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Do banks' overnight borrowing rates lead their CDS price? Evidence from the Eurosystem[☆]

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ABSTRACT

We construct a measure of a bank's relative creditworthiness from the Eurosystem's proprietary interbank loan data: average overnight borrowing rate relative to an overnight rate index (AOR). We then investigate the dynamic relationship between AOR and the credit default swap price relative to the corresponding market index of 60 banks during 2008–2013. Price discovery mainly takes place in the CDS market, but AOR also contributes to it. The lagged daily changes of AOR help predict CDS. This indicates that AOR includes private information, which the CDS market does not immediately incorporate. We further show that the private information advantage is concentrated on days of market stress and on banks, which mainly borrow from relationship lender banks. Such borrower banks are typically smaller, have weaker ratings, and are likely to reside in crisis countries. Competent authorities can use AOR as a complementary indicator of banks' concurrent health.

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1. Introduction

In the wake of the recent financial crises, the need to understand the functioning of inter-bank money markets has grown considerably. Money market data may also be a source of early-warning indicators for future banking problems. We contribute to the quest for early-warning indicators by forming a measure of a bank's creditworthiness: its average overnight money market borrowing rate relative to an overnight rate index (henceforth AOR). We then investigate whether this spread provides timely information of changes in the bank's creditworthiness in addition to the leading market-based indicator, the bank's CDS price relative to a market-wide CDS index for European financial institutions (henceforth CDS).[1]

We use the proprietary database of the Eurosystem's overnight money market, which operates in the so-called TARGET2 large value payment system (Trans-European Automated Real-time Gross Settlement Express Transfer System 2). The overnight market is the shortest-term component of the interbank money market through which banks manage their liquidity. It is the key transmission channel for monetary policy in major central banks including the European Central Bank (ECB) and the US Federal Reserve. At the

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[1] Specifically, we form AOR and CDS by deducting the Euro OverNight Index Average (EONIA) from a bank's average overnight borrowing rate and, respectively, the iTraxx-index for European financials from the bank's CDS price.

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shortest maturity, the money market is a liquid credit market with high frequency of observations.[2]

Earlier research has already considered whether interest rates on overnight loans taken by a bank, typically from a number of other banks, reflect the borrower bank's creditworthiness. Furfine (2001) has shown with the Fed Funds data that the overnight borrowing rates do indeed reflect accounting measures of the bank's credit risk. However, to the best of our knowledge previous research has not considered how efficiently and fast these markets react to changes in credit risk.

We choose CDS as a benchmark because it is a leading *public* indicator of the credit risk of both corporations and banks (see e.g. Blanco et al., 2005, Longstaff et al., 2005, Forte and Peña, 2009, Norden and Weber, 2009, and Annaert et al., 2012; see also Arora et al., 2012 and Berg 2010). In spite of their maturity mismatch and the effect of the term structure of credit risk, new information about bank creditworthiness should push both AOR and CDS in the same direction.[3] Note that by defining AOR and CDS in relation to the respective market indices, we control for the term structure of interest rates and effectively separate the bank-specific part of overnight rates and CDS prices from general market conditions such as liquidity conditions.[4]

AOR is not publicly observable (other than to the borrower bank itself and the competent authorities of the Eurosystem). Moreover, many of the overnight interbank loans are results of longer-term lending relationships (cf. e.g. Cocco et al., 2009, Bräuning and Fecht 2012, Abbassi et al. 2014, and Affinito 2012) in which the lender may have acquired *private* information of the borrower. It is hence possible that AOR aggregates private information of the borrower bank's condition, which CDS has not yet incorporated. Such a situation can prevail so long as the informed lenders choose not to trade on their private information in the CDS market in such a way that their information would be immediately and fully revealed via CDS.[5] Moreover, CDS prices are quotes rather than actual transactions, which is another reason why AOR may reflect changes in a bank's creditworthiness faster than CDS given that the bank is willing and able to borrow in the interbank market.[6]

Our data cover the period from the beginning of June 2008 to the end of June 2013, comprising 60 banks, 1300 business days, and around 470,000 loan transactions with average value of about 100 million EUR. These yield approximately 46,000 daily AOR observations.

To investigate AOR's contribution to information concerning a bank in addition to CDS, we use two conventional price discovery measures, which are based on the vector error correction (VEC) framework (Hasbrouck 1995 and Gonzalo and Granger 1995), and Granger causality tests in a standard VAR model. We use the VEC and the VAR models as complementary approaches because we find that AOR is stationary and the evidence of co-integration between AOR and CDS is mixed. We use daily changes of AOR and CDS and estimate the models both for the panel of 60 banks and for individual banks.

During tranquil times, the overnight lenders of a bank may be less concerned about changes in the borrower bank's creditworthiness. However, because overnight loans are typically quite large and uncollateralized, AOR may become more informative of the borrower's credit risk in times of stress when lender banks become concerned of the asset quality and liability structure of the borrower bank.[7] As described, e.g., by Dang et al., (2015), a money-like debt instrument (overnight interbank loans in our case) can become sensitive to the issuing institution's asset quality when there are sufficiently bad public news concerning the asset quality. This can trigger private information acquisition among investors (the lender banks in our case). We investigate whether AOR is more informative when the underlying overnight loans are arguably more information sensitive. We do this by using conditioning variables, such as an indicator for days of market stress, which proxy for intensified information sensitivity of the overnight loans.

Our empirical results from the Granger causality framework show that in daily differences, using the panel of 60 banks, AOR leads CDS by up to two lags while there is no similar lead for CDS over AOR. The price discovery measures obtained from the VEC model indicate that although price discovery mainly takes place in the CDS market, AOR also contributes to it, and its contribution appears to intensify during periods of market stress. Bank-specific results vary considerably, and for individual banks, CDS may Granger cause AOR.

A further investigation in the Granger causality framework using the panel of banks reveals that AOR helps to predict CDS mainly during periods of market stress in the case of banks that are relatively dependent on relationship lender banks. These banks tend to have poorer ratings and come from crisis countries. These findings are consistent with the information sensitivity hypothesis, suggesting that private information, which makes AOR useful in predicting CDS, is most plentiful when the information sensitivity of overnight loans is elevated.

Our results have the following implications. First, by using the proprietary interbank overnight loan interest rate data, the Eurosystem authorities can extract information concerning banks' current condition, which complements the information obtained from banks' CDS prices.[8]

Second, our results provide rare evidence on the value of private information. It is not common to have data on private information signals, which bilaterally negotiated overnight loan rates

[2] Money market transaction data are available for longer maturities as well but we will focus on the overnight data because of the far bigger market size and liquidity, and because the accuracy of identifying interbank loans out of the entire population of large value payment transactions in the data base is highest in case of the overnight loans.

[3] We use the five-year CDS contract, which is the most liquid of the CDS contracts.

[4] Schwarz (2014) argues that during the financial crisis liquidity risk has explained the major part of the general rise in Euribor and sovereign interest rate spreads.

[5] The seminal paper on the theory of privately informed trading is Kyle (1985). We can consider the overnight loans market as a fragmented market whereas the CDS market is relatively more centralized. Our setting corresponds to a situation where both types of markets are open at the same time on the same asset but where prices are public knowledge only in the centralized market (the CDS market) while they are private knowledge in the fragmented market (overnight loans). As a result, information flows between the two markets may be asymmetric. We are not aware of theoretical papers which would exactly consider a setting of this kind although price formation in fragmented vs centralized markets has been studied e.g. by Wolinsky, 1990, and Biais, (1993). Studies on the upstairs and downstairs markets on stocks may also provide some guidance (see e.g. Booth et al., 2002). As Biais (1993, p. 175) puts it, "(a)n issue is whether inside traders can use the lack of transparency of fragmented markets to exploit their private information." Though compared to the stock market the CDS market is more of an insider market; see e.g. Acharya and Johnson, (2007), the quotes available in Bloomberg are in principle public. On strategic behavior of informed and uninformed traders, see also O'Hara (1997; chapters 4 and 5).

[6] In stressful times a bank may be denied credit for a "fair" rate at least by some banks in the interbank market so that the bank may opt for the central bank's liquidity facilities instead (provided it has sufficient collateral). Such unrealized overnight loan transactions could in themselves be quite informative. This phenomenon may hence create a bias against finding that AOR is more informative than CDS.

[7] Afonso, Kovner and Schoar (2011) using US overnight money market data find that "the day after Lehman Brothers' bankruptcy, loan terms become more sensitive to borrower characteristics". See also Angelini et al. (2011). Further, Covitz and Downing (2007) provide evidence from commercial paper spreads of non-financial companies that credit risk dominates liquidity risk even at very short maturities.

[8] Earlier literature which may have lacked access to sufficient CDS data, has also studied the role of bond and equity prices as leading indicators of bank fragility; see e.g. Gropp et al. (2004) and (2006).

