviation

I impose two assumptions on level deviation and on the functional form of the posterior mean and the published quote. Thereby I maintain an analytical framework that allows for the presence of level deviation, but at the same time preserves the consistency of the BCK test. The assumption on level deviation is that it can be captured by a bank-specific, but time-invariant and additive component in the submitted quotes. This means that a bank which is trying to move the fixing upwards is doing so all the time and by a fixed percentage point. This assumption is motivated by both, analytical tractability as well as the extant literature on manipulative behavior in the IBOR surveys. Exploiting the trimming in the Libor aggregation mechanism Youle (2014) aims to estimate by how much the USD Libor was distorted between 2005 and 2009. He finds that the USD Libor was mostly accurate during the pre-crisis period (i.e. during my sampling period) and he reports a deviation of the fixing from the "true" rate of at most 4 bps during that period. Most importantly, he finds that *"Most of the banks wish to push the Libor downwards, but not all. Thus the Libor is the result of a 'tug of war' in which some banks wish to skew it upwards, and others wish to skew it downwards. Given banks' radically different locations, primary currencies of operation, and business models, this may be expected."*[19]. This finding is in line with my identifying assumption. A bank-specific, but time-invariant component in the quotes may be interpreted as banks' strategies to position themselves in the "tug of war" for the eventual fixing. Youle (2014) also captures level deviation by a bank-specific, but time-invariant set of parameters. The key consequence of time-invariant, additive level deviation is that its effect on the quotes vanishes in first differences Δq_{it}. Therefore, I apply the BCK test in Section 6 by calculating the test statistic S using the first differences of quotes, prior, and proxy as inputs, instead of their level equivalents. This raises the question whether the test statistic calculated in such a manner still classifies directional deviation as defined in Table 2. I show in Appendix A.2 that this is indeed the case when the posterior mean and the quotes are restricted to be linear functions of the prior mean and the signal.

$$x_{it} = (1 - \phi_i)c_t + \phi_i s_{it} \tag{4.12}$$

$$q_{it} = (1 - \theta_i)c_t + \theta_i s_{it} + \nu_i \tag{4.13}$$

Here, the parameter ϕ_i denotes the weight assigned to the signal by bank i when forming the Bayesian posterior mean. The parameter θ_i denotes the weight assigned to the signal in the

[19] Youle (2014, p.19)

published forecast. The parameter ν_i captures level deviation, i.e. bank i's position in the tug of war for the fixing. Banks with positive ν_i wish to skew the fixing upwards, banks with negative ν_i wish to skew it downward. Whereas the BCK test relies on non-parametric assumptions in its original form, the restrictions imposed by Equations (4.12) and (4.13) are parametric and they are primarily motivated by analytical tractability. However, Ottaviani and Sørensen (2006) also restrict their analysis to quoting rules that are linear functions of the prior mean and the signal. The authors discuss two alternative theories of strategic forecasting, where the first may lead to herding and the second to anti-herding. Under both theories the authors find a convex combination of the prior and the signal as the equilibrium forecasting policy, yet the respective weights differ. When normality is imposed on the prior uncertainty and the signal noise, the linearity of the posterior mean follows as a direct consequence. I use this property in Section 7. Directional deviation can be linked to the signal weights ϕ_i and θ_i. When banks choose the same weight in their published forecasts as is given by their posterior mean, they do not engage in directional deviation ($\theta_i = \phi_i$). When they choose a smaller weight ($\theta_i < \phi_i$) they herd and when they put a larger weight on the signal they anti-herd ($\theta_i > \phi_i$). In the present framework the effect of level deviation on the fixing does not change over time, as ν_i is time-invariant. However, 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.

Besides level deviation, the second key issue when implementing the BCK test in the Euribor context is the need for a proxy. In the next section I describe in detail how I construct a proxy from CDS spread data. Furthermore, I make the additional assumptions explicit that have to be imposed on the measurement error inherent in the proxy in order to maintain consistency of the BCK test.

5 Constructing the Proxy

5.1 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 positions prior to maturity. Therefore, one might suspect that term deposits exhibit a liquidity premium 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[20]. 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 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 $1+r = 1/B$.

$$1+r = \frac{1+r_f}{1-p(1-RR)} \tag{5.1}$$

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.

$$4S_{CDS} = \frac{p(1-RR)}{1+r_f} \tag{5.2}$$

[20] 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. Filipović and Trolle (2013) study the term structure of interbank risk for the period beginning in August 2007.

I may substitute the term $p(1 - RR)$ in Equation (5.1) by $4S_{CDS}(1 + r_f)$ to obtain a proxy for the bond yield based on the CDS spread.

$$1 + r = \frac{1 + r_f}{1 - 4S_{CDS}(1 + r_f)} \tag{5.3}$$

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 (5.3), 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[21]. In total, I gather 97,943 observations. I exclude 6,148 observations where the default probability as implied by Equation (5.2) exceeds 100%[22]. 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.

5.2 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

[21] 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.

[22] 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[23]. 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 that bank's CDS spread using Equation (5.3). 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.

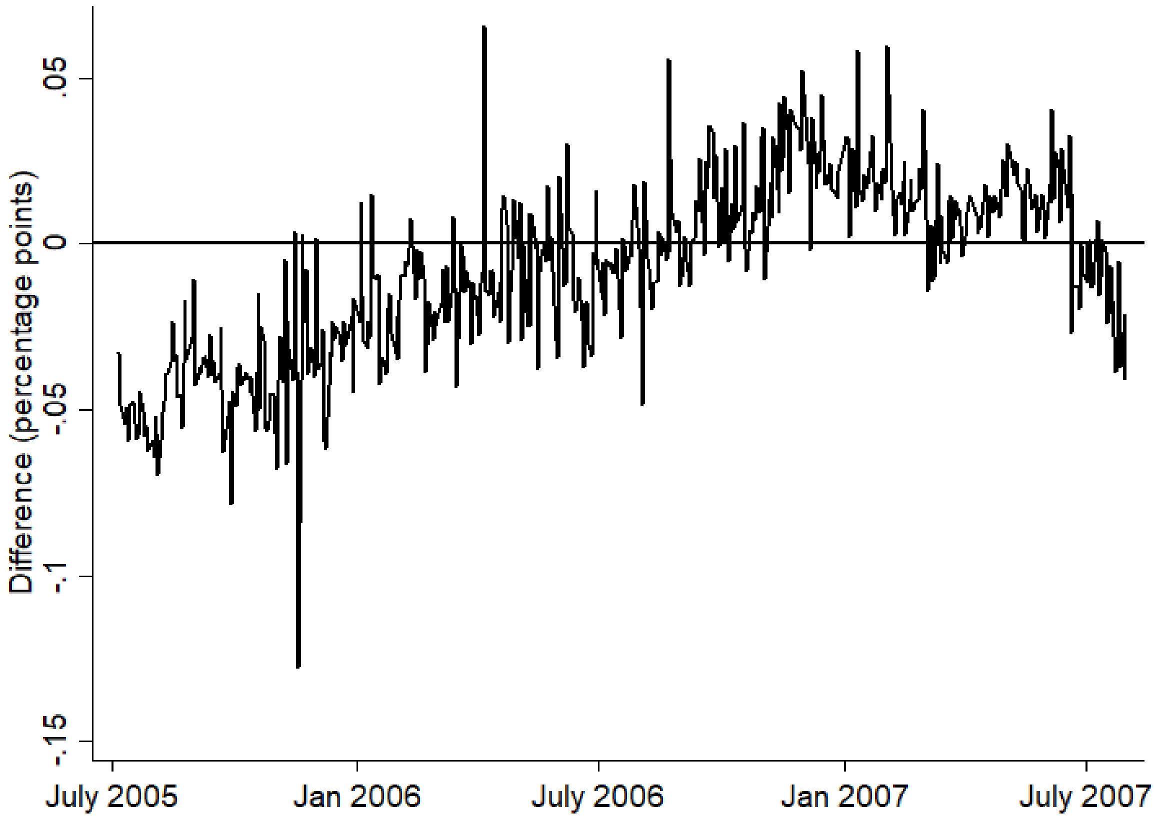
I consider two alternative definitions of the proxy as a robustness check. Under the first alternative I define the proxy rate as the mean of the rates from the five banks in the Euribor panel with the lowest CDS spreads on any given day. The resulting proxy remains virtually the same. Under the second 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 during the period after August 2007 in Figure 12.

5.3 Restrictions on 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

[23] 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.

Figure 5: Difference between Fixing and Proxy



This figure shows the difference between the 12-month Euribor fixing and the CDS-based proxy over the sampling period in percentage points. The difference remains lower than 5bps in absolute value on most of the days. It is increasing for most of the sampling period, which adds further plausibility to the assumption of a unit-root in the measurement error discussed in Section 5.3.

the first differences $\Delta\tilde{r}_t$ exhibit no ARMA components. This property is the key justification for the identifying assumption imposed on the proxy's measurement error.

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.

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. I clarify this point formally. Consider the unobserved "true" rate r_t, as introduced in Section 4. I define the measurement error ζ_t as

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 5. 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 $I(1)$.

the difference between the actual interest rate and the proxy.

$$\tilde{r}_t = r_t - \zeta_t \tag{5.4}$$

As stated in Equation (4.3), I assume that the actual interest rate follows a random walk with drift[24].

$$\begin{aligned} \Delta r_t &= \mu + \epsilon_t \\ E[\epsilon_t] &= 0 \end{aligned}$$

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 with drift.

$$\begin{aligned} H_0 : &\quad \zeta_t \overset{iid}{\sim} N(0, \sigma_\zeta^2) \\ H_1 : &\quad \Delta\zeta_t = \alpha + \omega_t, \quad \omega_t \overset{iid}{\sim} N(0, \sigma_\omega^2) \end{aligned}$$

Under the null hypothesis of a stationary measurement error the differenced series $\Delta\tilde{r}_t$ is negatively correlated with its first lag and lead: $E[\Delta\tilde{r}_t \cdot \Delta\tilde{r}_{t-1}] = -E[\zeta_{t-1}^2] = -\sigma_\zeta^2$. 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 for two reasons. First, it provides an empirical justification for the claim that the dgp of the actual rate is a random walk with drift (see Section 4.1). This in turn allows for an easy determination of the prior mean which is crucial for the BCK test. Second, the consistency of the BCK test depends on the assumption that the increments in the measurement error $\Delta\zeta_t$ are independently distributed, as explained in Appendix A.2.

[24]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.

To begin the analysis I provide graphs of the autocorrelation and of the partial autocorrelation function of $\Delta\tilde{r}_t$ in Figures 13 and 14, respectively. Neither the autocorrelation coefficients, nor the partial autocorrelation coefficients exceed the 95% confidence interval at any one of the first 10 lags. At the eleventh lag both coefficients are negative and exceed the 95%, but not the 99% confidence interval. There is no sign of significant autocorrelation at any other one of the first 20 lags. In total, 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 $p, q \in \{0, 1\}$.

$$\begin{aligned} \Delta\tilde{r}_t =& \gamma + \phi\Delta\tilde{r}_{t-1} + u_t - \psi u_{t-1} \\ & u_t \overset{iid}{\sim} N(0, \sigma_u^2) \\ & 0 \leq |\phi| < 1, \quad 0 \leq |\psi| < 1 \end{aligned} \tag{5.5}$$

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

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

Model type	I ARIMA(0,1,0)	II ARIMA(0,1,1)	III ARIMA(1,1,0)	IV ARIMA(1,1,1)
γ	0.005*** (0.0008)	0.005*** (0.0009)	0.005*** (0.0009)	0.005*** (0.0009)
ϕ			0.078** (0.0380)	0.067 (0.5834)
ψ		0.077** (0.0380)		0.010 (0.5836)
σ_u	0.018*** (0.0004)	0.018*** (0.0004)	0.018*** (0.0004)	0.018*** (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 (5.5) 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.

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.

$$\Delta\zeta_t = \alpha + \omega_t \tag{5.6}$$

Furthermore, I require that ω_t be distributed *iid* around a zero mean and that it be independent of the prior uncertainty ϵ_t and signal noise z_{it}. This is equivalent to 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[25].

$$E[\omega_t] = 0 \tag{5.7}$$

$$E[\omega_t \omega_{t+k}] = 0, \quad k \neq 0 \tag{5.8}$$

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

$$E[z_{it} \omega_{t+k}] = 0 \tag{5.10}$$

[25] Greene (2003, chpt. 5) provides an introduction to the treatment of measurement error in econometric models.

