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Do Private Signals of a Bank's Creditworthiness Predict the Bank's CDS Price? Evidence from the Eurosystem's Overnight Loan Rates

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Abstract

We investigate the relationship between the daily average interbank overnight borrowing rate (AOR) and the credit default swap price (CDS) of 60 banks using the Eurosystem's proprietary data from mid-2008 to mid-2013. We find that the AOR which is observable only by the competent Eurosystem authorities leads the CDS at least by one day. The lead was concentrated on days of market stress for banks which mainly borrow from "relationship" lender banks. Such borrower banks are typically smaller, have weak ratings, and likely reside in crisis countries.

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I. Introduction

In this paper we investigate whether micro-level data on banks' overnight money market borrowing are useful in probing and even predicting changes in banks' creditworthiness. Any early-warning indicators or timely information on banks' concurrent state would be valuable for monetary authorities who have access to such data, especially during times of market stress.

We use the proprietary data from 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 shortest maturity, the money market is an extremely liquid credit market with high frequency of observations.[1] This makes it an exceptional information source for studying the short term dynamics of counterparty risk. Investigating the potential of the Eurosystem data for gauging banks' stability has become increasingly important as the European Central Bank is starting its banking supervision function in 2014.

Our main research question is whether the average interest rate of the overnight loans taken by a bank, typically from a number of other banks, is informative in measuring banks' creditworthiness. Furfine (2001) has shown that the overnight borrowing rates do indeed reflect balance sheet measures of the bank's credit risk. However, previous research has not considered how efficiently and fast these markets price the credit risk.

[1] 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.

Because the average overnight borrowing rate (henceforth AOR) of a bank is generally not publicly observable to any market participant (other than the borrower bank itself and the competent authorities of the Eurosystem), we are in effect able to construct an aggregated measure of the *private* signals of the banks who lend to the borrower bank concerning the borrower bank's health. We then test whether this aggregate private measure adds value in gauging credit risk over the bank's CDS price. The CDS price is commonly seen as the leading *public* indicator of the credit risk of both corporations and banks (see e.g. Blanco et al., 2005, Longstaff et al., 2005, and Annaert et al., 2012).[2] In spite of the maturity mismatch and the term structure of credit risk[3], new information about counterparty risk should on average push both risk measures in the same direction. Moreover, as many of the overnight interbank loans are results of longer-term lending relationships (cf. e.g. Cocco et al. 2009, Bräuning and Fecht 2012, and Abbassi et al. 2014) in which the lender may have acquired private information of the borrower, it is possible that the average bilateral loan rate contains more information of the borrower bank's health than the public CDS price.[4] This will be our main hypothesis to be tested empirically.

Our data covers the period from the beginning of June 2008 to the end June 2013, comprising 60 banks, 1,300 business days, and around 470,000 loan transactions with

[2] There is no obvious alternative benchmark measure of bank creditworthiness based on public quotes as bond markets are generally less liquid than the CDS market.

[3] We control for the term structure of risk-free interest rates by working with credit spreads rather than rates.

[4] The overnight loans market can be considered as a fragmented market whereas the CDS market is relatively more centralized. Our setting corresponds to a situation where the 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) whereas 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." Hence we may hypothesize in the current paper that the aggregate of private signals, reflected in the privately negotiated overnight loan rates, and observable as a composite only to the competent authorities, may contain more information than the corresponding public signal (the CDS price; 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).

average value of about 100 million EUR. These yield approximately 46,000 daily AOR observations with daily turnover of about 50,000 million EUR.

We use Granger causality tests of the lag-lead relationship between the AOR and the CDS, both for the panel of 60 banks as well as for individual bank time series, to test our main hypothesis. If the AOR were found to "Granger cause" the CDS, then we would conclude that the AOR is more informative of changes in banks creditworthiness than the CDS price.

To account for the general conditions in both markets, and possible non-stationary properties of the corresponding time-series, we first deduct the Euro OverNight Index Average (EONIA) from the AOR and the iTraxx-index from the CDS. In contrast to corporate bonds and CDSs with matched maturities in Blanco et al. (2005), we find no compelling evidence of co-integration between the AOR and the CDS. However, the AOR and CDS are highly correlated (see Figures 1–2) while the daily cross-sectional correlation between the AOR and the CDS varies greatly (see Figure 3) suggesting that at least near co-integration might exist in certain subperiods, depending on the market conditions. In particular, during tranquil times, the overnight lenders to a bank may be less concerned about sudden changes in the borrower bank's creditworthiness. Because of the extremely short maturity (one day or even less) of the loan, other factors such as bank size, relationship with the lender, and general liquidity conditions may be important determinants of the AORs, making it difficult to disentangle the credit risk component.[5] Nevertheless, as overnight loans are typically quite large and uncollateralized, the 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

[5] Nevertheless, Covitz and Downing (2007) provide evidence from commercial paper spreads of non-financial companies that in actuality, credit risk dominates liquidity risk even at very short maturities.

bank.[6] This is what we also find: the cross-sectional correlation between the AOR and the CDS increases during the Lehman episode and again in the run-up to and during the so called Eurocrisis that started accelerating in the Spring of 2010 (see Figure 3). This finding is consistent with the theory of Dang, Gorton and Holmström (2012), according to which the price of a money-like debt instrument (the AOR in our case) becomes sensitive to the issuing institution's asset quality only when sufficiently bad public news concerning the asset quality inflict private information acquisition. Hence, it is understandable that in the depths of the Eurocrisis even the extremely short-maturity overnight interbank money market loans became increasingly sensitive to borrowing banks' credit risk.

Our main finding is that the AOR leads the CDS. The lead is at least one day long in a panel regression setting and largely supplementary to the lead of other factors (such as equity) over CDS. Conversely, no significant lead relationship is detected for the CDS over the AOR. When the lead for AOR over CDS is estimated over the entire data period, the relationship is significant but not very strong. However, the strength of the lead relationship varies strongly in time according to rolling panel estimation, reaching its peak in mid 2012 during the Euro's "existential crisis".[7] The lead-lag results may also be taken as being consistent with Dang et al. (2012): not only does the absolute information sensitivity of the AOR increase during market stress but also its relative informativeness with respect to the public signal of bank creditworthiness (the CDS) increases.