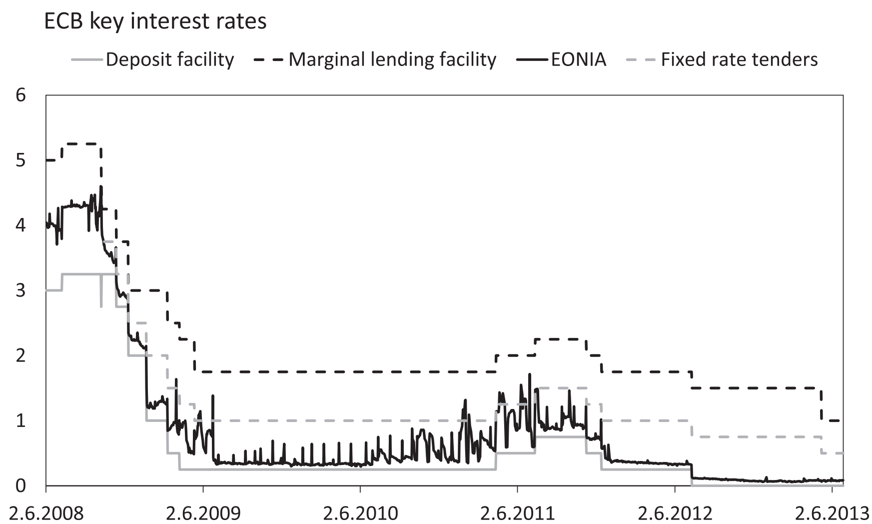

Fig. 1. ECB key interest rates for the sample period (beginning of June 2008 to end of June 2013).
The visible spikes in EONIA take place at the end of reserve maintenance periods and occasionally at the end of months. These spikes disappear starting from 2012 when the European banking system was flooded with unprecedented amounts of liquidity in the large long-term refinancing operations.

arguably reflect.[9] For comparison, Acharya and Johnson (2007) show that a firm's CDS price leads its stock price, and attribute this to private information in the CDS market. In a sense, our findings (using bank CDS data) take this a step further by showing that an aggregate of private information signals reflected in AOR can lead even CDS. Similarly, private information in AOR can explain our results with respect to Blanco et al., (2005) who show that CDS prices lead corporate bond spreads in the price discovery process.

We have organized the paper as follows. Section II describes the European interbank market and introduces the variables used. Section III presents the hypotheses, methodologies, co-integration tests, and empirical results. It also considers the economic significance of the results. Section IV concludes.

2. The data

2.1. Structure of the European interbank market

The Euro area monetary policy operations as well as the majority of transactions in the Euro area interbank market are settled in the TARGET2 system, which is the large value payment system of the Eurosystem.[10] Money market transactions are a subset of bank-to-bank large value payments. Bilateral loans are negotiated over-the-counter and are known only to the two parties involved in each transaction. The ECB's marginal lending facility and the deposit facility effectively set an upper bound and a lower bound, respectively, on the uncollateralized overnight loan rates.[11] The ECB's open market operations during the financial crisis and the subsequent European sovereign debt crisis have significantly increased the amount of excess reserves in the TARGET2, and have moved the average overnight rate (EONIA, see the description below) closer to the deposit facility rate. Further, the fixed tender rate of weekly main refinancing operations acts as a soft upper bound on the interbank rates (see Fig. 1). This is because a bank would be willing to borrow at a rate above the fixed tender rate only if it has no access to the ECB facilities, it has no available collateral, or it is concerned of reputational costs that could arise from borrowing from the central bank.

Regular "spikes" occur in the overnight rate series both on the last day of the reserve-maintenance period and typically on the last day of month. Spikes on the last day of the reserve-maintenance periods are caused by banks, which have a deficit in average reserves and borrow the gap for a premium from banks, which have accumulated an excess of reserves. Similar spikes on the last day of each month (especially quarter-ends and year-ends) apparently result from window dressing. However, because of the large excess reserves since the ECB's first long-term refinancing operations, these spikes no longer appear in the sample after December 2011. Unless noted otherwise, we report results with the special dates excluded from the data.

2.2. Panel and variables

2.2.1. 60 banks panel

Arciero et al. (2016) have provided the Eurosystem with a database of euro area money market transactions. They have identified money market loans from all TARGET2 transactions by an improved version of the algorithm originally suggested by Furfine (2001). The Arciero et al. (2016) algorithm is able to identify loan transactions with fair accuracy up to 3-month maturities, while the reliability is best for the overnight segment considered in this article.[12] The period of the dataset considered is from the beginning of June 2008, when the TARGET2 was fully operational, to the end of June 2013.

We identify the borrower and the lender with Business Identifier Codes (BICs). As one banking group may consist of several entities with their own BICs, we use information from the Swift BIC directory in order to consolidate the different entities under the common banking group and discard any loan transactions

[9] According to Garmaise and Moskowitz (2004), "(t)here are relatively few direct tests of the economic effects of asymmetric information because of the difficulty in identifying exogenous information measures".

[10] A number of European countries which do not belong to the Euro area are also connected to TARGET2 (for further details, see e.g. Arciero et al. 2016).

[11] These bounds are not strict because of two reasons. First, there may be banks without sufficient collateral who hence cannot access the ECB's liquidity facilities. Second, not all parties in the interbank market are eligible to access the central bank's facilities in the first place.

[12] We use a further improved version of the Arciero et. al. (2016) algorithm, which takes into account issues discussed in Armantier and Copeland (2012). We thank Arciero et. al. (2016) for providing this update.

Table 1
Descriptive statistics.
This table reports the number of observations each year that are used in the regressions and the mean and standard deviation for the key variables, AOR (EONIA subtracted) and CDS (iTraxx subtracted), and the bank relationship variables: Herfindahl–Hirschman Index (HHI), Borrower Preference Index (BPI), and bank size. AOR is defined as the average overnight borrowing rate minus the Euro OverNight Index Average (EONIA) and CDS is defined as the CDS price minus the iTraxx-index for European financials.

Year	Observations	AOR		CDS		HHI		BPI		Total assets	
		Mean	Std.	Mean	Std.	Mean	Std.	Mean	Std.	Mean	Std.
2008	6033	−0.141	0.166	0.311	0.807	0.069	0.128	0.083	0.135	639	604
2009	11,491	−0.151	0.119	0.542	1.040	0.089	0.142	0.101	0.138	648	623
2010	12,295	−0.078	0.113	0.558	1.575	0.098	0.156	0.113	0.155	635	597
2011	11,453	−0.081	0.176	1.062	3.072	0.083	0.152	0.100	0.150	670	595
2012	8983	−0.062	0.150	1.385	3.214	0.136	0.201	0.165	0.204	672	635
2013	3732	0.002	0.114	1.214	2.572	0.173	0.230	0.210	0.233	645	638
Total	53,987	−0.093	0.148	0.817	2.277	0.101	0.167	0.120	0.168	652	612

Observations for year 2008 start at the beginning of June and for 2013 end at the end of June. Total assets are in billions of US dollars.

that have taken place within banking groups. We match the BIC codes with Bloomberg CDS data and leave out banks with insufficient CDS data. As a result, our dataset has 60 borrower banks (domiciled in 19 different countries), 984 lender banks and 470,160 loan transactions. Taking the daily average yields 53,987 daily observations of AOR. Because of differencing and excluding the special dates with peaks, the final number of observations used in the regressions reduces to 33,823.

Table 1 includes descriptive statistics for the panel of 60 banks. For the period mid-2008 to mid-2012, there were around 12,000 observations per year. After mid-2012, the inter-bank overnight money market activity diminished because the ECB stepped up its liquidity providing operations and did not recover until the end of the data period. The decrease in money market activity is also accompanied with a change towards more concentrated markets with fewer counterparties, as measured by the bank relationship variables (see below for their precise definitions).

2.2.2. Average overnight rate with respect to EONIA (AOR)

For each business day, a bank may have borrowed from several lenders so we aggregate the daily rate from the multiple borrowings.[13] The loan issues generally take place between 7 a.m. and 6 p.m. Central European Time (CET) during the TARGET2 Day Trade Phase. Transactions towards the end of the day should contain the most recent information so we could use the time stamp as a weight in the aggregation.[14] The informativeness of a single transaction rate could also depend on the value of the loans or the intensity of the borrower-lender relationship. One could consider giving accordingly more weight to lenders that have close relationship with the bank (measured by past lending volume) or to loans that are of higher value or to use some percentile instead of average overnight rate. However, we found that different weighing schemes, or using percentiles of overnight rates, have only minor effect on the results so we simply use uniform weights in the daily rate aggregation per bank.

As already discussed above, to facilitate comparison with the CDS price, we transform the average overnight rates into average overnight rate spreads with respect to a suitable loan rate index. We find Euro OverNight Index Average (EONIA) a natural choice since it helps to account for general conditions in the euro money markets (e.g. the effects of policy rate changes, open market operations, and seasonal effects due to maintenance periods).[15] Hence, we define a bank's AOR as:

$$AOR_{B,t} = \frac{1}{N_{B,t}} \sum_{L} R_t^{L \to B} - EONIA_t. \tag{1}$$

Here $R_t^{L\to B}$ is the rate of an overnight loan from lender bank L to borrower bank B on day t. $N_{B,t}$ is the number of lender banks that lend to bank B on day t. For example, if on a given day EONIA is 1.016 % and banks A, B, and C, lend overnight to bank D at annualized rates of 1 %, 1.05 %, and 1.1 %, respectively, then AOR for bank D is calculated as $(1\% + 1.05\% + 1.1\%)/3 - 1.016\% = 0.034\%$.

2.2.3. Euro OverNight Index Average (EONIA)

The European Central Bank (ECB) calculates the EONIA rate every day based on the actual overnight loan transactions reported by a set of contributing banks. All overnight loans granted by the contributing banks before the close of TARGET2 at 6 p.m. CET are included and weighted according to their value. At the time of writing, the EONIA panel consists of 34 contributing banks.