6 Testing for Directional Deviation

I briefly summarize the assumptions imposed to guarantee the consistency of the BCK test. The key identifying restriction is that the posterior expectational errors be distributed symmetrically around a zero mean. I have imposed further assumptions to manage the potential issues of level deviation and measurement error in the proxy. These are that the posterior mean as well as the quote be linear functions of the prior and the signal, that level deviation be captured by an additive and time-invariant component in the quotes, and that the measurement error be governed by a random walk with drift. I demonstrate in Appendix A.2 that under these assumptions the BCK test correctly identifies herding and anti-herding when first differences instead of levels are used. Specifically, the test statistic S is constructed based on three inputs: The realized actual rate as proxied by $\Delta\tilde{r}_t$, quotes Δq_{it}, and the prior mean as proxied by $\Delta\tilde{r}_{t-1}$.

6.1 Construction and Estimation of the Test Statistic

In this section I employ the BCK test to provide evidence for directional deviation in the Euribor quotes. First, I calculate the test statistic S for the whole sample. Thereby I impose that all banks engage in directional deviation in the same way. Then, I calculate the S statistic at the bank level to allow for cross-sectional heterogeneity. The null hypothesis and the two alternative hypotheses are as stated in Section 4.2.

$$\begin{aligned} &H_0: && \text{No directional deviation} && S = \tfrac{1}{2} \\ &H_1: && \text{Herding} && S < \tfrac{1}{2} \\ &H_2: && \text{Anti-herding} && S > \tfrac{1}{2} \end{aligned} \tag{6.1}$$

I describe the construction of the test statistic using the notation for a test at the bank level. I follow Bernhardt, Campello and Kutsoati (2006, p.663) and determine two conditioning indicators $\gamma_{it}^+, \gamma_{it}^-$ as well as two overshooting indicators $\delta_{it}^+, \delta_{it}^-$.

$$\begin{aligned} \gamma_{it}^+ &= 1 && \Leftrightarrow \Delta\tilde{r}_{t-1} - \Delta q_{it} > 0, && \gamma_{it}^+ = 0 \quad \text{otherwise} \\ \gamma_{it}^- &= 1 && \Leftrightarrow \Delta\tilde{r}_{t-1} - \Delta q_{it} < 0, && \gamma_{it}^- = 0 \quad \text{otherwise} \\ \delta_{it}^+ &= 1 && \Leftrightarrow \gamma_{it}^+ = 1, \Delta\tilde{r}_t - \Delta q_{it} > 0, && \delta_{it}^+ = 0 \quad \text{otherwise} \\ \delta_{it}^- &= 1 && \Leftrightarrow \gamma_{it}^- = 1, \Delta\tilde{r}_t - \Delta q_{it} < 0, && \delta_{it}^- = 0 \quad \text{otherwise} \end{aligned} \tag{6.2}$$

The sample estimate of S_i is defined as follows.

$$\hat{S}_i = \frac{1}{2}\left(\frac{\sum_t \delta_{it}^-}{\sum_t \gamma_{it}^-} + \frac{\sum_t \delta_{it}^+}{\sum_t \gamma_{it}^+}\right) \tag{6.3}$$

When there is no directional deviation, i.e. H_0 holds true, $S_i = \frac{1}{2}$. When banks are herding $S_i < \frac{1}{2}$ and when banks are anti-herding $S_i > \frac{1}{2}$. As Bernhardt, Campello and Kutsoati (2006, p.664) point out, the key feature driving the robustness of their test is that the variance of S_i is maximized *when no measurement error is present.* The authors show that under the null hypothesis the variance of S_i is bounded from above by the following term.

$$Var(S_i) \leq \frac{1}{16}\left(\frac{1}{\sum_t \gamma_{it}^-} + \frac{1}{\sum_t \gamma_{it}^+}\right) \tag{6.4}$$

Therefore, using Equation (6.4) 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 (6.2) 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 9,665 observations with a gap of at least one business day for a given bank.

6.2 Results of the BCK Test

In this subsection I present and discuss the estimation results for the whole sample and at the bank level. Throughout this section I calculate the S statistic as defined by Equation (6.3) and I use the asymptotic variance from Equation (6.4) 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 48%. However, conditional on that event the probability of the quote falling short of the proxy, i.e. $\delta_{it}^- = 1$, is 60%. Likewise, the conditional probability of the quote exceeding the proxy is 60% as well. This gives a point estimate for the S statistic of 60%. The null hypothesis

Table 5: Estimation Results for S_i by banks

Bank name	N	$\Pr(\gamma_{it}^{-}=1)$	$\Pr(\delta_{it}^{-}=1)$	$\Pr(\delta_{it}^{+}=1)$	$\hat{S}$	95% CI	
Whole sample	9,665	47.73	59.77	59.70	**59.73**	[58.73,	60.73]
NORD/LB Norddeutsche Landesbank	216	46.76	50.50	53.91	**52.20**	[45.52,	58.89]
ING Bank	218	50.00	54.13	51.38	**52.75**	[46.12,	59.39]
Svenska Handelsbanken	207	52.66	56.88	52.40	**54.46**	[47.64,	61.28]
Banca Monte dei Paschi di Siena	220	49.90	52.78	57.14	**54.96**	[48.35,	61.57]
Crédit Industriel et Commercial	207	45.41	56.38	54.87	**55.63**	[48.78,	62.47]
West LB	212	49.60	53.85	58.33	**56.90**	[49.36,	62.82]
Fortis Bank	217	48.85	60.38	52.25	**56.31**	[49.66,	62.97]
Landesbank Hessen-Thüringen	218	51.38	54.46	58.49	**56.48**	[49.84,	63.12]
CECA	219	43.38	58.95	54.30	**56.49**	[49.81,	63.17]
Erste Bank der österreichischen Sparkassen	216	51.85	59.82	53.85	**56.83**	[50.16,	63.51]
KBC Bank	220	47.73	54.29	60.00	**57.14**	[50.53,	63.76]
UBS	216	43.98	51.58	62.81	**57.19**	[50.48,	63.91]
CAPITA	212	48.11	56.86	58.18	**57.52**	[50.79,	64.26]
Commerzbank	217	50.23	62.39	52.78	**57.58**	[50.93,	64.23]
Deutsche Bank	217	48.39	60.95	54.46	**57.71**	[51.50,	64.36]
JPMorgan Chase & Co.	208	46.63	55.67	60.36	**58.20**	[51.20,	64.83]
Intesa Sanpaolo	217	48.39	57.14	58.93	**58.40**	[51.38,	64.69]
Bank of Tokyo-Mitsubishi UFJ	219	47.30	58.25	59.48	**58.87**	[52.23,	65.50]
Banque et Caisse d'Epargne de l'Etat	219	48.86	58.88	58.93	**58.90**	[52.28,	65.53]
Landesbank Berlin	219	46.58	56.86	61.54	**59.20**	[52.56,	65.84]
Crédit Agricole	217	46.54	57.43	61.21	**59.32**	[52.65,	65.98]
Banco Bilbao Vizcaya Argentaria	217	45.16	59.18	59.66	**59.42**	[52.74,	66.11]
Natixis	216	46.76	59.41	60.00	**59.70**	[53.20,	66.38]
Citigroup	211	46.45	61.22	58.41	**59.82**	[53.50,	66.58]
Banco Santander	217	44.70	62.89	57.50	**60.19**	[53.50,	66.88]
UniCredit	217	48.39	60.00	60.71	**60.36**	[53.70,	67.10]
Caixa Geral de Depósitos	218	45.87	59.00	61.86	**60.43**	[53.77,	67.90]
Bank of Ireland	217	48.85	63.21	58.56	**60.88**	[54.23,	67.54]
National Bank of Greece	215	45.58	61.22	60.68	**60.95**	[54.24,	67.66]
Raiffeisen Zentralbank Österreich	217	46.54	59.41	62.93	**61.17**	[54.50,	67.84]
Rabobank	203	45.32	59.78	63.60	**61.42**	[54.51,	68.33]
Belfius Banque	217	47.93	60.58	62.83	**61.70**	[55.50,	68.36]
Bayerische Landesbank	218	48.62	65.90	58.93	**62.10**	[55.37,	68.65]
Landesbank Baden-Württemberg	215	54.88	62.71	61.86	**62.28**	[55.57,	68.10]
HSBC Bank	203	48.77	64.65	60.58	**62.61**	[55.73,	69.49]
ABN AMRO Bank	213	46.95	61.00	64.60	**62.80**	[56.70,	69.53]
Nordea Bank	218	44.50	65.98	60.33	**63.15**	[56.48,	69.83]
Allied Irish Banks	215	47.44	63.73	62.83	**63.28**	[56.59,	69.97]
Natexis/Groupe BPCE	203	46.31	61.70	65.14	**63.42**	[56.52,	70.32]
Deutsche Zentral-Genossenschaftsbank	218	46.33	62.38	64.96	**63.67**	[57.10,	70.32]
Société Générale	213	50.23	60.75	67.92	**64.34**	[57.62,	71.50]
Danske Bank	200	49.00	62.24	66.67	**64.46**	[57.52,	71.39]
Barclays Bank	217	46.54	68.32	61.21	**64.76**	[58.90,	71.43]
Dresdner Bank	220	48.64	63.55	67.26	**65.40**	[58.79,	72.10]
BNP Paribas	216	47.22	73.53	62.28	**67.91**	[61.23,	74.58]

This table shows the S statistic developed by Bernhardt, Campello and Kutsoati (2006) and defined in Equation (6.3) for the whole sample and at the bank level.
The number of observations is given in the column titled *N*. Figures in all other columns are given in percentage points. The S statistic is given in the column titled *S*, when $S = \frac{1}{2}$ the bank does not engage in directional deviation, when $S < \frac{1}{2}$ the bank is herding, and when $S > \frac{1}{2}$ it is anti-herding. The 95% confidence interval is calculated based in the robust variance estimator given in Equation (6.4).
The three columns titled $\Pr(\gamma_{it}^{-}=1)$, $\Pr(\delta_{it}^{-}=1)$, and $\Pr(\delta_{it}^{+}=1)$ indicate the probability of an observation to be classified as having received a "down signal", the probability of overshooting conditional on having received a down signal, and the probability of overshooting conditional on having received an "up signal", respectively. Please refer to Section 4 and appendix A for further details.

of no directional deviation, i.e. $S = 50\%$, is rejected at the 1% significance level in favor of anti-herding. Next, I perform the test for directional deviation at the bank level. The probability of the quote falling short of the prior is close to 50% for all banks, its range is $43 - 55\%$. The point estimate of the test statistic is larger than 50% for all banks. Moreover, it is statistically significantly different thereof in 36 out of 45 cases at the 5% level. This demonstrates that the tendency to anti-herd documented in the whole sample is also borne out at the bank level for a majority of banks in the Euribor panel. However, there is a minority that does not engage in directional deviation.

7 Parametric Model

The BCK test has revealed that banks engage in anti-herding in general. However, as the classification of the test is merely nominal, it cannot be determined whether some banks do so more than others and if so to what extent. In this section I modify the analytical framework introduced in Section 4. I require that both, prior uncertainty as well as signal noise obey normal distributions. This assumptions has two desirable implications. First, it provides a foundation for the ad-hoc assumption that the posterior mean be a linear combination of prior and signal. Second, the signal weights in the posterior and in the quotes can be estimated from second moments of observable quantities. This allows to quantify and compare directional deviation across banks.

7.1 Model Modification

As before, I assume that the actual rate is generated from a random walk with drift. I reproduce Equation (4.3) for convenience.

$$\Delta r_t = \mu + \epsilon_t$$

Whereas I have remained agnostic about the distribution of ϵ_t in Section 4, I impose normality on ϵ_t henceforth.

$$\epsilon_t \overset{iid}{\sim} N(0, \sigma_\epsilon^2) \tag{7.1}$$

Notice that the uncertainty of the prior expectation, i.e. the variance of banks' prior expectational error is determined by ϵ_t.