Further, we allow for separate lead-lag coefficients (with the help of a dummy variable) for various categories of banks, classified on the basis of relative weakness (measured

[6] Afonso, Kovner and Schoar (2011) find that "the day after Lehman Brothers' bankruptcy, loan terms become more sensitive to borrower characteristics."

[7] The gradual end of this episode is marked by the ECB president Mario Draghi's famous "whatever it takes" speech on July 26 2012 and the subsequent announcements by the ECB Governing Council later that year concerning its Outright Monetary Transactions (OMT) program.

by, e.g., the bank's credit rating), the bank's home country being a crisis country, the bank being mainly a relationship borrower[8], the size of the bank, or the liquidity of the bank's CDS. We find that the lead for AOR over the CDS is stronger for relatively weaker banks, for banks residing in crisis countries, for relatively relationship-intensive borrowers, for smaller banks, and for banks with a less liquid CDS market. The first two results are clearly consistent with the theory of Dang et al. (2012): a bank's overnight loans' information sensitivity, measured by the size and significance of the AOR's (positive) lead coefficient, is higher for relatively weaker banks, and for banks residing in crisis countries. These banks are less likely to get support from their crisis stricken governments, may have domestic sovereign debt holdings which have deteriorated in value, and suffer from an overall decline in their asset quality resulting from their depressed domestic economies. Regarding banks who are relatively relationship-intensive borrowers, it can be argued that, first of all, relationships become relatively more important in times of market stress when the information-acquisition sensitivity of the overnight loans increases (cf. Dang et al., 2012). Relationship lenders are likely to be best positioned to acquire further information in a stress situation while less informed lenders may reduce or stop their lending. This is what we find; the correlation between the iTraxx-index, measuring the level of market stress, and the average relationship-borrowing intensity of banks is 44% in our sample period[9]. Secondly, when the volume-weighted share of relationship lenders of a bank's all lenders is high, the bank's AOR should be more informative of the bank's health. This implies a stronger lead for such banks' AOR over their CDS. This is what we also find empirically. Finally both for smaller banks and banks with less liquid CDS, which also have a large overlap, the AOR

[8] We use the measure suggested by Cocco et al. (2009) and discuss below the details of how that is calculated on the basis of the proprietary Eurosystem data.
[9] When calculating the correlation we control for the potential effect of the ECB's July 2012 operations on the iTraxx index.

exhibits a stronger lead. This suggests that for smaller banks the overnight lenders' private information is relatively better. If CDS market itself is less well functional (as proxied by the bid-ask spread) the lead of the private money market signals may naturally increase.

With a similar dummy variable approach, we categorize the business days corresponding to various crisis periods or alternatively according to the stress of the financial markets, proxied by iTraxx CDS index. We find that during the sovereign debt crisis and generally during times of relatively high market stress, the lead of AOR over CDS is stronger. Finally, conditioning the lead relationship on the interactions between the different classifications of banks, we find that the lead for the AOR over the CDS is strongest and most robust on days of market stress for banks which are relatively relationship-intensive borrowers. Such banks are typically smaller, have weak ratings, and likely reside in crisis countries.

On balance, our results suggest that by aggregating the private overnight interbank-loan interest rate data, the Eurosystem authorities may be able to extract additional information concerning banks' current condition over and above the leading public market signals; banks' CDS prices. Consistent with the theory of Dang et al. (2012), the information sensitivity of the overnight loan rates relative to the CDS prices increases during market stress, and is accompanied with a relatively stronger presence of informed lenders in the over night market. Our results may also be among the first to provide support to a hypothesis that an aggregate of private signals concerning an asset's value may be more informative than the price of the same asset, formed in a simultaneous public market. This could be the case if some of the better informed agents do not want to reveal all their information so that it would simultaneously be reflected in the asset's public price.

The paper is organized as follows. Section II A shortly describes the European interbank market followed by an overview of variables in Section II B. Section III A covers time series properties of the data and the testing set-up. The main results and various robustness checks are presented in Section III B. The final Section IV concludes.

II. The data

A. Structure of the European interbank market

We start the description of our data by explaining the basic infrastructure of the Euro area interbank money market. The Euro area monetary policy operations as well as the majority of transactions in the Euro area interbank market are settled in the so called TARGET2 system which is the large value payment system of the Eurosystem.[10] Access to TARGET2 is granted primarily to credit institutions, national central banks, and treasury departments of European Union member states, which are active in the money market, while most other financial firms and non-financials have no access (see Heijmans et al., 2010). Money market transactions are a subset of bank-to-bank large value payments. In 2012, TARGET2 had a 92% market share in value terms of all large value payments in euro.[11] Payments are settled in central bank money with immediate finality (i.e., in real time). TARGET2 and Fedwire Funds for the US dollar are the two largest real-time gross settlement systems in the world.[12] In the current paper, our analysis is based on access to the proprietary TARGET2 database of the Eurosystem.

[10] The Eurosystem is formed by the national central banks of the European countries belonging to the European Monetary Union (having euro as their common currency) and the European Central Bank (ECB). In addition, a number of non-euro European countries, six in 2010, were also connected to TARGET2.
[11] See European Central Bank (2013). Another, privately owned euro payment system for banks operating in the European Union is called EURO1.
[12] See TARGET2 Newsletter, I Issue, number 3, October 2010.

B. Panel and variables

60 banks panel

Arciero et. al. (2013) have provided the Eurosystem with a database of euro area money market transactions. The money market loans are identified from all TARGET2 transactions by an improved version of the algorithm originally suggested by Furfine (1999). The Arciero et. al. algorithm is able to identify loan transactions with fair accuracy up to 3 month maturities, while the reliability is especially good for the overnight segment considered in this article. We use a further improved version of the Arciero et. al. (2013) algorithm, which uses the additional information on the originator and beneficiary fields of the transactions[13]. The time period of the dataset considered is from the beginning of June 2008 when the TARGET2 was fully operational to the end of June 2013.

The raw money market data is a list of pairs of transactions (the loan issue and refund amounts), while the related transaction details contain the information of the borrower and lender identity, the loan issue and payback values from which the loan interest rate can be calculated, and the time that the loan was issued and later paid back. The borrower and the lender are identified 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. At this point any loan transactions that have taken place within banking groups are discarded and we are left with 799,276 loan transactions and 1,177 banks. For all banks that are active in the money market during the time period, the corresponding Bloomberg CDS and stock ticker is matched if possible. Finally, those transactions in

[13] We thank Arciero et. al. for providing this update.

which the borrower bank has insufficient CDS data are left out so that a dataset with 60 borrower banks (domiciled in 19 different countries), 984 lender banks and 470,160 loan transactions is obtained. In 23% of the loans the lender is also within the 60 banks. Overall this translates into 53,987 daily observations.