2.2.4. Credit default swap price with respect to iTraxx

We obtain banks' CDS price data from Bloomberg. They are quotes rather than actual transaction prices. We use the last price field, which corresponds to the mid-quote at the end of trading. Because of time zone differences, the end of trading time may vary across the banks. Typically, the quotes take place 5 p.m. London time or 5 p.m. New York time and thus the price is quoted at the same time or later than the time at which the TARGET2 Day Trade Phase ends (5 p.m. London time).[16] Most of the overnight loans also take place well before closing; the average time a loan is advanced is 2 p.m. The CDS price is hence quoted somewhat more recently than the average money market transaction. This gives CDS price a small timing advantage, which creates a bias against finding a lead for AOR over CDS in the price discovery process. We only consider the most liquid CDS contract, the one with maturity of 5 years. To facilitate a comparison with AOR, we deduct the corresponding market index, the iTraxx Europe Financials CDS index (varying composition) from the bank's CDS price. We simply refer to the resulting "spread" as CDS, as already defined earlier.

Fig. 2 plots the daily AOR against CDS. Because of the much longer maturity of CDS (5 years) than of AOR (overnight), their re-

[13] In the case that a bank has not borrowed at all overnight on a given day, we treat this as a missing observation in our regressions.

[14] We find some evidence that "late" (after 12:00 CET) overnight loan transactions have a stronger impact on CDS than "early" (before 12:00 CET) overnight loan transactions but the difference is only marginally significant.

[15] Since the EONIA itself is not a risk-free rate, we transform the CDS prices in a corresponding manner (see the separate subsection below). The credit risk of EONIA is the value weighted credit risk of those who borrow from the EONIA panel banks.

[16] In other words, our main sample takes the most recent observation from either London or New York. In this way, we also maximize our sample size. However, as a robustness check, we have also run our main results with restricted London or New York samples and obtained similar results.

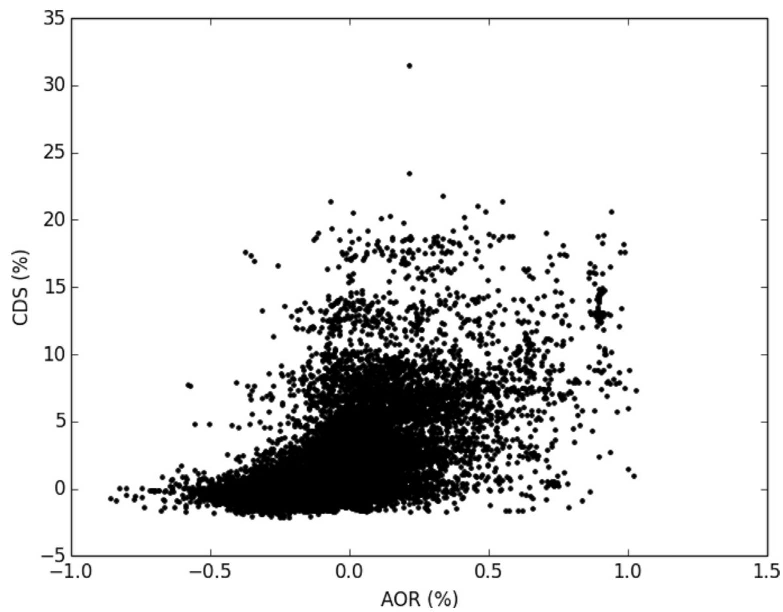

Fig. 2. Scatter plot of the daily AOR and CDS observations.

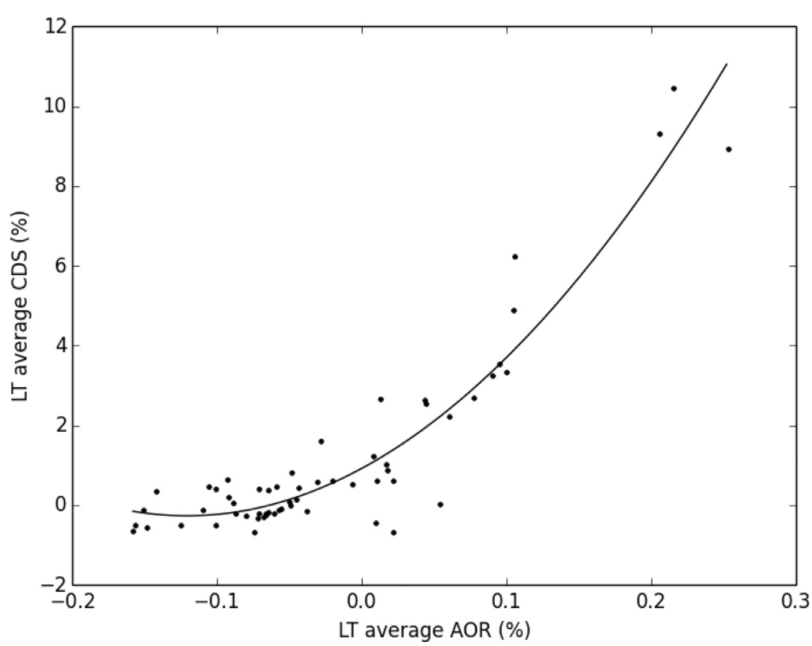

Fig. 3. Long-term average of AOR and CDS.
Each point corresponds to one of the 60 banks and the data are averaged over the whole period from begin of June 2008 to end of June 2013.

lationship is non-linear: higher values of AOR tend to be coupled with increasingly higher values of CDS. A similar pattern appears in Fig. 3 in which we have plotted the time-series averages of daily AOR and CDS over the entire sample against one another for each bank.

Fig. 4 provides an interesting insight by showing how the cross-sectional correlation between AOR and CDS varies in time. Before September 2008 and the ensuing global financial crisis the correlation was rather limited. In the aftermath of the Lehmann Brothers bankruptcy the correlation increased, and by the time the correlation reached its highest level, the Euro crisis had initiated from Greece. The change in the correlation would be consistent with AOR becoming more information sensitive during the sample period.

2.2.5. Markit iTraxx Europe senior financial sub index

The iTraxx Europe index is composed of the 125 most liquid CDS contracts of European entities. We use its sectoral sub index for financials, which consists of 25 equally weighted names most of which are direct participants in TARGET2. The iTraxx index has a high correlation (0.93) with the mean CDS price in our 60 banks panel.

2.2.6. Credit default swap bid-ask spread

The CDS bid-ask spread is used to proxy for the liquidity of CDS. We obtain the daily bid and ask CDS quote data from Bloomberg for 57 of the 60 banks (for three of the banks the data was unavailable) and calculate the bid-ask spread for each day. The bid-ask spread has a strong correlation (0.84) with the CDS price itself.

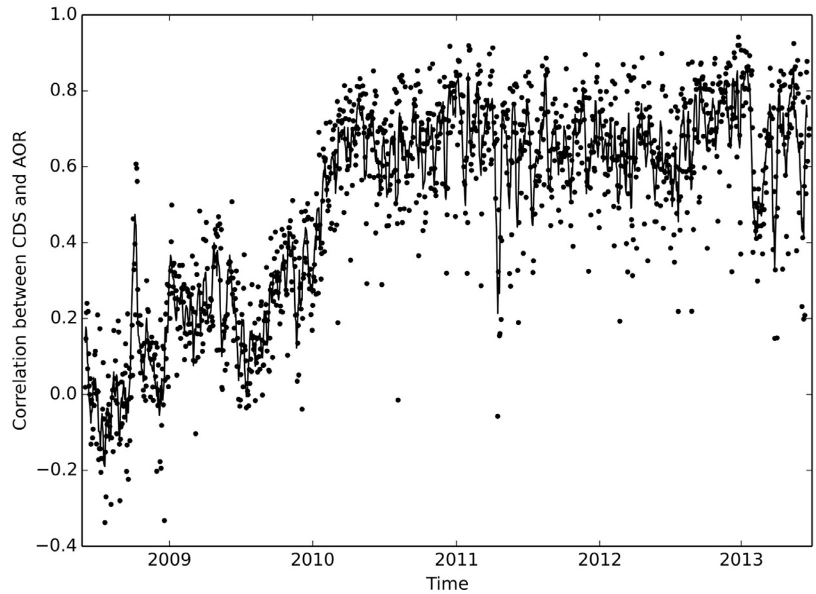

Fig. 4. The cross-sectional correlation between CDS and AOR.
The dots are the daily cross-sectional correlation values. The line shows 5 day moving averages. The correlation is calculated for those of the 60 panel banks that participate in the money market in the corresponding business day. The short-term variation may reflect different samples in different days.

2.2.7. Borrower Preference Index (BPI)

Similar to lending relationships between banks and corporates, there exist lending relationships between banks in the overnight loan market. Following Cocco et al., (2009), we measure the intensity of an interbank relationship by calculating how large a share that relationship contributes to the borrower's total borrowing during a certain period. The Borrower Preference Index (BPI) is the ratio of funds, F, that bank B has borrowed from bank L over a given time period Q_t, denoted by $F_{Q_t}^{L\to B}$, as a fraction of the total amount of funds that B has borrowed in the market in that period denoted by $F_{Q_t}^{ALL\to B}$:

$$BPI_{L,B,t} = \frac{F_{Q_t}^{L\to B}}{F_{Q_t}^{ALL\to B}}. \tag{2}$$

For each business day, t, we take period Q_t to be the last 62 business days which correspond to one quarter. Next, we define the average BPI as

$$\overline{BPI}_{B,t} = \frac{1}{N_{B,t}} \sum_{L} BPI_{L,B,t} \tag{3}$$

where the lender index, L, runs from 1 to $N_{B,t}$, which is the total number of lenders to bank B on day t. The higher the value of the average BPI on day t, the stronger is the relationship of the average lender to bank B on that day.