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

I use σ_ϵ^2 as a denominator to scale other variance terms in the model. Banks' signals are determined by the actual rate r_t and signal noise z_{it}, see Equation (4.5).

$$s_{it} = r_t + z_{it}$$

I require the signal noise z_{it} to be normally distributed around a zero mean and to be independent of its own leads and lags. I introduce the first of the two decisive parameters that govern directional deviation - κ_i - as the signal variance relative to the prior uncertainty.

$$z_{it} \sim N(0, \kappa_i \sigma_\epsilon^2), \quad \kappa_i > 0 \tag{7.2}$$

$$E[z_{it} z_{i,t+k}] = 0, \quad k \neq 0 \tag{7.3}$$

The larger κ_i, the less precise is bank i's private information relative to the common prior. Just as for the BCK test, I do not impose any restrictions on the cross-sectional distribution of signals. As before, I assume that posterior beliefs are formed by Bayesian updating. The assumptions of normality for ϵ_t and z_{it} imply the following closed form expression for the posterior mean $x_{it} = E\left[r_t|\mathcal{B}_{i,t-1}, s_{it}\right]$.

$$x_{it} = \frac{\kappa_i}{1+\kappa_i} c_t + \frac{1}{1+\kappa_i} s_{it} \tag{7.4}$$

The posterior mean is a convex combination of the prior mean and the signal. In Section 4 this was imposed by an ad-hoc assumption, now it follows as a consequence from the distributional assumptions on the model's error terms. Furthermore, the weight put on the signal (previously denoted by ϕ_i) is a function of the relative signal variance κ_i. 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 key identifying assumption for the BCK test is that the posterior expectational error $\eta_{it} = r_t - x_{it}$ be symmetrically distributed around a zero mean. It is easy to verify that this requirement is fulfilled under the assumptions of normality for ϵ_t and z_{it}. $\eta_{it} = \frac{\kappa_i}{1+\kappa_i}\epsilon_t - \frac{1}{1+\kappa_i} z_{it}$

As before, I maintain the assumption of a linear forecasting rule for the quotes. I introduce the parameter λ_i to match the functional form of the signal weight in the posterior mean.

$$q_{it} = \frac{\lambda_i}{1+\lambda_i} c_t + \frac{1}{1+\lambda_i} s_{it} + \nu_i, \quad \lambda_i > 0 \tag{7.5}$$

Hence, directional deviation is determined by the parameters λ_i and κ_i.

$$\begin{aligned} H_0 :& \quad \text{no directional deviation} & \lambda_i = \kappa_i \\ H_1 :& \quad \text{herding} & \lambda_i > \kappa_i \\ H_2 :& \quad \text{anti-herding} & \lambda_i < \kappa_i \end{aligned} \tag{7.6}$$

Under H_0 panel bank i does not engage in directional deviation. Accordingly, the weights put on the prior and the signal equal those of the Bayesian posterior $q_{it} = x_{it} + \nu_i$. Under H_1, panel bank i is herding and puts more weight on the prior than the Bayesian posterior does. Under H_2 the bank is anti-herding and puts more weight on the signal. There is a direct link between directional deviation and the orthogonality of forecasting errors to forecasts.

$$\begin{aligned} E[q_{it}(q_{it} - r_t)|\mathcal{B}_{i,t-1}, s_{it}] =& E\Bigg[\left(\mu + r_{t-1} + \frac{1}{1+\lambda_i}\epsilon_t + \frac{1}{1+\lambda_i} z_{it} + \nu_i\right) \\ & \left(\frac{1}{1+\lambda_i} z_{it} - \frac{\lambda_i}{1+\lambda_i}\epsilon_t + \nu_i\right)\Bigg] \\ =& \frac{\kappa_i - \lambda_i}{(1+\lambda_i)^2}\sigma_\epsilon^2 \end{aligned}$$

The forecasting errors are independent of the forecasts if and only if H_0 holds true, i.e. banks do not engage in directional deviation. $\lambda_i = \kappa_i \Leftrightarrow E[q_{it}(q_{it} - r_t)|\mathcal{B}_{i,t-1}, s_{it}] = 0$. Moreover, when banks engage in herding, the correlation is negative and it is positive when banks engage in anti-herding. This feature is also borne out in the framework of Ottaviani and Sørensen (2006).

7.2 Parameter Identification and Estimation

Here I describe how the additional identifying assumptions presented in Section 7.1 allow for estimation of the two parameters that govern directional deviation, κ_i and λ_i. Recall the forecasting policy from Equation (7.5) and consider the first differences $\Delta q_{it} = \frac{\lambda_i}{1+\lambda_i}\Delta c_t + \frac{1}{1+\lambda_i}\Delta s_{it}$ In terms of the fundamental sources of uncertainty - the series ϵ_t, ω_t, and z_{it} - the first differenced quotes are given as follows.

$$\Delta q_{it} = \mu + \frac{1}{1+\lambda_i}\epsilon_t + \frac{\lambda_i}{1+\lambda_i}\epsilon_{t-1} + \frac{1}{1+\lambda_i}\Delta z_{it} \tag{7.7}$$

Expressing the differenced quotes this way makes it easy to derive parametric expressions for the variance of Δq_{it} and its covariance with $\Delta\tilde{r}_t$ and $\Delta\tilde{r}_{t-1}$.

$$\begin{aligned}
Var[\Delta q_{it}] =& \frac{1+\lambda_i^2+2\kappa_i}{(1+\lambda_i)^2}\sigma_\epsilon^2 \\
Cov[\Delta q_{it},\Delta\tilde{r}_t] =& \frac{1}{1+\lambda_i}\sigma_\epsilon^2 \\
Cov[\Delta q_{it},\Delta\tilde{r}_{t-1}] =& \frac{\lambda_i}{1+\lambda_i}\sigma_\epsilon^2
\end{aligned}$$

The parameters λ_i, κ_i are identified by these second moments.

$$\lambda_i = \frac{Cov\left[\Delta\tilde{r}_{t-1},\Delta q_{it}\right]}{Cov\left[\Delta\tilde{r}_t,\Delta q_{it}\right]} \tag{7.8}$$

$$\kappa_i = \frac{1}{2}\left((1+\lambda_i)\frac{Var[\Delta q_{it}]}{Cov[\Delta q_{it},\Delta\tilde{r}_t]} - (1+\lambda_i^2)\right) \tag{7.9}$$

GMM estimation of λ_i and κ_i can be achieved using the following moment restrictions.

$$\begin{aligned}
E\left[\Delta\tilde{r}_t-\mu+\alpha\right] &= 0 \\
E\left[\Delta q_{it}-\mu\right] &= 0 \\
E\left[(\Delta q_{it}-\mu)(\Delta\tilde{r}_t-\mu+\alpha)-\sigma_{i,qr}\right] &= 0 \\
E\left[(\Delta q_{it}-\mu)(\Delta\tilde{r}_{t-1}-\mu+\alpha)-\lambda_i\sigma_{i,qr}\right] &= 0 \\
E\left[(\Delta q_{it}-\mu)^2-\sigma_{i,qr}\frac{1+2\kappa_i+\lambda_i^2}{1+\lambda_i}\right] &= 0
\end{aligned}$$

In Section 6 I perform the BCK test twice, once at the bank level and once pooling all observations. I maintain this approach for the GMM estimation. In the first step I impose the cross-sectional parameter restriction that λ_i and κ_i take the same values for all banks, λ and κ, respectively. Hence, the parameter vector has five elements. $\theta = [\mu,\alpha,\sigma_{qr},\lambda,\kappa]'$ The drift parameters of the actual rate and the measurement error are denoted by μ and α, respectively. $\sigma_{qr} = Cov[\Delta q_{it},\Delta\tilde{r}_t]$ is an auxiliary parameter and is used as a denominator for the other variance and covariance terms. In the second step I allow for bank-specific parameters. Then, the parameter vector contains $3N+2=137$ elements. $\theta = [\mu,\alpha,\sigma_{1,qr},\ldots,\sigma_{N,qr},\lambda_1,\ldots,\lambda_N,\kappa_1,\ldots,\kappa_N]'$ Both, in the whole-sample estimation as well as in the bank-level estimation there are $4N+1=181$ moment restrictions.

Directional deviation is determined by the signal weight being smaller or larger in the quote than in the posterior mean. Given the distributional assumptions of Section 7.1, the signal weight in the posterior is given by $\frac{1}{1+\kappa_i}$ and I call it the *Bayesian weight* henceforth. The *actual weight*, i.e. the signal weight applied in the published forecast is given by $\frac{1}{1+\lambda_i}$. When banks herd the *excess weight* $\frac{1}{1+\lambda_i} - \frac{1}{1+\kappa_i}$ is negative and it is positive when they anti-herd. Bayesian weight, actual weight, and excess weight are nonlinear functions of the underlying parameters λ_i and κ_i. In order to guarantee consistent hypothesis testing, I report standard errors based on $B = 999$ bootstrap samples and all reported confidence intervals are bootstrap percentile confidence intervals[26].

7.3 Estimation Results

The parameter estimates based on the pooled data are presented in Table 6. The point estimates for κ and λ are 2.34 and 1.76, respectively. Accordingly, the published forecast is a weighted average of the prior mean and the signal with a weight of around $\frac{1}{1+1.76} \approx 36\%$ attached to the signal. Given its relative precision, around $\frac{1}{1+2.34} \approx 30\%$ is the optimal value - the Bayesian weight. Hence, the excess weight amounts to 6%. This value is larger than zero at the 5% significance level, as can be seen from the reported confidence interval. This finding is consistent with the BCK test performed in Section 6, where I also document evidence in favor of anti-herding based on the whole sample of observations. Table 6 offers another interesting insight. The point estimate of κ is significantly larger than 1 at the 5% level. This means that the variance of the signal noise z_{it} is larger than the variance of the prior uncertainty ϵ_t. Put differently, on average the prior information is more precise than the private signals are. This may be due to the stable and smooth increase in interest rates during the sampling period - see Figure 3.

The bank-level estimates for κ_i and λ_i are presented in Table 7. The point estimates for κ_i are in the range of $[1.31, \quad 3.74]$. For 16 out of 45 banks κ_i is smaller than the whole sample estimate of κ at the 5% significance level and for three it is larger. This is illustrated in the lower panel of Figure 6. Furthermore, the null hypothesis of $\kappa_i = 1$ can be rejected in favor of $\kappa_i > 1$ at the 5% significance level for all panel banks but 13 of them. These two findings suggest that

[26]Given the fact that estimates are obtained by GMM and that the number of parameters in the bank-level analysis is rather large, bootstrapping is computationally demanding. A more convenient approach is to approximate the standard errors of the Bayesian weight, the actual weight, and the excess weight by the Delta method and then perform a Wald test. However, this approach leads to inconsistent results. For instance, there are several banks for which the hypothesis $\lambda_i = \kappa_i$ can be rejected, but the hypothesis $\frac{1}{1+\lambda_i} = \frac{1}{1+\kappa_i}$ cannot be rejected at a given significance level, although these expressions are mathematically equivalent. The root of this problem is the so called "manipulability of the Wald test", the phenomenon that Wald tests are not invariant to nonlinear transformations. The problem was discovered by Spitzer (1984) and is discussed - for instance - by Phillips and Park (1988). I circumvent the issue by avoiding Wald tests altogether and use bootstrapping despite the computational burden.

Table 6: Parameter estimates based on the whole sample of banks

Parameter	Point estimate	Bootstrap s.e.	95% CI
κ	2.34	1.13	[1.32, 8.54]
λ	1.76	0.60	[1.08, 4.10]
Actual weight on signal $\frac{1}{1+\lambda}$ (%)	36.21	7.13	[19.59, 48.02]
Bayesian weight on signal $\frac{1}{1+\kappa}$ (%)	29.96	8.14	[10.48, 43.10]
Excess weight on signal $\frac{1}{1+\lambda} - \frac{1}{1+\kappa}$ (%)	6.25	2.89	[0.82, 12.84]

This table shows GMM estimates of κ and λ based on $T = 222$ non-adjacent observations. Standard errors and bootstrap percentile confidence intervals are computed based on $B = 999$ bootstrap samples.
κ indicates the signal variance relative to prior variance. It determines the optimal ("Bayesian") weight attached to the signal when fixing the quote. $\kappa > 1$ implies that prior public information is more precise than banks' privately observed signal.
λ is a parameter to determine the "actual weight" attached to the signal when fixing the quote. $\lambda < \kappa$ implies that the excess weight is positive, i.e. banks attach more weight to the signal than is justified by the signal's precision and are hence anti-herding.

the Euribor panel is composed of two groups of banks. The first group contains around one third of the panel banks and these seem to be better informed about prevailing market rates than the remaining two thirds. Likewise, panel banks in the second group obtain private information that is less precise than the publicly available prior knowledge. I summarize these findings in Figure 6. The point estimates for λ_i are in the range of [1.14, 2.91]. For 17 out of 45 banks λ_i is smaller than the whole sample estimate of λ at the 5% significance level and for nine out of 45 it is larger. This shows that there is cross-sectional heterogeneity in the way banks combine public and private information.