Table 1 includes descriptive statistics for the 60 bank panel. For the time period mid-2008 to mid-2012 there were around 12,000 observations per year. After mid-2012 the overnight money market activity decreased due to change in the monetary policy rates 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).

Average Overnight Rate (AOR) spread

For each business day a bank may have borrowed from several lenders so we aggregate the daily rate from the multiple borrowings.[14] The loan issues generally take place between 7 am and 6 pm Central European Time (CET) during the TARGET2 Day Trade Phase. Rates in transactions towards the end of the day are likely more informative so the time stamp could be used as a weight in the aggregation.[15] The informativeness of a single transaction rate could also depend on the value of the loans or of the intensity of the borrower-lender relationship. One could imagine 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. However, we found that different weighing schemes

[14] In the case a bank has not borrowed at all overnight on a given day, this (spread value) will be treated as a missing observation in our unbalanced panel regressions.

[15] The correlation between "early" (before 12:00 CET) and "late" (after 12:00 CET) loan rate is 0.67, while the latter has slightly higher correlation with the CDS price (0.50 vs. 0.42). Also while both significant alone, the "late" rate has a larger (Granger) causal impact on the next day's CDS price.

have only minor effect on the results so we simply use uniform weights in the daily rate aggregation per bank.

To facilitate a comparison with the CDS price, which is a spread in itself, the average overnight rates need to be turned into average overnight rate spreads using suitable loan rate index. We find Euro OverNight Index Average (EONIA) the most natural candidate since using it helps to account for general conditions in the euro money markets (e.g. the effects of policy rate changes, liquidity operations, seasonal effects due to maintenance periods). Since the EONIA itself is not a risk-free rate[16], the CDS prices need to be transformed correspondingly (see next few subsections). Henceforth, we call the spread between AOR and EONIA simply AOR.

$$AOR_{B,t} = \frac{1}{N_{B,t}} \sum_i R_{i,t}^{L_{i,t} \to B} - EONIA_t \ . \qquad (1)$$

Here B refers to a borrower bank, $L_{i,t}$ is a lender bank for the ith loan in day t and $R_{i,t}^{L_{i,t} \to B}$ is the rate of the corresponding loan while there are total $N_{B,t}$ loans to bank B on day t. ISee also Figure 4 for illustration of the calculation of the AOR.

Figure 1 illustrates the variation of AOR and CDS across observations. Because of the differing maturity of AOR (1 night, EONIA deducted) and CDS (5 years, iTraxx deducted) the points do not fall around a straight line. Because the term structure of credit risk varies from observation to observation, one AOR is mapped to many different CDS values at different times. However, as shown in Figure 2, as we average over the different observations of each bank, the points fall around a curved line whose dimensions reflect the average term structure of credit risk, which most of the time was upward sloping during the data period. Hence small changes in AOR are accompanied

[16] The credit risk of EONIA is the value weighted credit risk of those who borrow from the EONIA panel banks.

with larger changes in CDS. Note that there is additionally a nonlinear effect whereby the changes in the AOR yield increasingly larger changes in CDS as AOR increases.

Euro OverNight Index Average (EONIA)

The EONIA rate is calculated each day by the European Central Bank (ECB) based on the actual overnight loan transactions reported by a set of contributing –banks. The overnight loans include all the overnight loans granted by the contributing banks before the close of TARGET2 at 6 pm CET and are weighted according to their value. At the time of writing, the EONIA panel consists of 34 contributing banks many of which (though not all) are included in our 60 banks panel. The correlation between EONIA and the mean unweighted rate of the 60 banks is very high (0.998) and the results presented later are robust towards selecting either EONIA or the mean rate as the reference rate in AOR.

Credit-Default-Swap (CDS) spread with respect to iTraxx

Banks' CDS price data are obtained from Bloomberg. We use the last price field, which corresponds to the mid-price at the end of trading. Because of time zone differences the end of trading time may vary across the banks. Typically the trades take place is in London and thus the price is quoted an hour or so later than the time at which the TARGET2 Day Trade Phase ends (most of the overnight loans also take place well before closing). The CDS quote is hence somewhat later than the average money market transaction, which gives the CDS a small informational advantage[17]. We only consider the CDS of the most liquid maturity, the 5 years. To facilitate a comparison with the AOR marginal, we need to deduct the general market risk present also in EONIA from the CDS. This is achieved by deducting the iTraxx Europe Financials CDS index

[17] This may slightly work against the likelihood of rejecting our key null hypothesis of interest that the AOR does not lead the CDS.

(varying composition) from the bank CDS. For brevity, in Part III we call this spread between the bank CDS and the iTraxx CDS index merely CDS. An exception is the Sovereign CDS used as a control in Section III.C, which is employed as such.

Markit iTraxx Europe Senior Financial subindex

The iTraxx Europe index also known as "The Main" is composed of the 125 most liquid CDS' of European entities. We use its sectoral subindex for financials, which consists of 25 equally weighted names most of which are direct participants in TARGET2. Similar to EONIA, the iTraxx index has a high correlation (0.93) with the mean CDS price in our 60 banks panel, and the results are robust against if the panel means are used instead of the indices.

Credit-Default-Swap (CDS) bid-ask spread

The CDS bid-ask spread is used to proxy the liquidity of the CDS. Because of the data availability issues we use two approaches for the bid-ask spreads. In the first approach we obtain the daily bid and ask CDS price 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. In a second approach, we obtain a snapshot of the real time bid-ask spread on a tranquil day in 2013, which is available to all 60 banks. Apart from small numerical differences the regression results are independent of, which CDS bid-ask spread dataset is used. We therefore prefer to use the snapshot bid-ask spread dataset, which allows to keep all 60 banks in the sample.