2.2.8. Herfindahl–Hirschman Index (HHI)

As an alternative proxy for the market structure and relationships we develop an application of the Herfindahl–Hirschman Index (HHI) to measure how concentrated the overnight borrowing activities of a given bank are on a given day. HHI is the total of squared daily market shares of each lender bank in the market of "all overnight lending to borrower bank B". If $F_t^{L\to B}$ is the amount of overnight funds bank B borrowed from bank L on day t, and $F_t^{ALL\to B}$ is the total amount of overnight funds bank B borrowed on day t, the HHI is then

$$HHI_{B,t} = \sum_{L} \left(\frac{F_t^{L\to B}}{F_t^{ALL\to B}} \right)^2. \tag{4}$$

Similar to BPI, the HHI index takes a value between 0 and 1. Generally, when the HHI is larger, the market is more concentrated. During times of financial market stress (as proxied by the iTraxx index) the average BPI and HHI tend to obtain higher values indicating more concentrated credit lines and more reliance on relationship lending.

2.2.9. Credit rating

As a bank credit rating, we use the Standard & Poor's long-term foreign currency issuer credit ratings. Following Covitz and Downing (2007), we convert the ratings to numbers from zero to 21.

2.2.10. TARGET2 excess reserves

As a response to the crisis, the ECB provided large amounts of liquidity to the banking system. We measure liquidity conditions by the amount of central bank money in the current account plus the deposit facility.

3. Dynamic relationship between AOR and CDS

3.1. Hypotheses

The following list summarizes our empirical hypotheses:

Hypothesis 1 (H1): Because of private information in the overnight loan market, AOR helps to predict CDS.

Hypothesis 2 (H2): The importance of AOR's private information in predicting CDS is greater

(i) *during financial market stress (crisis periods),*
(ii) *for relatively weaker banks,*
(iii) *for banks in countries with a sovereign debt crisis,*
(iv) *for banks which are relatively more dependent on relationship lenders,*
(v) *for banks whose CDS is relatively illiquid.*

H1 simply states our basic hypothesis that private information makes AOR a useful measure to predict CDS. AOR's predictive ability offers an implicit measure of the value of private information. Hypotheses *H2(i)–(iv)* refine *H1* and are motivated by potential

Table 2
Results from the panel vector error-correction analysis.
Panel (a) reports the panel tests for non-stationarity and co-integration. Panel (b) reports the maximum likelihood estimates for the vector error-correction (VEC) model. Panel (c) presents the price discovery measures that we compute based on the VEC-estimates.

(a) Tests for non-stationarity and cointegration.(i)

Hypothesis	Statistic	p
H_0: CDS is I(1), LLC	5.1	1.00
H_0: CDS is I(1), IPS	4.6	1.00
H_0: AOR is I(1), LLC	−12.2	0.00
H_0: AOR is I(1), IPS	−38.9	0.00
H_0: Zero cointegration vectors	1670.5	1.00

(b) Vector error-correction estimates.(ii)

Variable	ΔCDS_t	ΔAOR_t
ΔCDS_{t-1}	0.030	−0.008
	[0.71]	[0.86]
ΔAOR_{t-1}	0.031	−0.296
	[1.37]	[16.58]
$\lambda_{CDS/AOR}$	−0.001	0.004
	[1.86]	[15.58]
Constant	0.002	0.001
	[1.09]	[0.93]
Error-correction terms:		
CDS_{t-1}	1	1
AOR_{t-1}	−28.542	−28.531
Constant	−3.391	−3.260
R^2	0.002	0.168
N	33,823	33,823

(c) Price discovery measures.(iii)

Price discovery measures	
H_{LB}	0.99
H_{UB}	0.99
H_{MID}	0.99
GG	0.84

(i)LLC is Levin, Lin & Chu t* panel test for a common unit root process. IPS is Im, Pesaran, and Shin W-stat panel test for an individual unit root process. Co-integration test is the Johansen trace test.
(ii)Inside the brackets are robust t-statistics adjusted for clustering. N is the number of observations. The corresponding panel VEC equations are written as

$\Delta CDS_{i,t} = a_{11}\Delta CDS_{i,t-1} + a_{12}\Delta AOR_{i,t-1} + \lambda_{CDS}(CDS_{i,t-1} + b\ AOR_{i,t-1} + c) + \varepsilon_{1,i,t}$ and

$\Delta AOR_{i,t} = a_{21}\Delta CDS_{i,t-1} + a_{22}\Delta AOR_{i,t-1} + \lambda_{AOR}(CDS_{i,t-1} + b\ AOR_{i,t-1} + c) + \varepsilon_{2,i,t}$.

(iii)GG is the Gonzalo–Granger γ-measure, $\gamma = \lambda_{AOR}/(\lambda_{AOR} - \lambda_{CDS})$.
H is the Hasbrouck information share with $H_{MID} = (H_{UB} + H_{UB})/2$, where

$H_{UB} = (\gamma\sigma_{CDS} + \rho(1-\gamma)\sigma_{AOR})/[(\gamma\sigma_{CDS} + \rho(1-\gamma)\sigma_{AOR})^2 + (1-\gamma)^2\sigma_{AOR}{}^2(1-\rho^2)]$, and

$H_{LB} = \gamma^2\sigma_{CDS}{}^2(1-\rho)^2/[\gamma^2\sigma_{CDS}{}^2(1-\rho^2) + (\rho\gamma\sigma_{CDS} + (1-\gamma)\sigma_{AOR})^2]$,

Here σ^2 is the residual variance and ρ the respective correlation.

variation in a money-market debt contract's information sensitivity (see e.g. Dang et al., 2015). Hypothesis *H2(v)* can be motivated by the findings of Blanco et al., (2005) who argue that CDS leads the corresponding bond partly due to better liquidity. By the same logic, we can postulate that the role of private information in AOR in predicting CDS movements is bigger if the CDS contract is relatively illiquid.

3.2. Testing for co-integration between AOR and CDS

To test our hypotheses, we consider two alternative frameworks to model the dynamic relationship between AOR and CDS, which similar studies have used (see e.g. Blanco et al., 2005). The first of them, the vector error correction (VEC) model, establishes the long-term relationship between AOR and CDS by assuming they are co-integrated. The second is the Granger causality framework, using the standard VAR model, which does not include the co-integration relationship. Because AOR and CDS are essentially interest rate spreads, one can put forward an economic argument that they are stationary variables. However, similar studies have often found a co-integration relationship between the variables of interest (see e.g. Blanco et al., 2005), perhaps due to finite samples. Before proceeding, we test for stationarity and possible co-integration between AOR and CDS.

The co-integration analysis in the panel form is based on estimating the following VEC model:

$$\begin{aligned}\Delta CDS_{i,t} &= a_{11}\Delta CDS_{i,t-1} + a_{12}\Delta AOR_{i,t-1} \\ &\quad + \lambda_{CDS}(CDS_{i,t-1} + b\ AOR_{i,t-1} + c) + c_1 + \varepsilon_{1,i,t} \\ \Delta AOR_{i,t} &= a_{21}\Delta CDS_{i,t-1} + a_{22}\Delta AOR_{i,t-1} \\ &\quad + \lambda_{AOR}(CDS_{i,t-1} + b\ AOR_{i,t-1} + c) + c_2 + \varepsilon_{2,i,t} \qquad (5)\end{aligned}$$

OLS estimation of (5) assumes that the error term in both the CDS and AOR equation is independent over time and across banks. However, we find that while the autocorrelations of bank-specific error terms for both AOR and CDS are close to zero, the average pairwise correlation across banks is 17% for AOR errors and 26% for CDS errors. To account for the cross-sectional correlations we use robust t-statistics adjusted for clustering in all subsequent panel models. In our case, the sizes of the resulting robust t-statistics

Table 3
Results from the bank-specific vector error-correction analysis.
The banks are ordered by ascending Granger–Gonzalo price discovery measure.