Based on the estimates for κ_i and λ_i I calculate the actual weight on the signal $\frac{1}{1+\lambda_i}$, the Bayesian weight $\frac{1}{1+\kappa_i}$, and the excess weight $\frac{1}{1+\lambda_i} - \frac{1}{1+\kappa_i}$. The estimates for these three weights are presented in Table 8. The point estimates for the Bayesian weight are in the range of [21.12%, 43.37%] and the point estimates for the actual weight are in the range of [25.60%, 46.67%]. For the issue of directional deviation the excess weight is crucial. Here, the point estimates are in the range of [−0.56%, 14.51%]. For ten out of 45 panel banks the excess weight is larger than zero at the 5% significance level, i.e. these banks are anti-herding. There are no banks with an excess weight that is significantly smaller than zero, i.e. there is no evidence for herding. For eleven banks the excess weight is smaller than the whole sample estimate at the 5% significance level and for three it is larger. These findings suggest that there is cross-sectional heterogeneity in the extent of anti-herding and that only some banks engage in directional deviation altogether. However, it should be noted that the estimates for the excess weight are imprecise judged by the bootstrapped standard errors and the width of the confidence intervals. For 32 out of 45 panel banks the upper bound of the 95% confidence interval exceeds

Table 7: Parameter estimates at the bank-level

name	$\hat{\kappa}_i$	s.e.	95% CI		$\hat{\lambda}_i$	s.e.	95% CI	
Natexis/Groupe BPCE	1.306*	0.36	[0.79,	2.22]	1.143*	0.27	[0.71,	1.80]
West LB	1.420*	0.50	[0.81,	2.92]	1.416	0.36	[0.89,	2.40]
Crédit Agricole	1.462*	0.46	[0.82,	2.73]	1.386*	0.34	[0.86,	2.25]
Crédit Industriel et Commercial	1.661*	0.79	[0.85,	4.62]	1.394*	0.50	[0.78,	2.99]
KBC Bank	1.675*	0.92	[0.82,	5.31]	1.439*	0.57	[0.79,	3.15]
Commerzbank	1.767*	1.02	[0.97,	5.79]	1.687	0.66	[0.98,	4.05]
Natixis	1.780*	1.06	[0.91,	5.74]	1.451*	0.58	[0.79,	3.29]
Fortis Bank	1.803*	0.88	[0.97,	4.82]	1.444*	0.51	[0.80,	2.94]
Bayerische Landesbank	1.810*	0.74	[1.05,	4.41]	1.460*	0.45	[0.90,	2.89]
Landesbank Berlin	1.812*	0.92	[0.93,	4.94]	1.667	0.59	[1.01,	3.73]
Citigroup	1.843*	1.09	[0.94,	5.94]	1.587*	0.61	[0.93,	3.57]
NORD/LB Norddeutsche Landesbank	1.853	1.07	[0.93,	6.38]	1.546*	0.57	[0.91,	3.43]
Caixa Geral de Depósitos	1.880*	0.83	[1.03,	4.66]	1.462*	0.50	[0.83,	2.90]
Svenska Handelsbanken	1.883	0.64	[1.10,	3.63]	1.786	0.40	[1.20,	2.85]
Rabobank	1.913	0.85	[1.07,	4.95]	1.385*	0.49	[0.80,	2.82]
Landesbank Hessen-Thüringen	1.965*	1.00	[1.04,	5.24]	1.560*	0.56	[0.91,	3.45]
HSBC Bank	1.968	1.22	[1.03,	6.51]	1.540	0.64	[0.87,	3.62]
National Bank of Greece	1.971*	1.07	[1.04,	6.28]	1.581*	0.60	[0.88,	3.60]
Intesa Sanpaolo	2.110*	1.34	[1.01,	6.96]	1.895	0.79	[1.10,	4.45]
Bank of Tokyo-Mitsubishi UFJ	2.220	1.83	[0.99,	8.92]	2.740*	0.96	[1.21,	5.43]
Danske Bank	2.270	1.01	[1.07,	5.36]	1.433*	0.54	[0.75,	2.91]
Belfius Banque	2.550*	1.29	[1.05,	7.50]	1.567*	0.65	[0.86,	3.73]
CAPITA	2.670	1.74	[0.96,	9.92]	1.951	0.92	[1.09,	5.40]
Barclays Bank	2.750	1.20	[1.08,	6.95]	1.698	0.63	[1.01,	3.82]
Banque et Caisse d'Epargne de l'Etat	2.850	1.14	[1.09,	6.53]	1.559*	0.62	[0.88,	3.54]
ABN AMRO Bank	2.990	1.09	[1.13,	6.55]	1.553*	0.59	[0.89,	3.41]
Raiffeisen Zentralbank Österreich	2.108	0.93	[1.14,	5.67]	1.608	0.52	[0.97,	3.14]
ING Bank	2.255	2.04	[1.13,	12.02]	2.285*	1.18	[1.35,	7.73]
Whole sample	2.337	1.13	[1.32,	8.54]	1.761	0.60	[1.08,	4.10]
UniCredit	2.365	1.76	[1.15,	8.26]	1.717	0.77	[0.93,	4.35]
Deutsche Bank	2.374	1.36	[1.21,	7.17]	1.627	0.54	[0.97,	3.24]
Nordea Bank	2.483	1.43	[1.30,	7.21]	1.788	0.65	[1.07,	3.83]
CECA	2.504	2.24	[1.04,	10.23]	1.656	0.78	[0.93,	4.37]
Deutsche Zentral-Genossenschaftsbank	2.551	1.29	[1.37,	7.28]	1.621	0.59	[0.93,	3.77]
Landesbank Baden-Württemberg	2.557	2.13	[1.26,	11.42]	2.320*	0.91	[1.19,	5.71]
Erste Bank der österreichischen Sparkassen	2.599	1.80	[1.32,	9.75]	1.977	0.84	[1.14,	5.33]
Allied Irish Banks	2.700	1.71	[1.34,	8.82]	1.730	0.69	[0.96,	3.93]
Bank of Ireland	2.723	3.25	[1.39,	12.26]	2.283*	1.16	[1.37,	6.29]
Banco Bilbao Vizcaya Argentaria	2.751	1.99	[1.37,	10.49]	2.770*	0.87	[1.19,	5.84]
JPMorgan Chase & Co	2.822	3.77	[1.18,	19.95]	2.221*	1.28	[1.24,	8.63]
Banco Santander	2.848	3.76	[1.31,	17.27]	2.830	1.14	[1.15,	6.72]
BNP Paribas	3.261	1.93	[1.63,	8.91]	1.633	0.58	[0.88,	3.21]
Dresdner Bank	3.330*	2.72	[1.60,	13.07]	2.118*	0.98	[1.15,	5.22]
Banca Monte dei Paschi di Siena	3.392*	23.12	[1.44,	39.91]	2.907*	3.12	[1.60,	13.97]
Société Générale	3.431*	2.62	[1.75,	15.39]	2.122	0.94	[1.23,	5.32]
UBS	3.735	8.91	[1.39,	27.77]	2.286*	1.54	[1.19,	7.56]

This table shows GMM estimates of κ_i and λ_i based on $T = 222$ non-adjacent observations. Standard errors and Bootstrap percentile confidence intervals are computed based on $B = 999$ bootstrap samples. Banks are sorted by $\hat{\kappa}_i$ in ascending order.

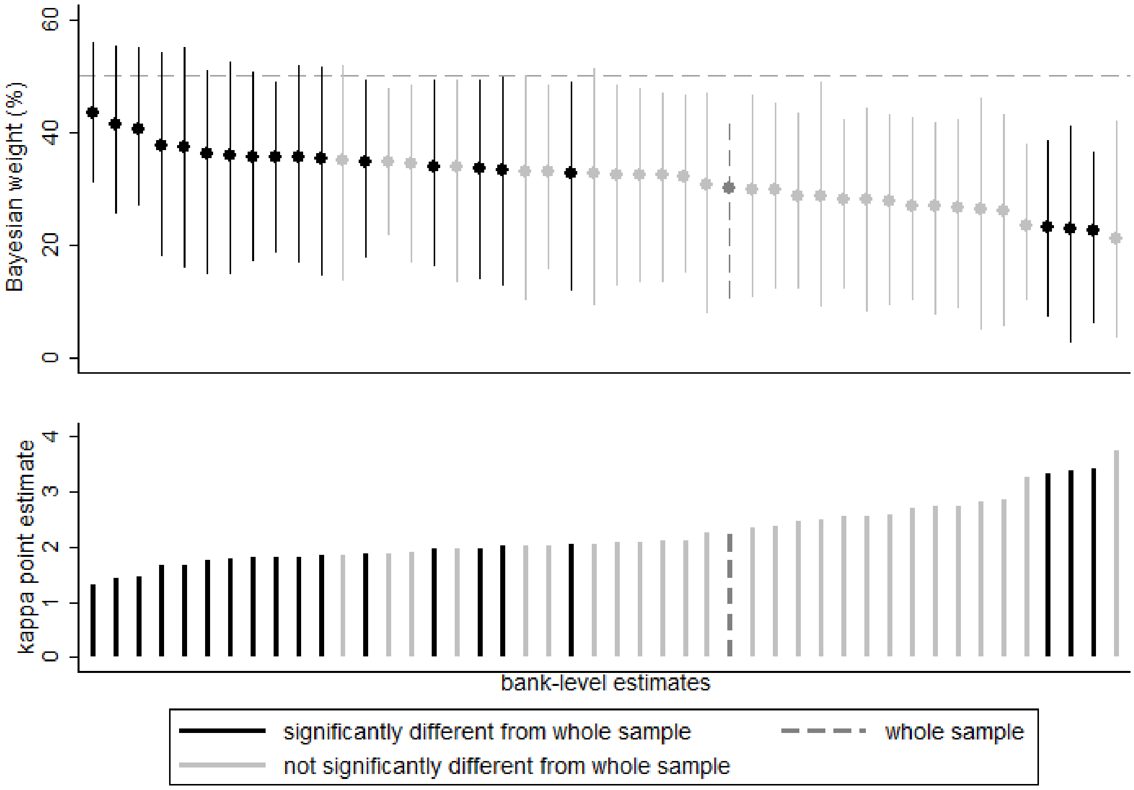
κ_i indicates the signal variance relative to prior variance. It determines the optimal ("Bayesian") weight attached to the signal when fixing the quote. $\kappa_i > 1$ implies that prior public information is more precise than bank i's privately observed signal.

λ_i is a parameter to determine the "actual weight" attached to the signal when fixing the quote. $\lambda_i < \kappa_i$ implies that the excess weight is positive, i.e. banks attach more weight to the signal than is justified by the signal's precision and are hence anti-herding.

The star * indicates that the null hypothesis of a bank-level parameter equal to the whole sample parameter ($\kappa_i = \kappa$ or $\lambda_i = \lambda$) can be rejected at the 5% significance level.

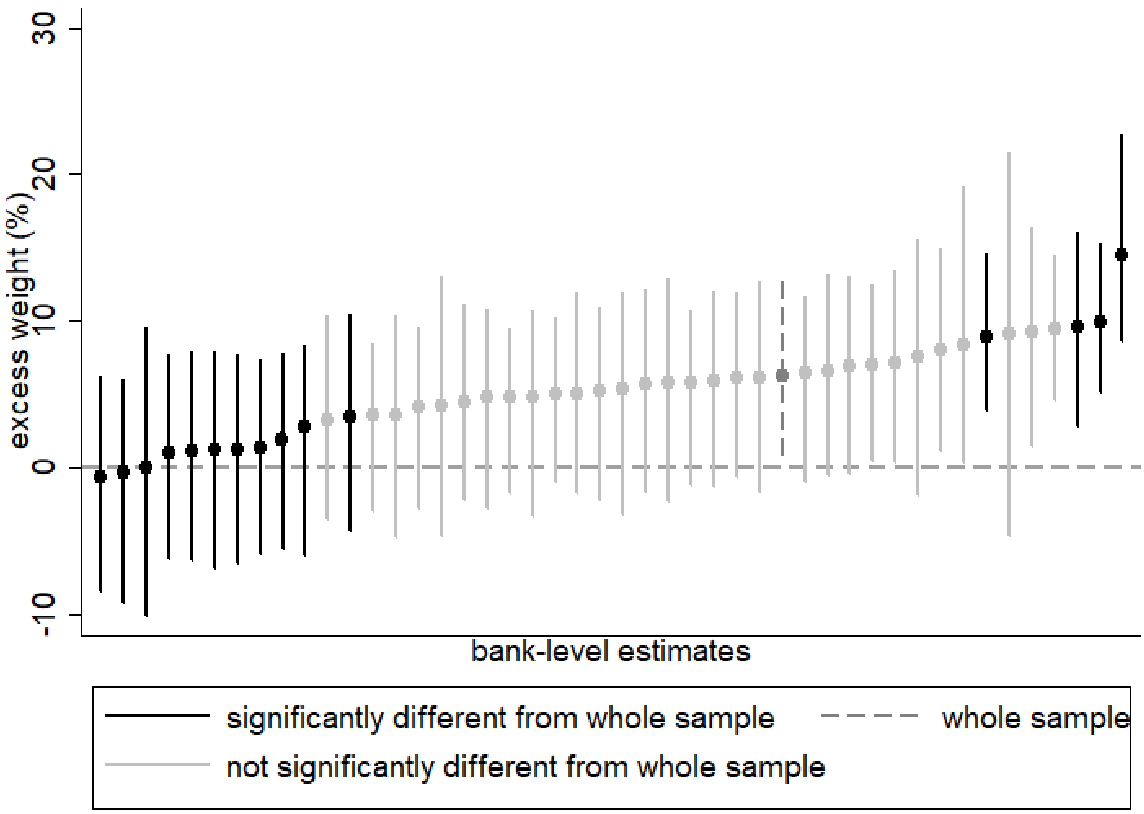
10%. I illustrate the findings on the excess weights in Figure 7.