Borrower Preference Index (BPI)

Following Cocco et al. (2009) we define the Borrower Preference Index (BPI) as the ratio of funds, F, that bank B has borrowed from bank L over a given time period Q_t, denoted $F_{Q_t}^{L\to B}$, as a fraction of the total amount of funds that B has borrowed in the market in that same period denoted $F_{Q_t}^{any\to B}$

$$BPI_{L,B,t} = \frac{F_{Q_t}^{L\to B}}{F_{Q_t}^{any\to B}} . \tag{3}$$

For each business day, we take the time period to be the last 62 business days including that day, t, which corresponds to one quarter.

To obtain a single number that quantifies the reliance on relationships of a given borrower on a given day, we further average over the different borrowings of that bank on that day:

$$BPI_{B,t} = \frac{1}{N_{B,t}} \sum_i BPI_{L_{i,t},B,t} . \tag{4}$$

As in Eq. (1), $L_{i,t}$ is a lender bank for the ith loan in day t while it is entirely possible to have several borrowings from the same lender bank. In the sum over loans it is natural to use the same weights as in the AOR i.e. in our case uniform weights. Note that both of the BPIs defined above attain a value between 0 and 1. Figure 5 shows the mean BPI and iTraxx CDS Index for 60 bank panel. The larger the value of $BPI_{L,B,t}$, the stronger the relationship. Similarly larger $BPI_{B,t}$ indicates on average larger reliance on relationships. Since averaging the BPI as above loses some amount of information and potentially lessens the relevance of BPI, it was checked that linear regressions between AOR on CDS and BPI yield similar enough coefficients irrespective of whether the bank relationships in BPI and AOR are taken explicitly into account or averaged over. The

finding was that for our panel, in both cases the BPI is informative and highly significant while the coefficient of $BPI_{B,t}$ is some 35 % smaller than the coefficient of $BPI_{L,B,t}$. Henceforth, we refer always to the $BPI_{B,t}$ when discussing of BPI.

Herfindahl-Hirschman Index (HHI)

As an alternative proxy for the market structure and relationships we develop and application of the Herfindahl-Hirschman Index (HHI) to measure how concentrated the 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 lending to borrower bank *B*". If $F_t^{L\to B}$ is the amount funds bank *B* borrowed from bank *L* on day *t*, and $F_t^{any\to B}$ is the amount funds bank *B* borrowed in total on day *t*, the HHI is written as

$$HHI_{B,t} = \sum_L \left(\frac{F_t^{L\to B}}{F_t^{any\to B}}\right)^2 . \tag{5}$$

Similar to BPI, the HHI index takes a value between 0 and 1. Generally when the HHI is larger, the market is more concentrated.[18] Figure 5 shows the mean HHI along with mean BPI and iTraxx CDS Index. During times of financial market stress (as proxied by the iTraxx index) the average BPI and HHI show also heightened values indicating more concentrated credit lines and more reliance on relationship lending.

Credit rating

As a credit rating proxy, we use the Standard & Poor's Long Term Foreign Currency Issuer Credit Ratings. Following Covitz and Downing (2007), the ratings are converted to numerical values by assigning a number to each credit rating such that the set of credit ratings AAA, AA+, AA, AA–, A+, A, A–, BBB+, BBB, BBB-, BB+, BB, BB-, B+, B,

[18] U.S. Department of Justice and Federal Trade Commission (2010) classify HHI<0.15 as unconcentrated market, 0.15<HHI<0.25 as moderately concentrated market, and HHI>0.25 as highly concentrated market.

B–, CCC+, CCC, CCC–, CC, C, and D maps to integers from 0 through 21. Higher number corresponds to higher credit risk. We have considered taking into account negative/positive outlook by adding/subtracting 0.5 but this seem not affect the leading decimals of the regression results.

Stock price

Stock price movements have been found to lead the CDS prices for investment grade entities while the CDS prices may lead in the high-yield credit market (see e.g. Fung et al. 2008, Marsh and Wagner 2011, Giannikos et al. 2013), and are therefore a natural factor to control for. The prices are quoted at the end-of-day for the particular stock exchange. Later we will find that both the AOR and stock prices lead the CDS prices with the stock price movements having a somewhat stronger effect. Yet, in contrast to CDS and AOR the stock price levels are not a credit risk measure as such.

Balance sheet variables

We obtain a set of balance sheet variables from Bloomberg as additional controls: 1) Total debt to total assets, 2) Total debt to common equity, 3) short-term (ST) debt to total liabilities, 4) long-term (LT) debt to total liabilities and 5) (logarithm of) total assets (or equivalently total liabilities). In 1 and 2 total debt includes ST borrowings, LT borrowing and securities sold with repo agreements and excludes total deposits and liabilities that do not bear explicit interest. ST debt includes the ST borrowings, securities sold with repo agreements and other ST liabilities (such as those that do not bear interest). LT debt goes similarly apart from the repos, which were already counted to ST liabilities. Total liabilities is ST and LT debt + total deposits.

TARGET2 liquidity

As a response to the crisis, the ECB provided large amounts of liquidity to the banking system. ECB's Statistical Data Warehouse offers public data on daily liquidity conditions. We define the liquidity to be the amount of central bank money in the current account plus in the deposit facility.

Other control variables from the TARGET2 money market data

The TARGET2 money market data offers a multitude of potentially interesting controls. First, we have the following bank-specific controls with daily frequency: (logarithm of) amount borrowed, (logarithm of) number of lenders, lending rate (spread to EONIA), and standard deviation of borrowing rates. Second, we have the following additional controls with daily frequency: (logarithm of) total overnight market volume, (logarithm of) total lender count, (logarithm of) total borrower count, standard deviation of all overnight market rates. As the credit risk is the leading cause of variation in overnight rates, the market wide standard deviation of overnight rates gives an idea on how the credit risk is distributed across the different banks. For the standard deviation variables we have also used percentile differences as alternative dispersion measures (and found the results unchanged).

Euro General Collateral Repo Market Rate (EUREPO)

EONIA is based on realized uncollateralized loans and contains credit risk. The risk premium in EONIA can be proxied by observing the spread to the less risky Euro Repo Market Rate (EUREPO), which is the rate at which at 11.00 am Brussels time, one bank offers funds in euro to another bank against European government guaranteed bonds and bills as collateral.

Figure 6 shows together the EUREPO-EONIA spread, the standard deviation of overnight rates in the money market and the iTraxx index. The high correlation between the three confirm that both the short-term and long-term credit risk has been relevant during the past years, and also that the risks have been unevenly distributed across banks.