Bank	H_0: CDS is I(1).	H_0: AOR is I(1).	Trace test	N	λ_{CDS}	t_{CDS}	λ_{AOR}	t_{AOR}	H_{LB}	H_{UB}	H_{MID}	GG
1	N	R	R	929	−12.5	4.23	−6.6	7.77	0.00	0.00	0.00	0.00
2	N	N	N	181	−23.9	3.10	3.8	1.63	0.21	0.23	0.22	0.14
3	N	R	R	632	−3.9	1.65	4.3	5.41	0.89	0.92	0.90	0.52
4	N	R	R	659	−6.2	2.58	7.4	6.68	0.83	0.88	0.85	0.54
5	N	R	R	634	−2.4	3.18	3.0	8.26	0.86	0.87	0.86	0.56
6	N	R	R	402	0.7	3.50	−0.9	12.87	0.95	0.93	0.94	0.57
7	N	R	R	882	−1.9	1.93	2.8	7.99	0.89	0.95	0.92	0.59
8	N	N	N	135	−20.3	1.86	34.6	3.32	0.79	0.75	0.77	0.63
9	N	R	R	866	−2.0	2.26	3.5	7.34	0.90	0.91	0.91	0.63
10	N	R	R	849	−14.4	2.59	25.1	5.89	0.85	0.84	0.84	0.64
11	N	R	R	788	7.2	2.16	−13.0	11.43	1.00	0.96	0.98	0.64
12	N	R	R	935	−8.9	2.73	18.1	8.41	0.93	0.90	0.92	0.67
13	N	R	R	757	0.7	1.20	−1.5	6.36	0.98	0.97	0.97	0.70
14	N	R	R	849	−2.6	1.38	7.7	5.63	0.94	0.94	0.94	0.75
15	N	R	R	791	−5.9	1.36	19.7	5.71	0.94	0.95	0.95	0.77
16	N	R	R	83	4.6	0.56	−17.4	5.46	1.00	0.99	0.99	0.79
17	N	R	R	361	3.3	1.17	−12.7	5.48	0.92	0.96	0.94	0.79
18	N	R	R	541	−0.7	0.79	2.7	6.04	1.00	0.98	0.99	0.79
19	N	R	R	689	1.0	1.58	−4.2	5.70	0.97	0.93	0.95	0.81
20	N	R	R	860	−8.1	2.40	35.7	9.96	0.95	0.94	0.95	0.82
21	N	R	R	920	−0.6	1.16	3.1	7.66	0.98	0.98	0.98	0.83
22	N	R	R	497	−0.2	0.83	0.9	4.97	0.97	0.97	0.97	0.84
23	N	R	R	563	−1.1	0.82	5.6	7.28	0.99	0.99	0.99	0.84
24	N	R	R	668	−1.3	0.78	8.3	7.20	0.97	0.99	0.98	0.87
25	N	R	R	178	5.2	1.02	−54.8	6.86	0.99	0.98	0.98	0.91
26	N	R	R	562	−1.3	0.66	14.5	6.26	0.99	0.99	0.99	0.92
27	N	R	R	892	−2.5	0.77	27.5	9.89	1.00	0.99	1.00	0.92
28	N	R	R	667	−0.7	1.25	8.8	10.88	0.99	0.99	0.99	0.92
29	N	R	R	307	−1.2	0.12	21.3	5.31	0.99	1.00	1.00	0.95
30	N	R	N	252	−0.1	0.05	4.0	4.17	1.00	1.00	1.00	0.97
31	N	R	N	166	−0.1	0.01	16.7	3.33	1.00	1.00	1.00	0.99
32	N	R	R	756	0.0	0.04	−5.9	5.76	1.00	1.00	1.00	0.99
33	N	N	R	434	0.3	0.06	13.0	7.22	0.99	1.00	0.99	1.00
34	N	R	R	365	−4.8	0.86	−18.1	4.31	0.98	1.00	0.99	1.00
35	N	R	N	62	0.2	0.09	1.4	2.77	0.92	1.00	0.96	1.00
36	N	R	R	363	−0.8	0.89	−1.6	4.29	1.00	1.00	1.00	1.00
37	N	R	R	266	−0.5	0.59	−9.1	7.67	0.99	1.00	1.00	1.00
38	N	R	R	730	−0.2	0.20	−4.5	8.76	0.99	1.00	1.00	1.00
39	N	R	R	848	−1.5	1.33	−8.2	8.92	1.00	1.00	1.00	1.00
40	N	R	R	602	0.8	1.31	2.8	6.05	1.00	1.00	1.00	1.00
41	N	R	R	171	2.0	0.58	9.6	5.48	0.98	1.00	0.99	1.00
42	N	R	R	875	−15.1	3.32	−22.6	9.06	1.00	1.00	1.00	1.00
43	N	R	R	806	−0.8	0.97	−3.7	5.23	1.00	1.00	1.00	1.00
44	N	R	R	456	3.8	0.97	4.4	4.83	0.99	1.00	1.00	1.00
45	N	R	N	142	−0.1	0.32	−1.0	4.43	0.99	1.00	1.00	1.00
46	N	R	R	901	−8.5	2.04	−13.6	7.20	1.00	1.00	1.00	1.00
47	N	R	R	647	−0.7	0.55	−3.8	6.09	1.00	1.00	1.00	1.00
48	N	R	R	575	0.0	0.02	−6.9	9.27	1.00	1.00	1.00	1.00
49	R	R	R	930	−4.1	0.97	−12.1	4.97	1.00	1.00	1.00	1.00
50	N	R	R	804	−1.0	1.07	−6.1	10.09	1.00	1.00	1.00	1.00
51	N	R	R	460	0.2	0.76	1.1	4.86	1.00	1.00	1.00	1.00
52	N	R	R	799	0.1	0.30	1.2	5.80	0.99	1.00	1.00	1.00
53	N	R	N	411	2.4	0.93	5.4	4.03	0.99	1.00	1.00	1.00
54	N	R	N	52	0.1	0.02	8.1	2.81	1.00	1.00	1.00	1.00
55	N	R	R	505	−0.1	0.20	−1.7	4.95	1.00	1.00	1.00	1.00
56	N	R	R	789	−2.6	1.86	−5.0	6.53	1.00	1.00	1.00	1.00
57	N	R	R	262	−0.1	0.28	−2.4	4.78	0.99	1.00	0.99	1.00
58	N	R	R	812	−1.1	0.93	−2.1	6.01	1.00	1.00	1.00	1.00
59	N	R	N	237	−3.0	0.92	−4.2	3.83	1.00	1.00	1.00	1.00
60	N	R	R	268	−1.5	1.80	−4.9	7.26	1.00	1.00	1.00	1.00
Mean/R	R (1)	R (57)	R (51)	564	− (43)	* (14)	− (28)	* (31)	0.94	0.94	0.94	0.86
Median/N	N (59)	N (3)	N (9)	617	+ (17)	** (8)	+ (32)	** (31)	0.99	1.00	0.99	0.98

R = H_0 rejected, N = H_0 not rejected. In last two rows R (.) and N (.) summarize the numbers of rejections and non-rejections (at the 0.05 significance level), respectively; **(.) and *(.) denote the number of significant coefficients in one-tailed t-test at 0.01 and 0.05 significance level, respectively; and − (.) and + (.) denote the number of negative and positive coefficients, respectively. N, λ, H, and GG are defined as in Table 2.

are about half of the corresponding unadjusted t-statistics. Table 2a presents the panel test results and Table 3 presents the bank-specific results.[17]

The evidence of stationarity of AOR and CDS and co-integration between them is mixed. We reject the non-stationarity of AOR in

[17] Note that the panel form model assumes that the coefficients are the same for all banks, whereas the bank-specific models naturally allow for different coefficients across banks. Hence, we may view the panel estimates as capturing the "average" relationships in the bank-specific AOR and CDS dynamics. Because of the high confidentiality of the individual bank data, individual bank results appear in a random order with no link to actual bank identities or bank attributes.

the panel model with two alternative tests (Table 2a). In bank-specific results (Table 3), we find AOR to be stationary in all other than three cases. In contrast, CDS is non-stationary in the panel model and in almost all cases in bank-specific results.

Despite the evidence of stationarity of AOR, we also conduct the co-integration tests. We reject the null hypothesis of no co-integrating vectors in the panel setting (see Table 2a). With individual banks in Table 3, we reject no co-integration for 51 out of 60 banks (at the 5% significance level).

As Kremers et al., (1992) note estimation of the error-correction coefficients in the VEC model provides a further test of the existence of co-integration. As Table 2b shows, the panel coefficients are significant and obtain the expected sign. However, the bank-specific results in Table 3 are more mixed. The error correction coefficient of the AOR equation (λ_{AOR}) is significant and of the expected (positive) sign for about half of the sample banks. The error correction coefficient of the CDS equation (λ_{CDS}) obtains the expected (negative) sign for two thirds of the sample banks but is significant only in 13 cases.

In summary, as AOR appears stationary and the results of co-integration tests are somewhat mixed, we apply both methodologies, the VEC model and the Granger causality framework, as complementary approaches in studying the price discovery process.

3.3. Measuring price discovery using VEC model

We consider two conventional price discovery measures computed from the VEC model parameters: the Hasbrouck (1995) measure and the Granger–Gonzalo (1995) measure.[18] We compute them for both the panel (Table 2c) and each individual bank (Table 3).

The price discovery measures obtained from the panel model in Table 2c indicate that price discovery mainly takes place in the CDS market, although the Gonzalo–Granger (1995) measure indicates that AOR also has a role.

Fig. 5 depicts the series of the price discovery measures from a rolling panel estimation with a six-month window. The rolling measures suggest that AOR's contribution to price discovery varies over time and seems to intensify during periods of market turbulence. This suggest, in accordance with our second hypothesis (*H2*), that the information potential of AOR may lie dormant for much of the time, apparently due to its short maturity, but comes to life when private information acquisition intensifies, as during a heightened financial crisis.

Table 3 reports the price discovery measures for individual banks, which vary considerably across banks. They indicate that on average price discovery mainly takes place in the CDS market. However, for some banks AOR strongly contributes to price discovery.

Overall, the results suggest that the value of private information in AOR in predicting CDS is rather specific to certain banks and periods. This is consistent with a varying degree of information sensitivity of overnight loans, as suggested by our second hypothesis, *H2*. We will investigate this further in section III.E below.

3.4. Granger causality

In this section, we test for Granger causality between AOR and CDS in the standard VAR framework, which does not include a co-integration relationship. Again, we report both panel estimation results and bank-specific results.