Figure 6: Sample distribution of Bayesian weights $\frac{1}{1+\kappa_i}$ and relative signal variance κ_i



This figure shows bank-level estimates of the Bayesian weight $\frac{1}{1+\kappa_i}$ in the top panel and of the relative signal variance κ_i in the bottom panel. In the top panel point estimates are denoted by full circles and 95% bootstrap percentile confidence intervals are denoted by spikes. In the bottom panel, merely point estimates are shown by bars. In both panels the whole-sample estimate is indicated by the dashed line. Where the null hypothesis $\kappa_i = \kappa$ can be rejected at the 5% significance level, the items are black, where the null hypothesis cannot be rejected the items are gray. The figure shows that there is cross-sectional heterogeneity in banks' relative signal precision. There is a significant minority of banks who receive more precise information than the panel average, i.e. those banks to the left of the sample average indicated in black. Most banks receive information that is less precise than the publicly available prior information, i.e. the null hypothesis $\kappa_i = 1$ can be rejected at the 5% significance level. Equivalently, the Bayesian weight $\frac{1}{1+\kappa_i} \neq \frac{1}{2}$. These banks can be identified in the top panel through the dashed horizontal reference line at 50%. Together, both panels show that the minority who receives better information than the average exhibits a signal precision that is about equal to prior signal precision.

Figure 7: Sample distribution of the excess weights $\frac{1}{1+\lambda_i} - \frac{1}{1+\kappa_i}$



This figure shows the distribution of excess weights $\frac{1}{1+\lambda_i} - \frac{1}{1+\kappa_i}$ among the Euribor panel banks in percentage points. Circles indicate point estimates, spikes indicate 95% percentile bootstrap confidence intervals. A panel bank is anti-herding when its excess weight is positive, it is herding when its excess weight is negative, and it is not engaging in directional deviation altogether when its excess weight is zero. The whole-sample estimate is indicated by gray dashed items. Banks whose excess weights are statistically significantly different from the whole-sample estimates are shown in black, otherwise in gray. The figure shows that there is cross-sectional heterogeneity in the extent to which panel banks engage in anti-herding. It furthermore shows that at the individual level the null hypothesis of a zero excess weight can be rejected only for a minority of panel banks.

Table 8: Excess weights at the bank-level

name	Actual weight	Bayesian weight	Excess weight	s.e.	95%	CI
Bank of Tokyo-Mitsubishi UFJ	32.53	33.09	-0.56*	3.91	[-8.44,	6.28]
ING Bank	30.44	30.72	-0.28*	3.95	[-9.19,	6.08]
West LB	41.40	41.32	0.70*	4.89	[-10.09,	9.62]
Commerzbank	37.22	36.15	1.70*	3.50	[-6.19,	7.69]
Svenska Handelsbanken	35.90	34.69	1.21*	3.61	[-6.27,	7.95]
CAPITA	33.89	32.60	1.28*	3.93	[-6.84,	7.89]
Crédit Agricole	41.91	40.61	1.30*	3.61	[-6.48,	7.70]
Intesa Sanpaolo	34.55	33.21	1.33*	3.53	[-5.81,	7.42]
Landesbank Berlin	37.49	35.56	1.93*	3.44	[-5.53,	7.85]
Banca Monte dei Paschi di Siena	25.60	22.77	2.83*	3.77	[-6.00,	8.41]
Natexis/Groupe BPCE	46.67	43.37	3.30	3.65	[-3.54,	10.41]
Citigroup	38.66	35.17	3.49*	3.76	[-4.33,	10.45]
Bank of Ireland	30.46	26.86	3.59	3.05	[-2.98,	8.54]
KBC Bank	41.00	37.39	3.61	3.79	[-4.68,	10.39]
Crédit Industriel et Commercial	41.77	37.58	4.18	3.11	[-2.68,	9.60]
NORD/LB Norddeutsche Landesbank	39.27	35.05	4.22	4.70	[-4.63,	13.10]
Barclays Bank	37.06	32.52	4.53	3.37	[-2.20,	11.12]
Natixis	40.80	35.97	4.82	3.46	[-2.77,	10.81]
Landesbank Baden-Württemberg	32.99	28.11	4.88	3.06	[-1.71,	9.49]
JPMorgan Chase & Co.	31.04	26.17	4.88	3.62	[-3.29,	10.68]
Bayerische Landesbank	40.64	35.59	5.50	2.98	[-0.98,	10.31]
National Bank of Greece	38.75	33.65	5.90	3.46	[-1.76,	11.90]
Fortis Bank	40.91	35.67	5.24	3.34	[-2.12,	10.92]
Landesbank Hessen-Thüringen	39.07	33.72	5.34	3.82	[-3.13,	11.94]
HSBC Bank	39.38	33.70	5.68	3.63	[-1.67,	12.18]
Erste Bank der österreichischen Sparkassen	33.59	27.79	5.80	3.82	[-2.32,	12.97]
Banco Bilbao Vizcaya Argentaria	32.50	26.66	5.83	3.08	[-1.17,	10.76]
Caixa Geral de Depósitos	40.62	34.73	5.89	3.34	[-1.23,	12.08]
Raiffeisen Zentralbank Österreich	38.34	32.18	6.16	3.14	[-0.57,	11.96]
Belfius Banque	38.95	32.73	6.21	3.59	[-1.65,	12.72]
Whole sample	36.21	29.96	6.25	2.89	[0.82,	12.84]
Banco Santander	32.43	25.99	6.45	3.30	[-0.99,	11.75]
Banque et Caisse d'Epargne de l'Etat	39.08	32.41	6.66	3.50	[-0.51,	13.13]
ABN AMRO Bank	39.18	32.27	6.91	3.35	[-0.37,	13.11]
UniCredit	36.81	29.72	7.90	3.08	[0.54,	12.53]
Nordea Bank	35.86	28.71	7.15	3.21	[0.41,	13.47]
Rabobank	41.94	34.33	7.61	4.38	[-1.86,	15.60]
Danske Bank	41.10	33.04	8.50	3.50	[1.12,	14.92]
Deutsche Bank	38.07	29.64	8.43	4.79	[0.37,	19.15]
Dresdner Bank	32.07	23.10	8.97*	2.45	[3.94,	14.57]
CECA	37.65	28.54	9.11	6.79	[-4.57,	21.47]
UBS	30.43	21.12	9.31	3.95	[1.53,	16.41]
Société Générale	32.03	22.57	9.47	2.53	[4.56,	14.52]
Allied Irish Banks	36.63	27.03	9.60*	3.30	[2.82,	16.08]
Deutsche Zentral-Genossenschaftsbank	38.16	28.16	9.99*	2.59	[5.13,	15.29]
BNP Paribas	37.98	23.47	14.51*	3.49	[8.63,	22.74]

This table shows GMM estimates of the Bayesian weight $\frac{1}{1+\kappa_i}$, the actual weight $\frac{1}{1+\lambda_i}$, and the excess weight $\frac{1}{1+\lambda_i} - \frac{1}{1+\kappa_i}$ based on $T = 222$ non-adjacent observations. Standard errors and Bootstrap percentile confidence intervals are computed based on $B = 999$ bootstrap samples. Banks are sorted by excess weight in ascending order. All figures are given in percentage points.
The Bayesian weight is the optimal weight attached to the signal when fixing the quote given bank i's signal precision. The excess weight is the difference between the actual weight and the Bayesian weight. A bank is anti-herding when its excess weight is positive.
The star * indicates that the null hypothesis of a bank-level excess weight equal to the whole sample excess weight ($\frac{1}{1+\lambda_i} - \frac{1}{1+\kappa_i} = \frac{1}{1+\lambda} - \frac{1}{1+\kappa}$) can be rejected at the 5% significance level.

8 Discussion

In this section I summarize and discuss my findings on directional deviation in the Euribor survey. The BCK test performed in Section 6 suggests that panel banks are anti-herding in general, but that there is a minority that does not engage in directional deviation. The BCK test does not rely on the assumption of normally distributed disturbances and is robust to measurement error and cross-sectionally correlated information, so this finding can be considered robust. However, the BCK test merely classifies banks on a nominal scale (herding, no directional deviation, anti-herding). Hence, a quantification of directional deviation and an analysis of potential heterogeneity in its extent is not possible with the BCK test. This motivates the introduction of the parametric model in Section 7. I introduce the two parameters κ_i and λ_i that govern directional deviation. The estimation of κ_i relies on the assumption that variation in the quotes can only arise from two sources: Variation in the true interest rate (ϵ_t, ϵ_{t-1}) and signal noise (z_{it}). Hence, all variation in the quotes that is not explained by variation in the true rate is attributed to signal noise. Put differently, "signal noise" is a catchall term for all variation from sources other than the true rate. These could be changes over time in the perception of the prime bank definition or "professionalism". For instance, some banks might have a more streamlined internal process on how to aggregate market data and how to report the quotes. These banks may be less prone to "internally" generated noise and hence may have less variation in their quotes which would result in a lower estimate of their signal noise.

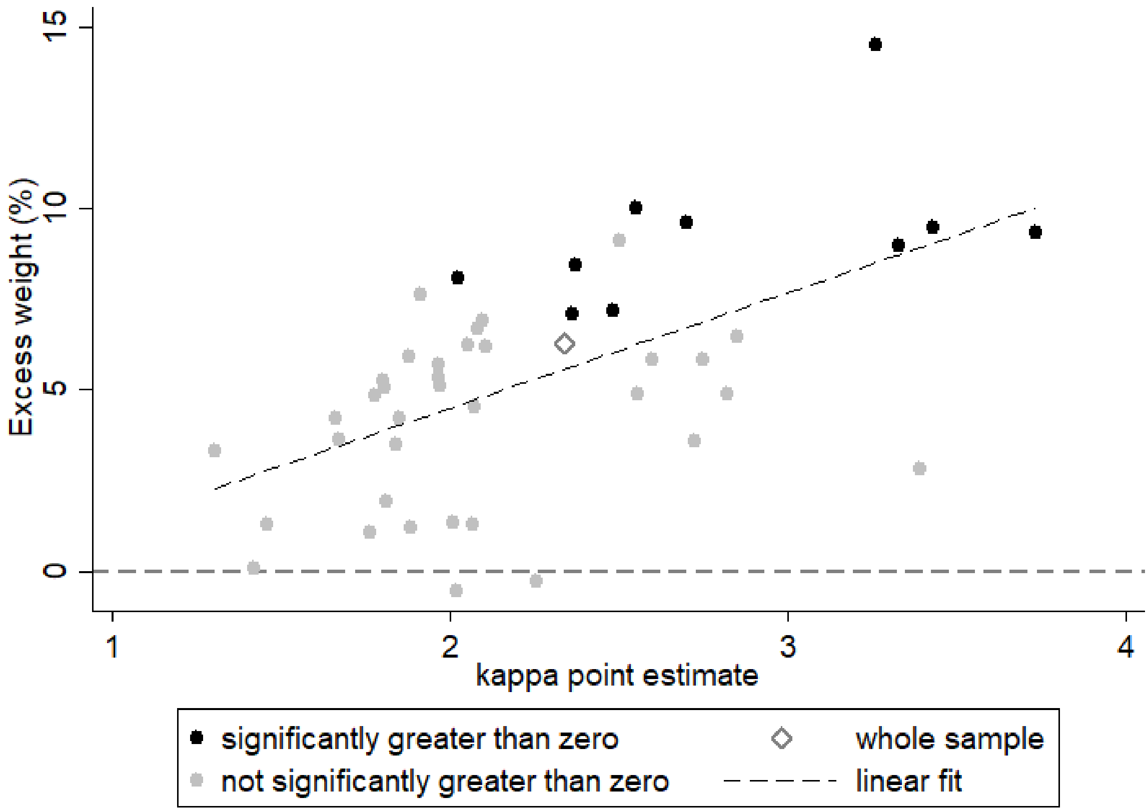
The findings from the parametric model are broadly in line with the findings from the BCK test, which is reassuring. In both analyses the whole sample results indicate banks are anti-herding in general. The whole sample S statistic is around 60% and the excess weight is quantified at about 6 percentage points in the parametric analysis. When looking at individual banks the BCK test suggests the majority of banks is anti-herding, whereas in the parametric analysis there is evidence in favor of anti-herding only for a minority of banks. This may be a result of imprecise estimates of the excess weight in the parametric analysis. Notably, point estimates of the excess weight are positive for the vast majority. The parametric analysis furthermore shows that there are distinctive differences at the bank level, as there is a minority of banks whose excess weights significantly differ from the whole-sample estimate. Combining the findings from the BCK test and the parametric analysis the following three conclusions can be considered robust. First, banks seem to anti-herd in general. Second, there are significant differences in the extent of anti-herding across banks. Third, there is at least a of minority of banks that does not seem to engage in anti-herding.