III. Empirical analysis

A. Testing for co-integration between the AOR and the CDS

From purely theoretical viewpoint it is difficult to see why interest rates or interest rate spreads would be non-stationary. However, in finite time-series samples such evidence is often found. Hence, we also start our empirical analysis by testing for the stationarity of and co-integration between the bank-specific time series of the AOR (spread) and the CDS (spread); cf. e.g. Blanco et al. (2005). Obviously, the AOR and the CDS could be closely related if they reflect the same fundamentals concerning a bank's creditworthiness, unless the AOR is relatively information insensitive (cf. Dang et al. 2012) in normal times due to its very short maturity (overnight). Hence, it is possible that a co-integration relationship between the AOR and the CDS exists only during crisis periods when the AOR's information sensitivity increases.

The Augmented Dickey-Fuller (ADF) test, when performed separately for each bank, detects no unit roots for the AORs of the sample banks. In contrast, a unit root in the CDS is detected for around half of the banks. Unit root tests in the panel setting give consistent results. Despite the failure of the ADF test to detect unit roots for the AORs, the Johansen co-integration test finds one co-integrating vector between the AOR and the CDS for around one third of the sample banks. These test results appear to be rather

robust to lag order selection. In sum, because the evidence for non-stationarity and co-integration is not compelling, we use the standard Vector Autoregressive model in the subsequent analyses. To control the robustness of our results, we will estimate the lead-lag model for the AOR and the CDS both in levels and differences.

B. The lead-lag relationship between the AOR and the CDS

The test for our main hypothesis that the AOR may lead the CDS is conducted in the standard VAR framework, using the Granger causality setup. We focus on a panel VAR but provide also bank-specific time series results. When controlling for various bank characteristics, we use interactions between the lead-lag relationship of the AOR over the CDS and various dummy variables to test whether the lead relationship is stronger for certain bank types and time periods, consistent with the information sensitivity hypothesis. Our empirical hypotheses are summarized in the following list. Hypothesis *H2(v)* that the lead for the AOR over the CDS is stronger for banks whose CDS is relatively illiquid is added to hypotheses *H2(i)–(iv)* which are directly motivated by the theory of Dang et al. (2012). Hypothesis *H2(v)* could be justified by the findings of Blanco et al. (2005) who argue that the CDS leads the corresponding bond price partly due to better liquidity. By the same logic we could postulate that if the AOR were to lead the CDS, the lead should be stronger if the CDS market is relatively illiquid.

Hypothesis 1: The AOR leads the CDS in the sense that it "Granger causes" the CDS (henceforth H1)

Hypothesis 2: The AOR's lead over the CDS is stronger (henceforth H2)

- *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 price is relatively illiquid*

The VAR model in the panel setting takes the form:

$$y_t^{(b)} = a_0 + \sum_{i=1}^{k} A_i y_{t-i}^{(b)} + e_t^{(b)} \text{ for each business day } t \text{ and bank } b. \qquad (6)$$

Here vector a_0 and matrix A_j are the panel regression coefficients shared by all banks and obtained by ordinary least squares (OLS). Elements of vector $y_t^{(b)}$ are the daily change in the AOR for bank b, the daily change in the CDS for bank b, and the control variables.

In order to fix the lag length of the VAR process we use the conventional information criteria. The Schwarz Bayesian information criterion (SBIC) has a minimum at 5 lags for the CDS. This corresponds to one week since only business days are included. In the case of the AOR, no clear minimum was found. In reporting our main results, we use one lag for both the AOR and the CDS, but consider also 5 lags to ensure robustness of results.

Table 2 reports results for the basic panel VAR, both in levels (panel a) and differences (panel b), in which we include only the AOR and the CDS. Panel c) further tests if our main result is due to system wide or idiosyncratic shocks. The results clearly indicate that there is a lead only for the AOR over the CDS, but not the other way around. Especially from the difference form (panel b) we readily see that the lead is positive. Equations (1) and (2) in panel c) of Table 2 confirm that the results hold even if the indices are not explicitly subtracted. Moreover, as the EONIA and iTraxx do not lead one another, we infer that the lead is due to idiosyncratic rather than system-wide shocks in the credit risk. These results are consistent with hypothesis *H1*. Note that the equations where the

AOR is the dependent variable exhibit strong negative autocorrelation which apparently captures the occasional peaks and reversals in the AOR series.[19] A robust estimation of the Table 2 regressions shows, however, that the results are not driven by outliers. Below we will work with and extend the difference form of the model in Table 2 because that lends itself more readily for interpreting the sign and size of the lead coefficient.

Table 3 (panel A) extends the model of Table 2 by considering a large set of control variables, added to the basic model one at a time. The lead for the AOR over the CDS stays statistically very significant in all cases although a number of the control variables obtain simultaneously significant coefficients. For instance, consistent with Acharya et al. (2007) we find that the lagged log difference of bank's stock price negatively predicts the bank CDS price change. Also the lagged change of the sovereign CDS price of the country in which the bank resides predicts the change in the bank CDS price. Since the coefficient of AOR remains largely intact despite the additional controls, the information in the AOR appears to be supplementary to the information in the equity and the sovereign CDS.

In Table 4 we report the basic VAR results (without control variables) for individual banks.[20] The purpose of these results is to show the large variation of the lead-lag relationship between the AOR and the CDS among individual banks. Only a relatively small subset of banks (7 out of 60) exhibits a statistically significant coefficient with 5 % significance level on the lead for the AOR over the CDS. However, each of the significant coefficients is positive, and more than two thirds of all coefficients are

[19] There are a number of reasons related to the functioning of the overnight money market, which may cause these peaks and immediate reversals. In particular, until 13 December 2011 the Eurosystem used one-day liquidity absorbing fine-tuning operations related to changes of the reserve maintenance period, which typically had the effect that the overnight rates temporarily rose towards the monetary policy steering rate. Moreover, the peaks are not always uniformly distributed across banks so that after the EONIA is subtracted, occasional peaks remain.

[20] Note that because of the high confidentiality of the individual bank data, individual bank results are numbered in a random order with no link to actual bank identities or bank attributes.

positive. In the other direction, the lead for the CDS over the AOR, there is also a small subset of banks (6 out of 60) with statistically significant coefficients but with occurrences of both signs of the coefficients. These results further motivate our focus on the panel VAR results, with conditioning market and bank characteristics for the strength of the lead, to which we turn next.