We readily obtain the VAR model with one lag in the panel form by setting parameters λ_{CDS} and λ_{AOR} equal to zero in Eq. (6):

$$\begin{aligned} \Delta CDS_{i,t} &= a_{11}\Delta CDS_{i,t-1} + a_{12}\Delta AOR_{i,t-1} + c_1 + \varepsilon_{1,i,t} \\ \Delta AOR_{i,t} &= a_{21}\Delta CDS_{i,t-1} + a_{22}\Delta AOR_{i,t-1} + c_2 + \varepsilon_{2,i,t} \end{aligned} \tag{6}$$

Regarding the lag length of the VAR, we start by considering only the first lag for both AOR and CDS, as specified in Eq. (6), but then extend the analysis to multiple lags. Table 4 reports results. Considering first the results in the first two columns with the one-lag model, the positive and significant coefficient on the lagged AOR in the CDS equation implies that AOR causes CDS. This supports the first hypothesis (*H1*) that private information in AOR has value in predicting CDS. The corresponding coefficient on the lagged CDS in the AOR equation is not significant.[19]

The Granger causality results with the one-lag VAR model hold with respect to the following robustness checks.[20] First, they hold even if we do not subtract the respective indices from AOR and CDS but include them as control variables. We further find that EONIA and iTraxx do not cause one another, which indicates that the lead for AOR over CDS is due to idiosyncratic (bank-specific) rather than system-wide shocks. Second, the results are robust with respect to the following exogenous control variables. We add the lagged stock return in both the CDS and AOR equation, motivated by Acharya and Johnson (2007) who have studied the dynamic relationship between CDS and equity returns (see also Fung et al., 2008, Marsh and Wagner 2011, and Giannikos et al., 2013). Further, we add the lagged sovereign CDS because of the intensified bank-sovereign loop during the Euro crisis. Lastly, we include the CDS bid-ask spread, which aims to control for the possibility that AOR's ability to predict CDS relates to CDS market liquidity conditions.

Consider next the VAR results with multiple lags in Table 4. With multiple lags we run into a problem that especially many smaller banks in both the CDS and AOR data have missing observations. As a result, the sample size shrinks considerably as we add lags. This does have an effect on our results, which are largely driven by the smaller and weaker banks. We use two alternative approaches to deal with this issue. In the first approach, we simply fill the "holes" in the data by the most recent observation. The second uses the Kalman filter to estimate the entire VAR system in the presence of missing observations.[21] We report results with both approaches. For the panel VAR model, the value of the SBIC information criterion starts stabilizing after the third lag. However, already the model with two lags appears to be sufficient in terms of capturing the Granger causality between AOR and CDS. For comparison, we report the model with two lags and with four lags.[22]

Columns 3 and 4 in Table 4 show results for the model with two lags in both the AOR and CDS equation using the Kalman

[18] With the Hasbrouck (1995) measure we consider the average of the lower and upper bound of that measure, which we denote in Table 2c by H_{MID}, H_{LB}, and H_{UB}, respectively (see e.g. Blanco et al. 2005). Both Hasbrouck (1995) and Gonzalo-Granger (1995) measure in theory obtain values between zero and one. In the current specification, values closer to one indicate a higher share of price discovery taking place in the CDS market.

[19] These estimated lag coefficients of the VAR system are in line with those obtained from the VEC model in Table 2 although the VEC model-based estimates are not significant with the robust t-ratios. Note also that the AOR's own lag in the AOR equation is negative even though we have excluded the special dates causing spikes in the data (see section II.A).

[20] The results are not reported but available from the authors upon request.

[21] Following Commandeur et al. (2011), we formulate the VAR system as a state-space model and estimate it using maximum likelihood. In the presence of missing observations, the log-likelihood function reduces to the usual VAR log-likelihood function, where any missing observations are replaced by states predicted by the Kalman filter. The maximization is done using the EM algorithm, see Dempster et al. (1977).

[22] We study the optimal lag length up to ten lags by using both approaches to deal with the missing observations (results are available from the authors upon request). The value of the SBIC criterion declines (almost) monotonously but does not reach a local minimum. This is not uncommon in studies using very large samples like ours (cf. Granger 1998).

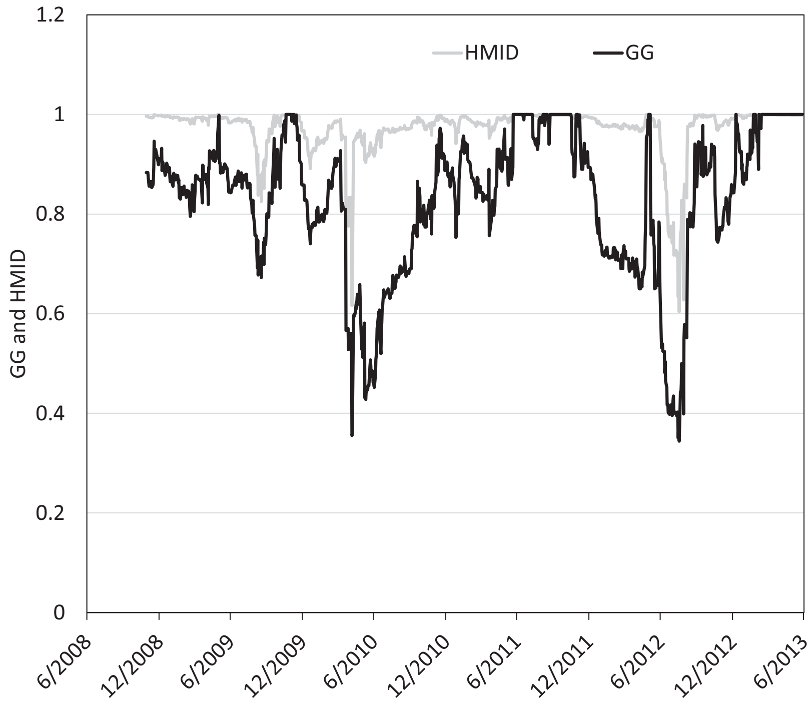

Fig. 5. The time-variation of price discovery measures.
The black line shows the Granger–Gonzalo (GG) price discovery measure and the gray line shows Hasbrouck information share mid-point value (HMID). Both measures are calculated with a six-month moving window with the model in Eq. (5) using daily observations.

Table 4
Estimates of a panel VAR with different lag structures.
In the models with 2 or 4 lags, we use two alternative approaches to deal with missing observations. In "Last price" we replace the missing observations by the most recent observation. Alternatively, we use Kalman filter to estimate the VAR system in the presence of missing observations.

Variable	1 daily lag		2 daily lags Kalman filter		2 daily lags Last price		4 daily lags Kalman filter		4 daily lags Last price	
	ΔCDS_t	ΔAOR_t	ΔCDS_t	ΔAOR_t	ΔCDS_t	ΔAOR_t	ΔCDS_t	ΔAOR_t	ΔCDS_t	ΔAOR_t
ΔCDS_{t-1}	0.030	−0.006	0.029	−0.005	0.029	−0.005	0.029	−0.003	0.029	−0.003
	[0.70]	[0.63]	[0.68]	[0.48]	[0.68]	[0.51]	[0.68]	[0.30]	[0.69]	[0.30]
ΔCDS_{t-2}			0.015	−0.005	0.015	−0.004	0.017	−0.003	0.017	−0.003
			[0.50]	[0.78]	[0.50]	[0.75]	[0.59]	[0.57]	[0.59]	[0.53]
ΔCDS_{t-3}							−0.027	−0.005	−0.027	−0.004
							[1.31]	[0.78]	[1.31]	[0.74]
ΔCDS_{t-4}							−0.025	0.003	−0.025	0.003
							[1.52]	[0.56]	[1.52]	[0.52]
ΔAOR_{t-1}	0.042	−0.354	0.056	−0.442	0.058	−0.437	0.054	−0.482	0.058	−0.474
	[2.02]	[18.99]	[2.51]	[23.57]	[2.60]	[23.37]	[2.26]	[25.48]	[2.40]	[25.25]
ΔAOR_{t-2}			0.037	−0.221	0.040	−0.207	0.034	−0.293	0.041	−0.274
			[1.62]	[14.08]	[1.90]	[13.61]	[1.29]	[17.12]	[1.66]	[16.65]
ΔAOR_{t-3}							−0.006	−0.189	−0.002	−0.176
							[0.27]	[11.30]	[0.10]	[11.11]
ΔAOR_{t-4}							−0.008	−0.085	0.004	−0.086
							[0.33]	[6.11]	[0.16]	[6.21]
Constant	0.002	0.001	0.002	0.001	0.002	0.001	0.002	0.001	0.002	0.001
	[1.09]	[0.98]	[1.09]	[0.99]	[1.09]	[1.01]	[1.15]	[0.90]	[1.15]	[0.94]
R^2	0.001	0.127	0.002	0.174	0.002	0.171	0.003	0.196	0.004	0.193
N	33,823	33,823	33,781	33,781	33,781	33,781	33,700	33,700	33,700	33,700

Inside the brackets are robust t-statistics adjusted for clustering. N is the number of observations.

filter approach. Columns 5 and 6 show the corresponding results with the simple approach to fill in missing observations. Further, columns 7 to 10 show results with the four-lag model for both approaches. Overall, all models confirm the result that AOR Granger causes CDS but not the other way round. The coefficient estimates are quite stable across different models. Compared to the one-lag model, the coefficient on the first lag of AOR is somewhat bigger in models with two or four lags. The second lag also obtains a positive coefficient but is significant only in the two-lag model of column 5, which uses the simple approach to replace the missing observations. In the models with four lags, coefficients on both the third and the fourth lag are not significantly different from zero. In sum, the VAR models with two lags (in both the AOR and CDS equation) in columns 3 to 6 seem sufficient to capture the joint

Table 5
Results from the bank-specific vector autoregression analysis.
Lag length is selected using the Bayesian information criterion (SBIC). Missing observations are filled using the last observed price. Banks are ordered first according to the sign of the sum of AOR coefficients in the CDS equation, second according to the *p*-value of the corresponding Granger causality test.