The incentives that lead to anti-herding in the Euribor survey - and possibly in the surveys underlying other reference rates from the IBOR family as well - remain an open question and a possible avenue for future research. A stylized fact that may be reflected in theoretical considerations is that the excess weight is increasing as signal precision deteriorates. This is illustrated in Figure 8 and means banks who produce less precise information exhibit a higher excess weight. Reputational cheap talk can be ruled out as a possible explanation, because Ottaviani and Sørensen (2006) show that this will give rise to herding, not anti-herding. However, it is not immediately apparent that the forecasting contest model is a plausible alternative description of the incentives leading to anti-herding in the Euribor survey. After all, the setting originally considered by the authors is that of professional forecasters, i.e. equity research analysts or macroeconomic forecasters. For these, successful participation in a forecasting contest may play a relevant part in engaging their potential clients. It remains unclear how similar incentives could arise in the daily Euribor survey, i.e. what payoff banks could derive from providing the winning guess. In the Euribor context there may be one or several quotes located most closely to the "true rate", i.e. the interest rate paid by the hypothetical prime bank, but the true rate is not directly related to the terms at which any particular panel bank enters trades in the interbank market. Ottaviani and Sørensen (2006) derive the equilibrium weight forecasters attach to the signal in the forecasting contest model. One of their underlying assumptions is that all forecasters exhibit the same signal precision, which is not the case in my setting. Nevertheless, I compare actual weights $\frac{1}{1+\lambda_i}$ to the weights predicted by the forecasting contest model. Adjusting the notation to that of Section 7, Ottaviani and Sørensen (2006) derive the following equilibrium signal weight.

$$C_i = \frac{1}{2}\left(\sqrt{\left(\frac{1}{\kappa_i}\right)^2 + 4\frac{1}{\kappa_i}} - \frac{1}{\kappa_i}\right) \tag{8.1}$$

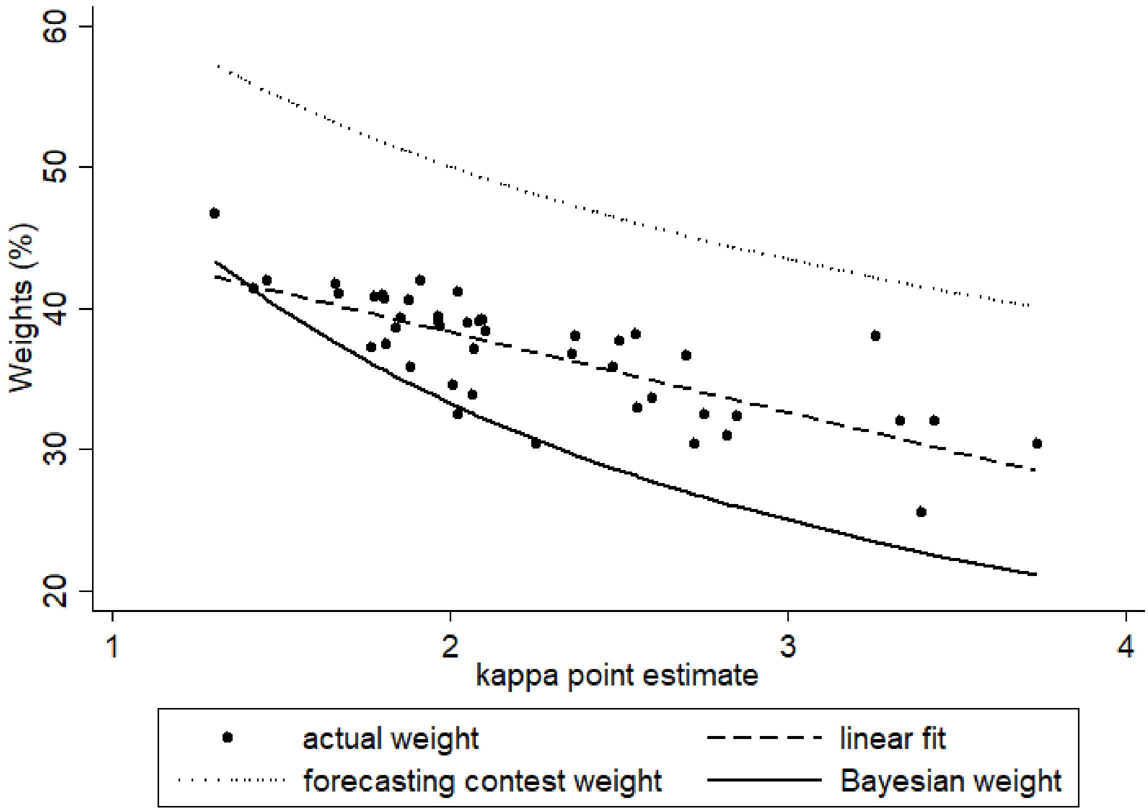
I show Bayesian weights $\frac{1}{1+\kappa_i}$, actual weights $\frac{1}{1+\lambda_i}$, and weights as predicted by the forecasting contest model C_i in Figure 9. Two main observations become apparent. First, actual weights are decreasing with deteriorating signal precision, i.e. as the relative signal variance κ_i increases, banks attach less weight to the signal. However, the decrease is not as pronounced as prescribed by the optimal weight. Hence, the gap between actual weight and Bayesian weight increases as signal precision deteriorates, which results in the positive correlation of excess weight and relative signal variance already illustrated in Figure 8. The second observation emanating from Figure 9 is that in general actual weights are much closer to Bayesian weights than to the weights predicted from the forecasting contest model. This is particularly the case for the banks with more precise private signals, i.e. lower estimates of κ_i. I formally test the null hypothesis that the actual weight equals the equilibrium weight from the forecasting contest model at the bank-level, i.e. $\frac{1}{1+\lambda_i} = C_i$. The null hypothesis is rejected at the 5% significance level for 43 out of 45 panel banks. This strongly suggests that the forecasting contest model is not an adequate description of the incentives leading to anti-herding in the Euribor survey.

Figure 8: Excess weight over κ_i



This figure shows point estimates of the excess weight $\frac{1}{1+\lambda_i} - \frac{1}{1+\kappa_i}$ over point estimates of the relative signal variance κ_i. Banks whose excess weight is greater than zero at the 5% significance level are marked in black, those whose excess weights are not significantly greater than zero are marked in gray. The whole-sample estimate is indicated through a hollow diamond. Excess weights are given in percentage points. There is a clear positive correlation between excess weights and relative signal variance. This suggests that banks who produce less precise information exhibit greater excess weights, i.e. overemphasize their private signals to a greater extent.

Figure 9: Actual weight over κ_i



This figure shows point estimates of the actual weight $\frac{1}{1+\lambda_i}$ over point estimates of the relative signal variance κ_i as black circles. The Bayesian weight $\frac{1}{1+\kappa_i}$ is indicated as a function of κ_i through a solid black line. The equilibrium weights under the forecasting contest model as described by Ottaviani and Sørensen (2006) are also given as a function of κ_i and are indicated through a black dotted line. Figures for actual weights, Bayesian weights, and weights from the forecasting contest model are given in percentage points.

9 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. One of the contributions of this paper is the development of a proxy for the true 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. As the BCK test classifies quotes on a nominal scale, it does not allow for a cross-bank comparison. I develop a parametric model of herding and anti-herding that allows to investigate cross-sectional heterogeneity in directional deviation. I corroborate the evidence for anti-herding based on the whole sample and I furthermore document significant cross-sectional variation in the extent of anti-herding. Ottaviani and Sørensen (2006) develop a model of a forecasting contest that is consistent with anti-herding among forecasters. However, I show that actual rate submissions differ significantly from the predictions of the forecasting contest model. This calls into question whether this model provides an adequate description of the incentives leading to anti-herding in the Euribor survey. In my opinion this remains an avenue for future research and I present stylized facts that may inform theoretical considerations. In particular, the excess weight increases with signal variance, i.e. less informed banks seem to engage in anti-herding to a greater extent. In any case, my findings have two implications. First, forecasts are more dispersed than under truthful reporting when agents are anti-herding. As Eisl, Jankowitsch and Subrahmanyam (2017) note, the potential for manipulating the fixing of an IBOR benchmark increases with the variation across quotes. Accordingly, the scope to manipulate the benchmark increases the more panelists engage in anti-herding. Second, a benchmark's fixing may become more volatile than the underlying rate it is supposed to track when panelists anti-herd. In summary, my results strengthen the cause for transactions-based rate setting processes in the ongoing policy debate on the reform of IBOR benchmarks.

A Consistent Estimation of the Test Statistic

This section consists of two parts. First, I briefly summarize the intuition of the test developed by Bernhardt, Campello and Kutsoati (2006). Then I demonstrate that under the additional assumptions made in the main body of the text the test statistic S identifies directional deviation when calculated based on first differenced series.

A.1 Intuition of the Test

In order to lay out the intuition behind the BCK test I abstract from the two main challenges in the main text, measurement error and level deviation. Assume the series r_t, c_t, q_{it} - i.e. the actual rate, the common prior, and the quotes, respectively - are observable. The bank-specific posterior mean x_{it} is unobservable. The bank-specific posterior expectational error is given by $\eta_{it} = r_t - x_{it}$. The BCK test relies on two identifying assumptions.

1. The posterior expectations are unbiased. Hence, η_{it} has a zero mean, both unconditionally as well as conditional on any entity in the bank's information set. $E[\eta_{it}|\mathcal{B}_{i,t-1}, s_{it}] = 0 \Rightarrow E[\eta_{it}] = 0$

2. η_{it} is distributed symmetrically such that its mean equals its median. $Pr[\eta_{it} \leq 0] = \frac{1}{2}$

The null hypothesis is that banks report without bias, the first alternative hypothesis is that banks are herding and the second alternative hypothesis is that banks are anti-herding, see Table 2. BCK define the test statistic in terms of population moments.

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

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, focus on the first summand $Pr[r_t < q_{it}|c_t < q_{it}]$. All arguments apply to the second summand analogously. Under the null hypothesis $q_{it} = x_{it}$.

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

The conditioning event $c_t < q_{it}$ allows the econometrician to identify those observations where the prior c_t is smaller than the signal s_{it}, because $c_t < q_{it} \Leftrightarrow c_t < s_{it}$. Those observations where the prior is larger than the signal are captured by the second summand in Equation (A.1). Notice that these events are observable for the bank before the quote has been submitted. As stated before, η_{it} is symmetrically distributed around zero, both unconditionally as well as conditional on any event in the bank's information set. Hence, $Pr[r_t < q_{it}|c_t < q_{it}] = Pr[\eta_{it} < 0|c_t < q_{it}] = \frac{1}{2}$ when the bank reports truthfully. Now turn to the case when banks engage in directional deviation.

$$r_t < q_{it} \Leftrightarrow \eta_{it} < q_{it} - x_{it} \tag{A.2}$$

Given the conditioning event $c_t < q_{it} \Leftrightarrow c_t < s_{it}$ the sign of the RHS $q_{it} - x_{it}$ is determined by the type of directional deviation, i.e. herding or anti-herding (see the top row in Table 2). When the bank is herding $q_{it} - x_{it} < 0$ and $q_{it} - x_{it} > 0$ when the bank is anti-herding. In words: Given the signal is larger than the prior, the quote is smaller than the posterior when the bank is herding and it is larger than the posterior when the bank is anti-herding. Hence, the sign of the RHS of Equation (A.2) is negative when the bank is herding and it is positive when the bank is anti-herding. As the LHS is distributed around zero this implies the following. $Pr[r_t < q_{it}|c_t < q_{it}] = Pr[\eta_{it} < q_{it} - x_{it}|c_t < s_{it}] < \frac{1}{2}$ when the bank is herding. When the bank is anti-herding the conditional probability is greater than $\frac{1}{2}$. The analogous arguments apply to the second summand in Equation (A.1).