Table 5 extends the basic results of Table 2 by adding conditioning variables. The idea in Table 5 estimating equations is that we condition the lead for the AOR over the CDS (henceforth "the lead") on a number of dummy variables which proxy for the factors listed in hypotheses *H2: i) – v)* above plus some additional controls.

Concerning hypothesis *H1*, equations in Table 5 show that the coefficient of the (daily change in) AOR, lagged by one day, is positive in all except for two cases (regressions A(6) and D(1)), and the coefficient is statistically significant in about half of the regressions, depending on the specific conditioning dummy-variables included in the various equations. The conclusion from these results is that the lead is not a general phenomenon, or is at least quite weak, but may rather be specific to banks and times when, apparently, the information sensitivity of the AOR increases. We next turn to evidence on this.

Consistent with hypothesis *H2(i)*, Panel A of Table 5 provides evidence that the lead for AOR over the CDS depends on general market conditions and is stronger during crisis periods, especially during the sovereign debt crisis in Europe (see regression A(3)). The crisis effect on the lead is best captured by the dummy variable which indicates days when the iTraxx index has been above its sample time-series median (regression A(4)). The TARGET2 liquidity measure, appearing in equations A(5)-A(6), and reflecting the ECB's liquidity support measures during crisis periods, also indicates periods of

strengthened lead. Note that according to regression A(2) the lead is quite weak during the period after Lehman's bankruptcy but before the escalation of the sovereign debt crisis in 2010. This is consistent with that soon after Lehman the EU governments essentially guaranteed their banking sectors. However, the sovereign debt crisis questioned the solidity of these guarantees in many countries. Our results show that the information sensitivity of overnight loans changed accordingly from quite insensitive to sensitive: the effective size of the AOR's lead coefficient in regression A(2) is 0.015 while in regression A(3) it is 0.065, more than a quadruple, and statistically very significant.

In panel B of Table 5, the lead is conditioned on alternative proxies of bank quality as well as on the bank domicile, hence testing for hypotheses *H2(ii)–(iii)*. We use three alternative indicators to proxy for (relative) bank quality on a daily basis: 1) if a bank's daily CDS is above the same day's cross-sectional median CDS of all sample banks, 2) if a bank's daily AOR is above the same day's cross-sectional median AOR of all sample banks, and 3) if a bank's public credit rating (measured on the 21-notch numbered scale) is below (numerically above) the daily cross-sectional median rating of all sample banks. The first three of these quality proxies supports hypothesis *H2(ii)* that the lead is stronger for weaker banks, being consistent with the view that weaker quality increases bank debt's information sensitivity; see equations B(1)–B(3), respectively. Also bank domicile in a crisis country strengthens the lead (regression B(4)), which is consistent with hypothesis *H2(iii)*.[21] However, when the alternative bank quality measures appear jointly (equations B(5) and B(6)), only the rating-based relative quality indicator remains statistically significant.

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

Equations in panel C of Table 5 test hypotheses *H2(iv)–(v)*. Regressions C(1) and C(2) indicate that the statistically significant lead is concentrated on days on which a bank borrows mainly from its relationship lenders, measured by the BPI index, and the borrowing is relatively concentrated, as measured by the HHI index. Regressions C(5)–(6) further confirm that the relationship indices (BPI and HHI) as a conditioning variable are also quite robust. Hypothesis *H2(v)* that the lead is stronger for banks with a less liquid CDS gets supported by regression C(4) but the result is not robust when all variables in panel C are included (regression C(5)). Bank size could also be a proxy for a bank's reliance on relationship lenders, but also for bank quality or the illiquidity of its CDS. Regression C(3) shows that smaller banks exhibit a stronger lead and that the effect is not entirely related to relationship lending as bank size as a conditioning variable maintains its significance against the BPI index (regression C(6)).

In panel D of Table 5 we consider together all variables in panels B and C and the most promising combinations of them. The only conditioning dummy-variables which are statistically significant when all these variables are present are the BPI and HHI indices (regression D(1)). The robustness is further confirmed in equations D(2)–(5) where the BPI index is controlled against other selected variables one by one. Similar robustness checks for the HHI index (not shown) yield much the same results.

In panel E of Table 5 we add double interaction terms such that we simultaneously condition the strength of the lead on periods of market stress, proxied for by the iTraxx index from panel A, and on each of the most promising conditioning variables detected in panels B and C. Equations E(2)–E(5) show that the effect of each of the conditioning variables which performed relatively well in the previous regressions gets further amplified on days of market stress. In fact, in each case the effective lead coefficient is essentially zero during "normal" times. Note that the lead coefficient conditioned on one

of the double interaction terms is almost identical throughout all equations E(2)–E(5). This hints that the different conditioning variables together with the market stress indicator may proxy for the same fundamental factors. Equations E(1) and (6) show that when the different double interaction terms appear jointly, the two statistically significant conditioning double interaction terms are the BPI index together with the market stress indicator and the HHI index alone without the market stress indicator (the latter being somewhat less significant). Moreover, by comparing say regression A(4) with E(4) we see that conditioning on the BPI index indeed increases the lead coefficient and hence has an independent effect over and above the market stress. We may conclude on the basis of Table 5 that there is a robust lead for the AOR over the CDS for banks which are relatively reliant on relationship lenders and (to some extent) for banks with below median size, on days of market stress. An (unreported) auxiliary regression shows that a low bank rating and small bank size are related to a high value for the bank's BPI index. These results are similar to those of 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". We also find that the BPI index is on average higher for banks in crisis countries. So, although it is understandable that reliance on relationship lenders together with market stress are the conditioning dummy-variables that best capture the relative informativeness of the bank's AOR (measured by the strength of the lead), there are more fundamental bank characteristics such as quality and size which in turn explain a bank's reliance on relationship lenders. As a robustness check, Table 6 reports largely similar results corresponding to those in Table 5 but using the conditioning variables as such in multiplicative interactive terms instead of first transforming them into dummy variables.