Bank	H_0: AOR G-causes CDS		H_0: CDS G-causes AOR				Bank	H_0: AOR G-causes CDS		H_0: CDS G-causes AOR			
	Sum of coefficients	*p*	Sum of coefficients	*p*	*N*	Lags		Sum of coefficients	*p*	Sum of coefficients	*p*	*N*	Lags
1	0.419	0.000	0.314	0.000	784	5	31	0.038	0.843	0.053	0.610	601	2
2	1.807	0.000	1.815	0.863	181	3	32	0.098	0.856	0.107	0.446	811	2
3	0.190	0.000	0.217	0.615	632	3	33	0.006	0.869	0.047	0.169	806	1
4	0.353	0.000	0.418	0.287	497	2	34	0.012	0.906	−0.007	0.729	166	1
5	0.079	0.004	0.006	0.000	726	5	35	0.069	0.909	0.049	0.347	631	3
6	0.207	0.007	0.205	0.923	411	1	36	–	–	–	–	588	0
7	0.224	0.010	0.201	0.086	401	2	37	–	–	–	–	672	0
8	0.356	0.048	0.334	0.065	456	1	38	−1.269	0.001	−1.261	0.060	927	5
9	0.158	0.068	0.137	0.105	882	1	39	−0.150	0.017	−0.157	0.710	866	1
10	0.148	0.078	0.134	0.690	857	4	40	−0.321	0.027	−0.393	0.000	363	4
11	0.211	0.088	0.233	0.568	562	2	41	−0.302	0.040	−0.369	0.002	252	1
12	0.064	0.129	0.039	0.727	665	3	42	−0.239	0.160	−0.163	0.231	268	2
13	0.145	0.148	0.129	0.644	788	2	43	−0.076	0.207	−0.076	0.261	306	2
14	0.183	0.155	0.157	0.268	932	4	44	−0.512	0.211	−0.554	0.610	52	2
15	0.223	0.200	0.240	0.198	434	1	45	−0.557	0.254	−0.591	0.199	871	5
16	0.066	0.208	0.030	0.418	668	2	46	−0.248	0.255	−0.201	0.010	502	4
17	0.098	0.245	0.032	0.664	262	2	47	−0.036	0.263	0.144	0.186	178	1
18	0.076	0.310	0.011	0.000	659	1	48	−0.026	0.346	−0.045	0.738	846	3
19	0.077	0.318	0.146	0.421	142	1	49	−0.072	0.357	−0.088	0.666	646	2
20	0.100	0.319	0.119	0.027	929	2	50	−0.112	0.402	−0.112	0.898	459	2
21	0.020	0.329	−0.004	0.134	847	3	51	−0.039	0.436	−0.055	0.130	918	3
22	0.127	0.342	0.130	0.968	900	2	52	−0.063	0.437	−0.129	0.167	364	2
23	0.074	0.355	−0.003	0.204	688	2	53	−0.164	0.540	−0.140	0.028	802	3
24	0.028	0.377	0.025	0.938	562	1	54	−0.049	0.710	−0.040	0.913	790	2
25	0.141	0.394	0.116	0.290	237	1	55	−0.094	0.833	−0.081	0.737	797	3
26	0.155	0.463	0.068	0.081	171	2	56	−0.027	0.867	−0.176	0.091	265	2
27	0.135	0.537	0.103	0.031	575	2	57	−0.011	0.915	−0.063	0.450	755	2
28	0.044	0.554	0.053	0.703	541	1	58	−0.029	0.925	−0.076	0.138	848	2
29	0.104	0.655	0.086	0.354	756	2	59	−0.050	0.950	0.065	0.228	135	2
30	0.027	0.697	−0.017	0.485	360	2	60	−0.006	0.993	0.021	0.611	890	3

N is the number of observations, *t* denotes the *t*-statistic, and *F*-statistic and *p*-values are those for the Granger causality test.

dynamics of AOR and CDS, regardless of the approach adopted to deal with missing observations.[23]

Table 5 reports results for each bank separately with the lag-length selected by the SBIC information criterion.[24] As with bank-specific VEC model results in Table 3, there is a large variation across banks. In only a few banks AOR Granger causes CDS, with a positive sum of the lagged AOR coefficients in the CDS equation. The lag-length also varies with some banks having a higher lag-order than two. As already discussed, the heterogeneity of the bank-specific results suggests that the AOR's role in providing a measure of private information may not be a general phenomenon but concentrated in certain periods and certain banks, according to the information sensitivity hypothesis (*H2*). Therefore, we next refine our analysis by conditioning the Granger causality tests on market conditions and bank characteristics.

[23] As a further alternative approach, we also estimate the one-lag VAR system using weekly or monthly data frequency. We do this by forming weekly and monthly average observations, respectively, of the daily data. In this procedure, even if we simply ignore the missing daily observations, we obtain a sample, which is balanced across banks of all size. Especially with the monthly data, we get results, which are consistent with those obtained with daily data although with robust t-ratios the AOR's (monthly) lead over CDS is not significant. Moreover, the monthly results suggest that there is also a lead for CDS over AOR. The results are available from the authors upon request.

[24] In order to facilitate the bank-specific analysis with multiple lags, we replace missing observations with the most recent observation. Table 4 suggests that multiple-lag models estimated with the help of this simple method are similar to those obtained with the Kalman filter.

3.5. Testing for the information sensitivity hypothesis

Table 6 extends the panel results of Table 4 by focusing on the CDS equation in (6), and conditioning the coefficient on the lagged AOR on a number of dummy variables, D_i^j, which can also be interacted with one another (cf. Acharya and Johnson, 2007). The dummy variables proxy for the factors listed in hypotheses *H2: i) – v)* plus some additional controls. This gives us the following equation for CDS within the VAR system:

$$\Delta CDS_{i,t} = a_{11}\Delta CDS_{i,t-1} + a_{12}\Delta AOR_{i,t-1} + \sum_j b_{11}^j \Delta AOR_{i,t-1} D_{i,t-1}^j + \sum_j b_{12}^j D_{i,t-1}^j + c_1 + \varepsilon_{1,i,t} \quad (7)$$

where index *j* refers to the different dummies and index *i* to individual banks, as earlier.

Table 6a focuses on conditioning the coefficient on the lagged AOR on different phases of the crises. We use the following dummy variables:

"Pre Lehman (before 15 Sep 2008)": equal to one from the beginning of our sample period until 15 September 2008;

"Post Lehman (before 2010)": equal to one from 16 September 2008 until the end of 2009; and

"Sovereign Crisis (2010 onwards)": equal to one from 1 January 2010 until the end of our sample period.

In addition, we also consider the following two dummies indicating conditions of relatively stressed markets, measured by the iTraxx index, and the intensity of the ECB's liquidity operations, respectively:

Table 6
Conditionality of the daily lead-lag relationship.
The table reports results for the following CDS equation of panel VAR regressions for CDS, AOR and interactions of the lagged AOR with a variety of dummy variables (see Section III.E for definitions of the dummies):

$$\Delta CDS_{i,t} = a_{11}\Delta CDS_{i,t-1} + a_{12}\Delta AOR_{i,t-1} + \sum_j b^j_{11}\Delta AOR_{i,t-1}D^j_{i,t-1} + \sum_j b^j_{12}D^j_{i,t-1} + c_1 + \varepsilon_{1,i,t}.$$

We report coefficient estimates for a_{12} and $b^j{}_{11}$ ($a_{11}, b^j{}_{12}$ and c_1 are not reported). For brevity, the name of the dummy, e.g., "Pre Lehman (before 15 Sep 2008)", stands for the respective interactive term, $\Delta AOR_{i,t-1}D^j{}_{i,t-1}$. The number of observations is 46,729 (44,398 if credit rating is used). Special dates (see Section II.A) are included. Inside the brackets are robust t-statistics adjusted for clustering.

(a) Conditioning on stressed time periods.

Variable	ΔCDS_t	ΔCDS_t	ΔCDS_t	ΔCDS_t	ΔCDS_t	ΔCDS_t
ΔAOR_{t-1}	0.048	0.064	0.018	0.004	0.031	−0.009
	[3.01]	[2.98]	[1.21]	[0.29]	[1.67]	[0.55]
Pre Lehman (before 15 Sep 2008)	−0.005	–	–	–	–	–
	[0.18]					
Post Lehman (before 2010)	–	−0.0491	–	–	–	–
		[1.82]				
Sovereign Crisis (2010 onwards)	–	–	0.048	–	–	–
			[1.76]			
Higher iTraxx	–	–	–	0.081	–	0.078
				[2.83]		[2.71]
Higher excess reserves	–	–	–	–	0.041	0.035
					[1.33]	[1.15]

(b) Conditioning on bank characteristics.

Variable	ΔCDS_t	ΔCDS_t	ΔCDS_t	ΔCDS_t	ΔCDS_t	ΔCDS_t	ΔCDS_t
ΔAOR_{t-1}	0.018	0.002	0.025	0.031	0.024	0.025	−0.035
	[1.20]	[0.13]	[2.37]	[2.67]	[2.37]	[2.36]	[1.37]
Higher BPI	0.053	–	–	–	–	–	0.030
	[2.03]						[1.37]
Higher HHI	–	0.068	–	–	–	–	0.061
		[2.85]					[2.68]
Worse rating	–	–	0.052	–	–	–	0.032
			[1.56]				[1.15]
Domicile in GIIPS	–	–	–	0.038	–	–	−0.004
				[1.16]			[0.16]
Smaller bank	–	–	–	–	0.051	–	0.041
					[1.62]		[1.59]
Larger CDS bid/ask	–	–	–	–	–	0.046	−0.012
						[1.56]	[0.44]

(c) Conditioning simultaneously on stressed time periods and bank characteristics.