One of the major advantages of the BCK test 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, I maintain the assumption that c_t is observable. Hence, $\tilde{r}_t = r_t - \zeta_t = x_{it} + \eta_{it} - \zeta_t$. Let $H(\cdot)$ denote the cdf of η_{it}. Under the null hypothesis of truthful reporting $\tilde{r}_t < q_{it} \Leftrightarrow \eta_{it} < \zeta_t$. Provided that the measurement error ζ_t is independent of the two conditioning events in Equation (A.1), the two summands in the test statistic cancel out the disturbance through the measurement error.

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

This simplified example demonstrates that the S statistic detects directional deviation despite the presence of measurement error provided that the measurement error be distributed independently of the two conditioning events. (Bernhardt, Campello and Kutsoati, 2006, p.664) show that if this condition is fulfilled, the presence of measurement error reduces the variance of S.

This means measurement error increases the probability of Type II errors. Hence, I may falsely fail to reject the null hypothesis because of the measurement error in the CDS-based proxy for c_t and r_t. However, the probability of Type I errors (i.e. falsely rejecting the null hypothesis) remains unaffected by measurement error.

A.2 The BCK Test Based on First Differenced Series

I reproduce those features of the analytical framework that are essential. 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} and I have imposed the additional restriction of linearity in the prior and the signal. $x_{it} = (1 - \phi_i)c_t + \phi_i s_{it}$ The posterior expectational error is denoted by $\eta_{it} = r_t - x_{it}$. Whereas it may be correlated in the cross-section, it is independent of its own leads and lags. Its first differences $\Delta\eta_{it}$ are autocorrelated of order one by construction. Let $G(\cdot)$ denote the cdf of $\Delta\eta_{it}$. The first thing to show is that under the null hypothesis of no directional deviation, i.e. $\Delta q_{it} = \Delta x_{it}$ the test statistic S as defined in Equation (6.3) is indeed one half in the population. As before, consider the first summand.

$$\Delta\tilde{r}_t - \Delta q_{it} < 0 \Leftrightarrow \Delta\eta_{it} < \Delta\zeta_t \tag{A.3}$$

I have assumed that $\Delta\zeta_t = \alpha + \omega_t$ and presented empirical evidence in favor of that assumption in Section 5.3. $\Delta\eta_{it}$ is symmetrically distributed around zero conditional on any event in the information set of bank i. Hence, the S statistic equals $\frac{1}{2}$ under the null hypothesis when the following holds true.

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

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 $\Delta r_{t-1} = \Delta c_t$.

$$\begin{aligned}
\Delta\tilde{r}_{t-1} - \Delta q_{it} &< 0 \\
\Leftrightarrow \Delta c_t - \Delta x_{it} &< \Delta\zeta_{t-1} \\
\Leftrightarrow \Delta\eta_{it} - \Delta\epsilon_t &< \alpha + \omega_{t-1}
\end{aligned}$$

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 its own leads and lags, of ϵ_t and z_{it}, and by extension also of η_{it}. This is a direct consequence of the ARIMA(0,1,0) structure of ζ_t established in Section 5.3.

The second thing to show is that $S < \frac{1}{2}$ in case of herding and $S > \frac{1}{2}$ in case of anti-herding. Notice that because of the assumption of linearity imposed on the posterior x_{it} and the quote q_{it} their first differences can be rearranged as follows.

$$\Delta x_{it} - \Delta c_t = \phi_i \left(\Delta s_{it} - \Delta c_t\right) \tag{A.4}$$

$$\Delta q_{it} - \Delta c_t = \theta_i \left(\Delta s_{it} - \Delta c_t\right) \tag{A.5}$$

It follows that when the signal increment is larger than the prior increment then the increment in the quote is larger than the increment in the prior as well: $\Delta c_t < \Delta s_{it} \Leftrightarrow \Delta c_t < \Delta q_{it}$ It is by this property that the conditioning event γ_{it}^- singles out those observations where $\Delta s_{it} > \Delta c_t$.

$$\gamma_{it}^- = 1 \Leftrightarrow \Delta c_t < \Delta q_{it} + \Delta\zeta_{t-1}$$

If there were no measurement error and the term $\Delta\zeta_{t-1}$ could be neglected, the conditioning event would classify observations perfectly. $\gamma_{it}^- = 1 \Leftrightarrow \Delta c_t < \Delta q_{it} \Leftrightarrow \Delta c_t < \Delta s_{it}$ In the presence of measurement error there is the possibility of misclassifying observations. I come back to this issue, but for the moment I abstract from the problem of misclassification. Consider the first summand in the S statistic under the assumption of directional deviation.

$$\Delta\tilde{r}_t - \Delta q_{it} < 0 \Leftrightarrow \Delta\eta_{it} < \Delta q_{it} - \Delta x_{it} + \Delta\zeta_t$$

The key thing to notice here is that given $\Delta c_t < \Delta s_{it}$ the sign of $\Delta q_{it} - \Delta x_{it}$ is determined by the type of directional deviation - herding or anti-herding. This becomes evident from Equations (A.4) and (A.5). In the case of herding ($\theta_i < \phi_i$) it is negative and in the case of anti-herding ($\theta_i > \phi_i$) it is positive. An analogous argument can be made for the second summand.

Two issues remain to be addressed. The first is the possibility of misclassifying observations because of measurement error. The second is the autocorrelation of η_{it}. First, I discuss the former one. Bernhardt, Campello and Kutsoati (2006, p.669) suggest to introduce a threshold

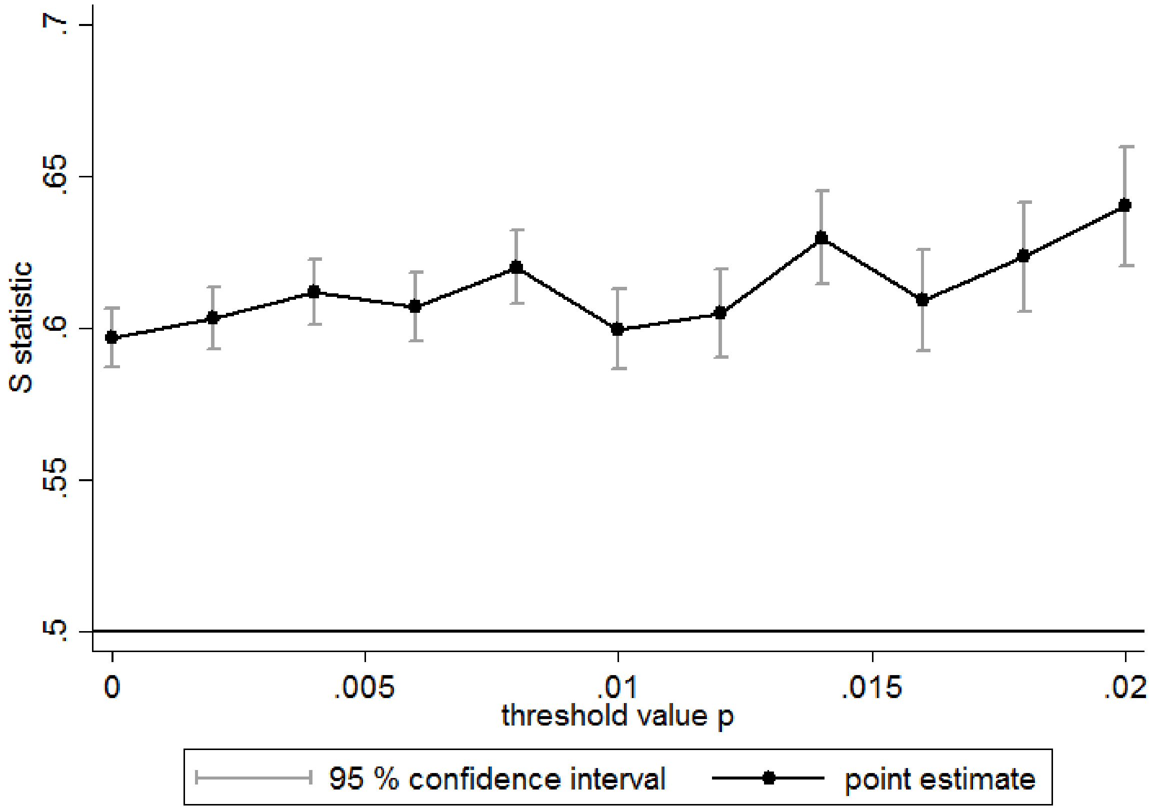
$p > 0$ in the conditioning events.

$$\gamma_{it}^{+} = 1 \quad \Leftrightarrow \Delta\tilde{r}_{t-1} - \Delta q_{it} > p, \quad \gamma_{it}^{+} = 0 \quad \text{otherwise}$$
$$\gamma_{it}^{-} = 1 \quad \Leftrightarrow \Delta\tilde{r}_{t-1} - \Delta q_{it} < -p, \quad \gamma_{it}^{-} = 0 \quad \text{otherwise}$$

Thereby, the probability of misclassifying observations is reduced, because the realization of $\Delta\zeta_{t-1}$ must exceed p in absolute value to produce a misclassification. In other words only those observations are considered for the calculation of the S statistic, where the increment in $\Delta\tilde{r}_{t-1}$ deviates by at least p in absolute value from the increment in the quotes. The higher p, the less likely it is that an observation where the (unobservable) increment in the prior Δc_t exceeds the increment in the quotes Δq_t is classified as Δc_t falling short of Δq_t and vice versa. At the same time, the numerical value of the S statistic is artificially driven away from one half as p is increased, because only those observations where $\Delta s_{it} - \Delta c_t$ is large in absolute value enter the calculation of the test statistic. Notice however, that under the null hypothesis of no directional deviation misclassification cannot affect the test statistic, because $\Delta\eta_{it}$ is symmetrically distributed around zero conditional on *any* event in the bank's information set. I recalculate S based on the pooled sample for a range of thresholds as a robustness check against the possibility that the results in the main body are affected by misclassification. I chose a range of $0 - 2$bps for the threshold p. Thereby, I exclude up to 75% of the sample and consider only those observations where misclassification is least likely. The results are plotted in Figure 10. The point estimate $\hat{S}$ increases gradually with the threshold p to a value of 64%. The null hypothesis of no directional deviation ($S = \frac{1}{2}$) can be rejected at the 5% significance level in all configurations. This reaffirms the findings of the main text and suggests that these are not affected by possible misclassification.

The last issue to discuss is the autocorrelation of η_{it}. It arises from the fact that I use first differences to account for level deviation in the quotes. 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 (6.2). However, $\Delta\eta_{it}$ is correlated with its first lead and lag by construction: $E[\Delta\eta_{it}\Delta\eta_{i,t+1}] = -E[(\eta_{it})^2]$. 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