Finally, we evaluate the economic significance of the lead coefficient for AOR over CDS. Consider an increase of 30 bps in the AOR, which is roughly the estimated long-term change in the AOR corresponding to a 1000 bps change in the CDS; see Figure 2. Based on the basic VAR model from panel b) of Table 2, the estimated change in the next day's CDS would equal $0.0474 \times 30 \text{ bps} \approx 1.5 \text{ bps}$. This magnitude corresponds to the size of a bid-ask spread of a highly liquid bank CDS in our data. In any case, even for a quite extreme change in the CDS, the additional contribution from the AOR would be very small in absolute terms. The economic significance of the lead would of course be higher for some banks, as the individual bank coefficients suggest in Table 4. Moreover, as results in Table 5 have shown, it would be stronger during market stress, especially for banks borrowing mainly from relationship lenders. Even stronger impact would follow if we used the level form specification (panel a of Table 2) and introduced a permanent change in the AOR. Due to the high persistence of the CDS rates the long-run impact would be even of the magnitude of 15 per cent.

To sum up, the economic significance of the predictive power of the AOR regarding the CDS probably remains modest in most circumstances. It is nevertheless useful to know on the basis of our results that the AOR's information content regarding a bank's health fares well compared to, and even better than, the CDS. To extrapolate this result, the AOR may provide quite reliable information during market stress also of banks without a CDS.

IV. Conclusions

In this paper we have investigated the informativeness of banks' average overnight interbank borrowing rates over and above their CDS price. Because the overnight

borrowing rates are privately negotiated between the borrower and the lender bank, they may reflect lenders' private signals concerning the borrower bank's financial health. In spite of their overnight maturity, these rates may become informationally sensitive during market stress. Because all private information may not be simultaneously reflected in the public CDS market, because of market frictions or possibly strategic reasons, it is possible that a bank's average overnight borrowing rate, which aggregates the private information signals, is more informative, at least in some periods, than the CDS price. To test this hypothesis we have used proprietary data on banks' overnight rates from the Eurosystem's main large value payment system, TARGET2, over the period from mid-2008 to mid-2013.

We find that the daily changes of the average overnight rate spreads lead (in the sense of Granger causing) the respective CDS spreads for relatively weaker and smaller banks, for banks in crisis countries, for banks with a relatively illiquid CDS market, and for banks which are relatively reliant on relationship lenders. When these effects are allowed to control for one another, a robust lead exists for banks which are relatively reliant on relationship lenders and (to some extent) for banks with below median size, on days of market stress. These results are consistent with the general predictions from theories such as Dang et al. (2012). Our results may be informative to the authorities responsible for banks' stability in providing an additional source of short-term information for assessing the risk of financial crises and current state of the banking system.

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Table 1

Descriptive statistics

This table reports the number of observations each year that are used in the regressions and the mean / standard deviation statistics for the key variables, AOR (EONIA subtracted) and CDS (iTraxx not subtracted), and the bank relationship variables: Herfindahl-Hirschman Index (HHI), Borrower Preference Index (BPI), and number of lenders of a bank (NL). For regressions involving stock price or credit rating the numbers of observations can be smaller than reported here due to lack of stock price information or credit rating for some dates. *Observations for year 2008 start at the beginning of June and for 2013 end at the end of June.

Year:	**2008***	**2009**	**2010**	**2011**	**2012**	**2013***	**Total**
Observations	6,033	11,491	12,295	11,453	8,983	3,732	53,987
mean(AOR)	-0.141	-0.151	-0.078	-0.081	-0.062	0.002	-0.093
σ(AOR)	(0.166)	(0.119)	(0.113)	(0.176)	(0.150)	(0.114)	(0.148)
mean(CDS)	134.207	164.605	183.193	308.788	368.270	272.659	237.386
σ(CDS)	(86.271)	(114.724)	(162.363)	(317.592)	(321.608)	(256.795)	(244.545)
mean(HHI)	0.396	0.468	0.491	0.465	0.556	0.627	0.490
σ(HHI)	(0.290)	(0.306)	(0.314)	(0.314)	(0.315)	(0.307)	(0.315)
mean(BPI)	0.083	0.101	0.113	0.100	0.165	0.210	0.120
σ(BPI)	(0.135)	(0.138)	(0.155)	(0.150)	(0.204)	(0.233)	(0.168)
mean(NL)	9.974	7.342	7.006	7.715	4.834	3.372	6.947
σ(NL)	(10.305)	(7.512)	(7.290)	(7.799)	(4.573)	(2.788)	(7.464)

Table 2

Basic lag-lead result for AOR and CDS

Panel a and b report the results of panel VAR regression for CDS (iTraxx subtracted) and AOR (EONIA subtracted). In parentheses are the standard errors. Panel c reports similar VAR regression where EONIA and iTraxx indices are not explicitly subtracted as well as a VAR for the indices alone. Superscripts ***,**,* indicate p-value less than 0.001, 0.01 and 0.05, respectively. † denotes the case that EONIA or iTraxx is not subtracted.

a) Variables in levels

	CDS_t	AOR_t
AOR_{t-1}	0.0572***	0.5182***
	(0.0073)	(0.0044)
AOR_{t-2}	-0.0376***	0.3276***
	(0.0074)	(0.0044)
CDS_{t-1}	0.9969***	-0.0001
	(0.0046)	(0.0028)
CDS_{t-2}	0.0018	0.0056*
	(0.0047)	(0.0028)
constant	0.0037***	-0.0189***
	(0.0009)	(0.0005)
No. of obs	46,729	46,729
R^2	0.9964	0.7285

b) Variables in differences

	ΔCDS_t	ΔAOR_t
ΔAOR_t	0.0474***	-0.4053***
	(0.0069)	(0.0043)
ΔCDS_t	-0.0026	-0.0034
	(0.0046)	(0.0029)
No. of obs	46,729	46,729
R^2	0.0010	0.1613

c) Variables in differences

	ΔCDS_t†	ΔAOR_t†	$\Delta iTraxx_t$	$\Delta EONIA_t$
ΔAOR_{t-1}†	0.0317***	-0.3279***	-	-
	(0.0074)	(0.0069)		
ΔCDS_{t-1}†	0.0105*	0.0062	-	-
	(0.0049)	(0.0045)		
$\Delta EONIA_{t-1}$	-0.0051	0.0426***	0.0313	-0.2043***
	(0.0079)	(0.0080)	(0.0180)	(0.0273)
$\Delta iTraxx_{t-1}$	0.3378***	0.1278***	0.1234***	0.0336
	(0.0087)	(0.0073)	(0.0276)	(0.0418)
No. of obs	46 729	46 729	1 293	1 293
R^2	0.0381	0.0632	0.0169	0.0425

Table 3

Controls for robustness of the lag-lead relationship

This table reports the relevant coefficients from panel VAR regressions and results of Granger Causality tests for CDS (iTraxx subtracted), AOR (EONIA subtracted) and a set of control variables. Panel A reports the tests that a variable Granger causes CDS, Panel B reports similar results for causal sources for AOR, and Panel C for each of the control variables. We perform the VAR for each control variable separately. For example the VAR component for CDS reads $\Delta \boldsymbol{CDS_t} = \boldsymbol{\beta_1} \Delta \boldsymbol{CDS_{t-1}} + \boldsymbol{\beta_2} \Delta \boldsymbol{AOR_{t-1}} + \boldsymbol{\beta_3}\ \boldsymbol{CTRL_{t-1}} + \boldsymbol{\beta_0}$ where *CTRL* is the control variable.