Variable	ΔCDS_t	ΔCDS_t	ΔCDS_t	ΔCDS_t	ΔCDS_t	ΔCDS_t	ΔCDS_t
ΔAOR_{t-1}	−0.033	0.018	0.002	0.025	0.031	0.024	0.025
	[1.28]	[1.21]	[0.14]	[2.38]	[2.68]	[2.38]	[2.36]
Higher BPI	−0.009	−0.019	–	–	–	–	–
	[0.40]	[0.88]					
Higher HHI	0.050	–	0.011	-	–	–	–
	[1.98]		[0.51]				
Worse rating	0.018	–	–	−0.026	–	–	–
	[0.49]			[0.87]			
Domicile in GIIPS	−0.012	–	–	–	−0.035	–	–
	[0.44]				[1.32]		
Smaller bank	0.046	–	–	–	–	−0.019	–
	[1.51]					[0.74]	
Larger CDS bid/ask	−0.045	–	–	–	–	–	-0.030
	[1.02]						[1.12]
Higher BPI x Higher iTraxx	0.072	0.130	–	–	–	–	–
	[1.92]	[3.06]					
Higher HHI x Higher iTraxx	0.025	–	0.104	–	–	–	–
	[0.83]		[2.84]				
Worse rating x Higher iTraxx	0.009	–	–	0.128	–	–	–
	[0.17]			[2.29]			
Domicile in GIIPS x Higher iTraxx	0.008	–	–	–	0.123	–	–
	[0.18]				[2.24]		
Smaller bank x Higher iTraxx	0.012	-	–	–	–	0.123	-
	[0.25]					[2.24]	
Larger CDS bid/ask x Higher iTraxx	0.042	–	–	–	–	–	0.127
	[0.71]						[2.54]

"Higher iTraxx": equal to one on days when the iTraxx index is above its time-series median;[25] and

"Higher excess reserves": equal to one on days when the TARGET2 excess reserves exceed their time-series median (see section II.B).

Consistent with hypothesis *H2(i)*, there is clear evidence in regressions 4 and 6 in Table 6a that AOR's ability to predict CDS depends on market stress, measured by the "Higher iTraxx" dummy. There is also some evidence that the effect is weaker during the period after Lehman's bankruptcy but before the escalation of the European sovereign debt crisis in 2010. This can be seen from the effective coefficient on the lagged AOR, which is smaller in regression 2 (conditioning on "Post Lehman (before 2010)") than in either regression 1 (conditioning on "Pre Lehman (before 15 Sep 2008)") or regression 3 (conditioning on "Sovereign Crisis (2010 onwards)") in Table 6a. This is consistent with the fact that soon after Lehman's bankruptcy the EU governments provided various forms of state guarantees to their banks (see e.g. Panetta et al., 2009) but that the subsequent European sovereign debt crisis questioned the solidity of these guarantees in many countries.

In Table 6b, we test hypotheses *H2(ii–v)* and condition the coefficient on lagged AOR on the following bank-specific dummy variables:

"Higher BPI": relative dependence on relationship lending, which is equal to one on days when a bank's BPI measure, defined in section II.B above, is above the daily cross-sectional median BPI;

"Higher HHI": relative concentration of borrowing, equal to one on days when a bank's HHI measure, also defined in section II.B, is above the daily cross-sectional median HHI;

"Worse rating": bank credit quality, equal to one on days when a bank's public credit rating is weaker than the daily cross-sectional median rating;

"Domicile in GIIPS": bank domicile in a crisis country;[26]

"Smaller bank": bank size, equal to one for banks whose total assets are below the cross-sectional median total assets; and

"Larger CDS bid/ask": illiquidity of a bank's CDS contract, equal to one on days when a bank's CDS bid-ask spread is above the daily cross-sectional median spread.

The interaction term between any of these bank-specific dummies and the lagged AOR obtains a positive coefficient but only the ones indicating relatively strong dependence on relationship lending ("Higher BPI") and relative concentration of borrowing ("Higher HHI") are significant, rendering the base coefficient insignificant (see regressions 1 to 6 in Table 6b). When we condition the coefficient on the lagged AOR on all the bank-specific dummies at the same time (see regression 7 in Table 6b), the interactive term with "Higher HHI" is the only statistically significant one.[27]

Finally, we consider the coefficient on the lagged AOR under double-interaction dummies. We multiply each dummy from Table 6b by the market stress dummy, "Higher iTraxx", from Table 6a. We then augment the regressions in Table 6b by these double-interaction terms. The results appear in Table 6c. Regressions 2–7 in Table 6c show that conditioning on the market stress dummy strongly increases the impact of the other conditioning dummy variables on the coefficient of the lagged AOR. All double-interaction terms are significant and render the "single-interaction" terms, introduced in Table 6b, insignificant. However, when comparing with the effective size of the coefficient on the lagged AOR in Table 6a, it is also clear that the other conditioning variables strengthen the effect of market stress. In regression 1 of Table 6c where all variables appear simultaneously, the double-interaction between market stress "Higher iTraxx" and the relative dependence on relationship borrowing, "Higher BPI", together with single-interaction term of relatively concentrated borrowing, "Higher HHI", emerge as the conditions under which the lagged AOR obtains a significant positive coefficient.

An (unreported) auxiliary regression shows that a weak bank rating and small bank size relate to a high value of the bank's BPI index. Further, we also find that the BPI index is on average higher for banks in crisis countries. Hence, although the BPI index helps explain much of the variation in information sensitivity of AOR, the more fundamental bank characteristics, such as credit quality, domicile, and size, in turn explain a bank's reliance on relationship lenders. This is in line with Cocco et al., (2009) who find that "smaller banks and banks with more nonperforming loans tend to have limited access to international markets, and rely more on relationships".

Overall, results in Tables 6a–c clearly support the information sensitivity hypothesis, *H2*.

3.6. Economic significance

In order to assess the economic significance of our results further, we provide a numerical example of the impulse response of CDS to a shock in AOR. One way to interpret this is that it demonstrates how much we can improve a forecast for the future CDS price, based on the current CDS price, by incorporating the private information in AOR and its dynamic relationship with CDS.

We use the panel VAR model with two lags reported in Table 4. The long-run impulse response of CDS for a 10 basis point shock in AOR is 0.6 basis points.[28] The VEC model in Eq. (5), which establishes a long-run relationship between AOR and CDS via the error-correction term, would give a much stronger impulse response. In this respect, the above numerical example based on the VAR model, demonstrating the economic significance of using AOR to predict CDS is conservative. Note also that impulse responses based on the panel coefficients hide the large variation in the dynamic relationship between AOR and CDS across banks and periods, which we have documented in Tables 3 and 5 and especially Table 6. Based on the conditional coefficients in Table 6, the impulse responses in the panel VAR would be 1.5–2 times bigger during periods of market stress for relationship-oriented borrower banks.

4. Conclusions

We have constructed a measure of a bank's relative creditworthiness, the average overnight borrowing rate in relation to EONIA index (AOR), by using Eurosystem's proprietary inter-bank overnight loan data. Because banks bilaterally agree the overnight loan rates, and any bank can have several lending relationships of this kind, the average overnight rate arguably aggregates lender banks' private information signals concerning the borrower bank's

[25] The median value for iTraxx turned out to be 140 bps, which is quite high because the period contains the financial crisis and the Euro crisis.

[26] A crisis country is defined as being one of the so-called GIIPS countries; Greece, Ireland, Italy, Portugal or Spain.

[27] As a measure of bank quality, we also consider a dummy for overnight loans for which the borrower bank pays a rate that exceeds the ECB's fixed rate tender rate. There are 1284 such observations in our data, and these probably indicate heightened bank risk (the filter used to extract overnight loan transactions from the TARGET2 raw data essentially leaves out overnight loans with a rate higher than in the ECB's marginal lending facility, which in principle could be another similar bank quality measure). We find (in unreported results) that the coefficient on lagged AOR is much larger for these banks.

[28] The standard deviation of $\varepsilon_{1,i,t}$ (see Eq. 6) is 6 basis points. The impulse response stabilizes after five days. The impulse response estimates are similar regardless of whether we use the two-lag model in Table 4 estimated with Kalman filter or by filling in the most recent observation for missing observations.

creditworthiness. Our main hypothesis is that because of the private information, a bank's AOR helps to predict its CDS.

Standard price discovery measures suggest that price discovery mainly takes place in the CDS market, but AOR also contributes to it. Granger causality tests in a panel framework further show that the first two lags of the differenced AOR help predict the differenced CDS. These results support the hypothesis that AOR includes private information, which the CDS market does not immediately incorporate.

We further identify periods and banks for which overnight loans have heightened information sensitivity, indicated by how strongly AOR Granger causes CDS. This is the case for periods of market stress and for banks, which mainly borrow from relationship lender banks. Such borrower banks are typically smaller, have weak ratings, and are likely to reside in crisis countries.

The paper provides rare evidence of the value of private information in predicting future market prices. The results should also be interesting to competent authorities who have access to the interbank rate data. They indicate that inter-bank overnight loan rates are a valuable source of information in monitoring changes in banks' health in addition to the information contained in the CDS market. Unlike CDS quotes, overnight borrowing rates data are available for practically all banks.

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