Figure 10: Robustness of the test statistic to misclassification

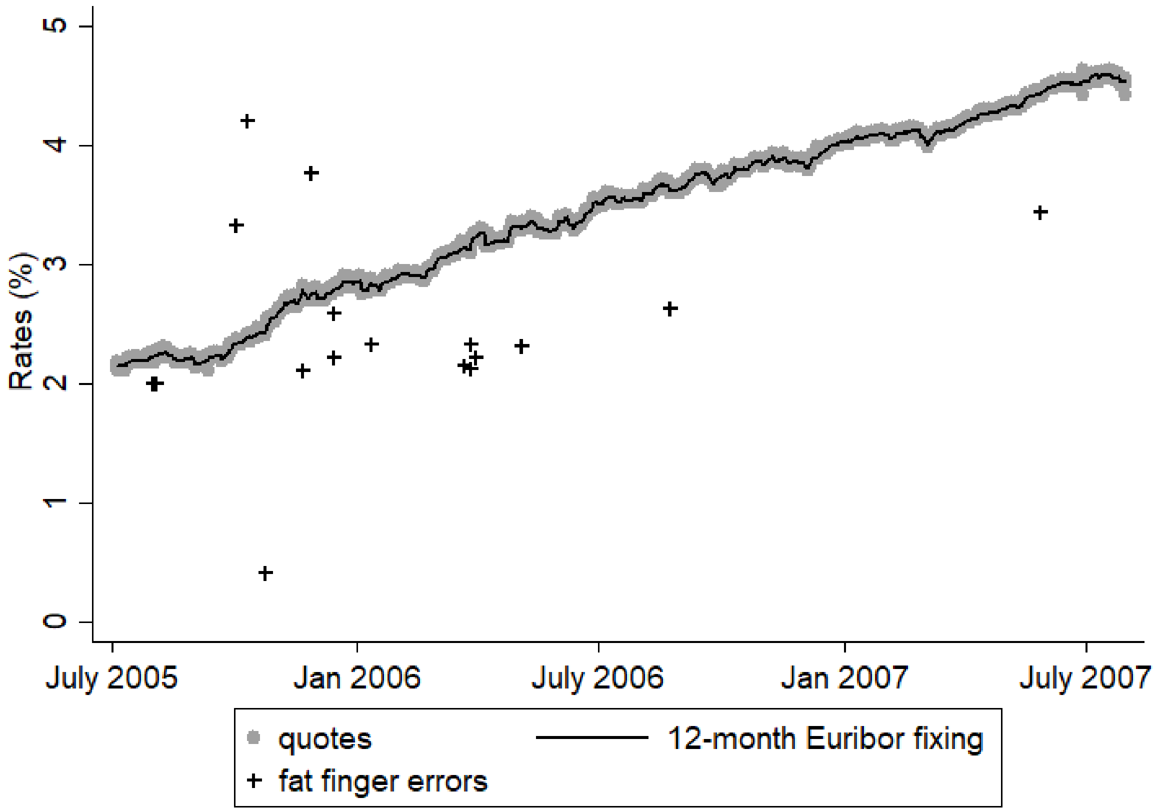


This figure shows the S statistic based on observations from all banks with modified conditioning events γ_{it}^{-} and γ_{it}^{+}. The modification requires that $|\Delta\tilde{r}_{t-1} - \Delta q_{it}| > p$, i.e. the larger p the less likely it is that the measurement error in the prior proxy $\Delta\tilde{r}_{t-1}$ leads to a misclassification. At $p = 0.1$ around 45% of observations are excluded, at $p = 0.2$ around 75% are excluded. Confidence intervals are calculated based on the robust variance estimator in Equation (6.4). The null hypothesis of no directional deviation ($S = \frac{1}{2}$) can be rejected at the 5% significance level in all configurations.

another day is picked at random for the estimation sample, etc.

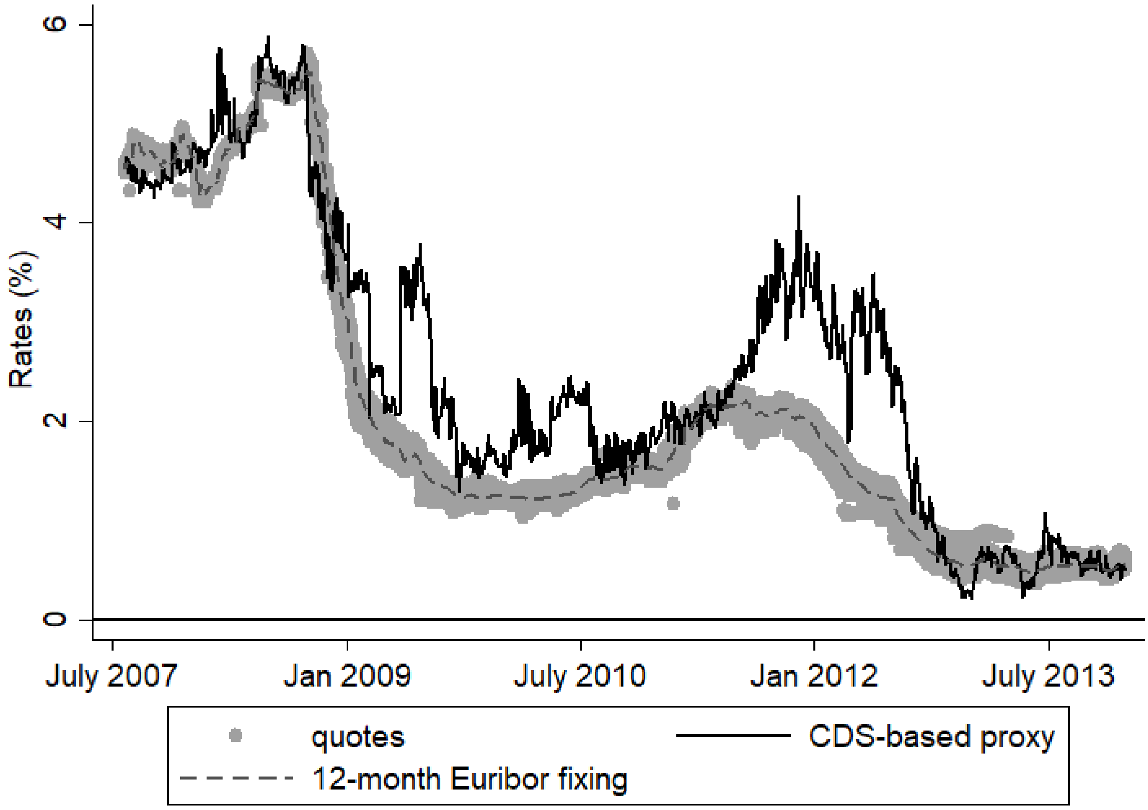
B Figures and Tables for the Main Text

Figure 11: Quotes, Fixing and Fat Finger Errors



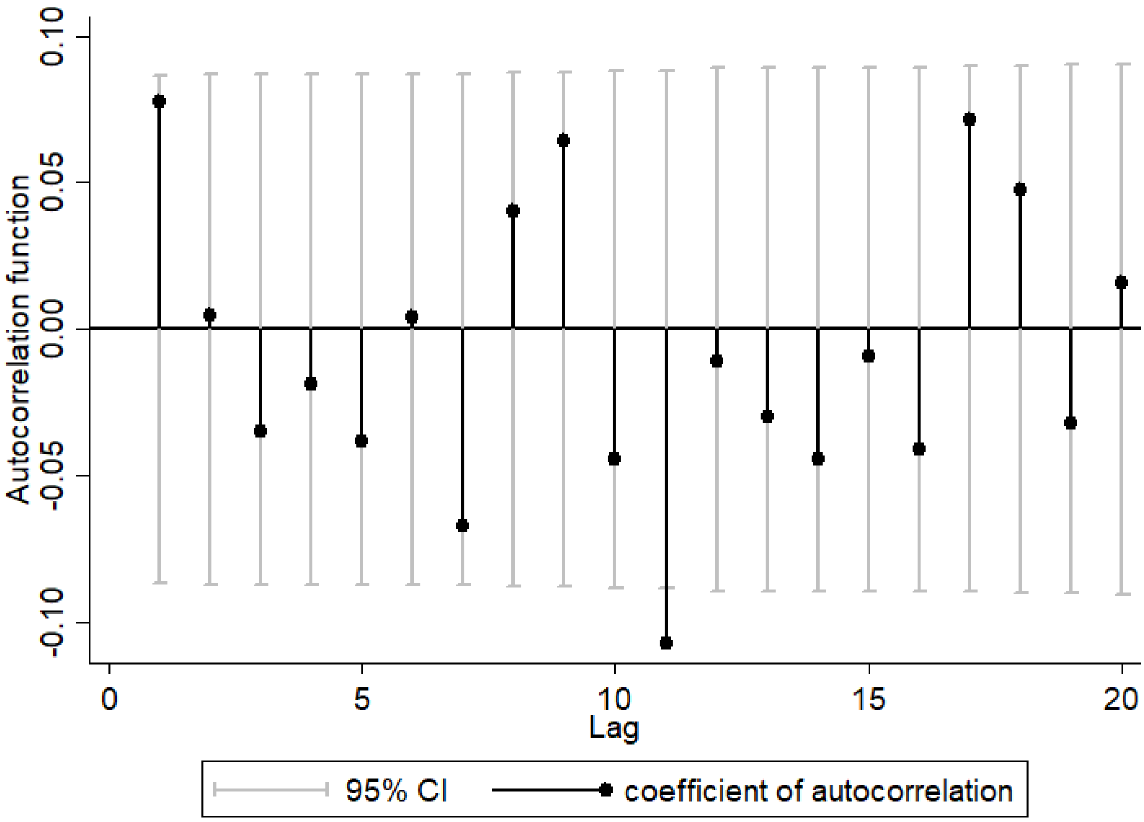
This figure shows the quotes for and the fixing of the 12-month Euribor rate during the sampling period in percentage points. Regular quotes are marked in gray, quotes that I classify as fat finger errors are marked by a black cross, and the Euribor fixing is designated by the solid black line. A total of 18 quotes are marked as fat finger errors and replaced by missing values.

Figure 12: Difference between Fixing and Proxy as of August 2007



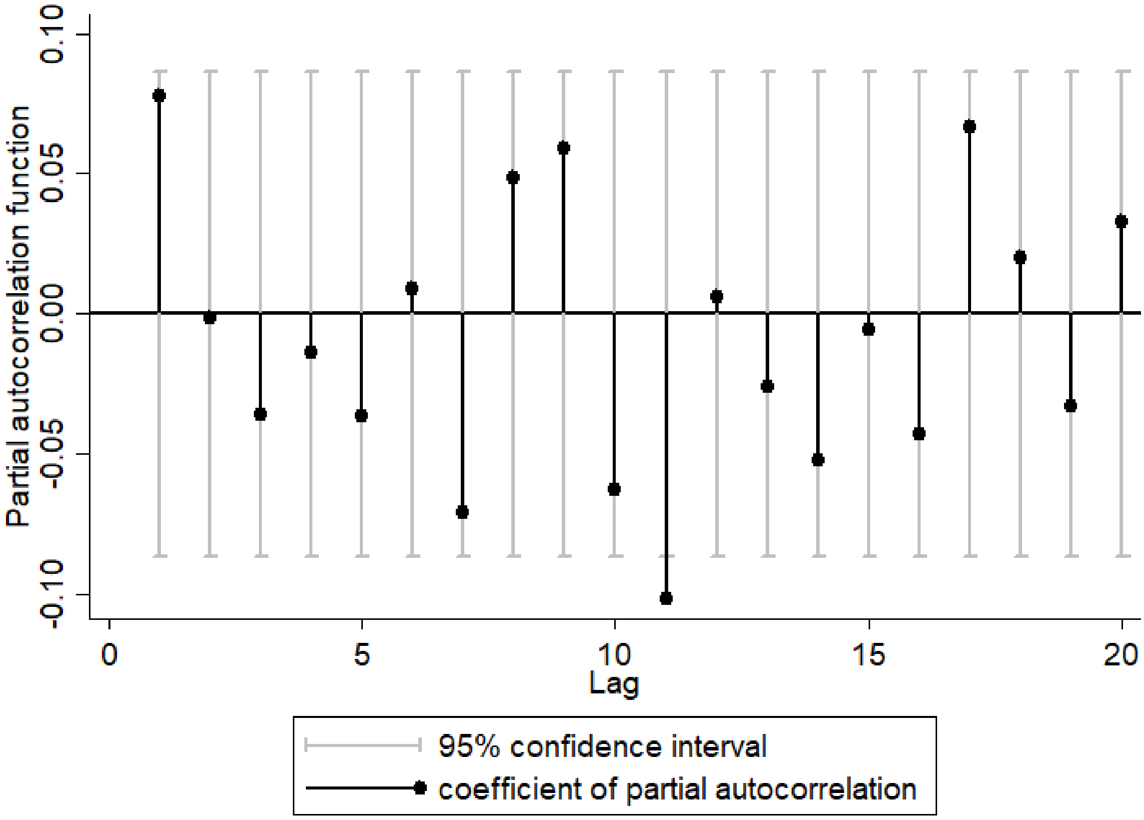
This figure shows the quotes and the fixing of the 12-month Euribor rate as well as the CDS-based proxy used in the main text for the period after the sampling period of this paper, i.e. August 2007 - December 2013. The deviation of the latter two rates is considerable, in particular during the European sovereign debt crisis. Possible explanations are intensified manipulation of the Euribor, frictions in the CDS market, or a higher market premium on liquidity risk that is inherent in term deposits, but not in bonds.

Figure 13: Autocorrelation Function of the Proxy



This figure shows the autocorrelation function of $\Delta\tilde{r}_t$ for the first 20 lags. The autocorrelation coefficients are not statistically different from zero at any one of the lags with the exception of lag 11, where the null hypothesis of a zero autocorrelation can be rejected at the 5% significance level, but not at the 1% significance level.

Figure 14: Partial Autocorrelation Function of the Proxy



This figure shows the partial autocorrelation function of $\Delta\tilde{r}_t$ for the first 20 lags. The partial autocorrelation coefficients are not statistically different from zero at any one of the lags with the exception of lag 11, where the null hypothesis of a zero partial autocorrelation can be rejected at the 5% significance level, but not at the 1% significance level.

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