Panel A	H0: AOR causes CDS			H0: Control causes CDS		
Control variable	Coefficient x 1000	F-statistic	p-Value	Coefficient x 1000	F-statistic	p-Value
Log(ST and LT debt)	47.244	41.851	0.000	-0.898	2.765	0.096
ST debt / total assets	49.156	31.921	0.000	0.867	0.027	0.868
LT debt / total assets	46.875	39.666	0.000	-0.075	0.000	0.985
Total debt / total assets	47.263	41.884	0.000	0.043	1.254	0.263
Total debt / common equity	47.289	41.884	0.000	0.000	1.204	0.273
Total Liabilities	47.256	41.872	0.000	0.000	3.467	0.063
Rating	47.225	46.418	0.000	-0.008	0.004	0.951
CDS bid-ask spread	47.389	46.896	0.000	0.001	0.275	0.600
Log(ON borrows value)	47.600	47.239	0.000	-0.230	0.487	0.485
Log(ON lender banks count)	47.396	46.895	0.000	0.036	0.004	0.951
Log(ON lends value)	29.923	13.158	0.000	0.657	2.704	0.100
Log(stock price)	49.146	35.263	0.000	-0.728	2.143	0.143
EONIA-EUREPO spread	47.361	46.455	0.000	-0.372	0.005	0.946
ON lending rate	30.218	13.419	0.000	1.694	9.215	0.002
Domicile country CDS	46.822	44.432	0.000	0.227	5.694	0.017
Percentile dispersion of OR	46.934	46.012	0.000	22.372	20.399	0.000
Standard deviation of OR	45.895	43.895	0.000	37.345	18.941	0.000
Log(total ON value)	47.158	46.458	0.000	4.771	20.097	0.000
Log(total number of lender banks)	47.889	47.891	0.000	7.196	14.027	0.000
Log(total number of borrower banks)	47.956	48.034	0.000	14.664	21.490	0.000
Total lender banks / total borrower banks	47.650	47.402	0.000	4.181	3.540	0.060
Total liquidity	48.462	48.896	0.000	-3.392	7.290	0.007
Standard deviation of all OR	47.596	47.241	0.000	6.692	0.541	0.462
BPI	47.621	47.345	0.000	-7.010	3.105	0.078
HHI	47.355	46.815	0.000	-0.761	0.153	0.696
Δ(Log(ON borrows value))	46.942	45.196	0.000	0.271	0.246	0.620
Δ(Log(ON lender banks count))	47.291	46.455	0.000	0.236	0.050	0.823
Δ(Log(ON lends value))	27.375	9.752	0.002	0.907	2.487	0.115
Δ(Log(stock price))	48.162	33.368	0.000	-311.023	346.837	0.000
Δ(EONIA-EUREPO spread)	45.936	41.742	0.000	-7.292	0.809	0.369
Δ(ON lending rate)	24.948	7.970	0.005	-10.231	4.842	0.028
Δ(Domicile country CDS)	46.939	44.772	0.000	14.967	148.559	0.000
Δ(Standard deviation of OR)	43.936	39.836	0.000	42.591	20.294	0.000
Δ(Log(total ON value))	46.712	45.241	0.000	4.304	1.386	0.239
Δ(Log(total number of lender banks))	46.063	44.031	0.000	-15.697	5.834	0.016
Δ(Log(total number of borrower banks))	47.671	47.389	0.000	6.849	1.018	0.313
Δ(Total lender banks / total borrower banks)	45.727	43.525	0.000	-17.795	16.304	0.000
Δ(Total liquidity)	44.875	40.632	0.000	5.268	3.812	0.051
Δ(Standard deviation of all OR)	46.238	43.770	0.000	-19.624	1.418	0.234
Δ(Percentile dispersion of all OR)	46.676	44.521	0.000	-5.400	0.505	0.477
Δ(BPI)	47.026	46.061	0.000	6.886	1.124	0.289
Δ(HHI)	47.059	46.123	0.000	-2.432	0.931	0.334

Table 3 continued

Panel B	H0: CDS causes AOR			H0: Control causes AOR		
Control variable	Coefficient x 1000	F-statistic	p-Value	Coefficient x 1000	F-statistic	p-Value
Log(ST and LT debt)	-3.279	1.244	0.265	-0.115	0.122	0.727
ST debt / total assets	-5.180	2.518	0.113	0.322	0.011	0.916
LT debt / total assets	-3.300	1.219	0.269	-0.284	0.014	0.905
Total debt / total assets	-3.268	1.236	0.266	-0.002	0.004	0.948
Total debt / common equity	-3.242	1.215	0.270	0.000	0.057	0.811
Total Liabilities	-3.272	1.239	0.266	0.000	0.012	0.912
Rating	-3.481	1.475	0.225	0.006	0.007	0.935
CDS bid-ask spread	-3.415	1.416	0.234	0.001	0.316	0.574
Log(ON borrows value)	-3.446	1.442	0.230	-0.924	20.656	0.000
Log(ON lender banks count)	-3.438	1.435	0.231	-1.154	9.856	0.002
Log(ON lends value)	2.107	0.269	0.604	-0.157	0.341	0.559
Log(stock price)	-4.125	1.767	0.184	-0.079	0.073	0.787
EONIA-EUREPO spread	-3.655	1.623	0.203	23.898	50.188	0.000
ON lending rate	2.211	0.296	0.586	-0.567	2.274	0.132
Domicile country CDS	-3.361	1.319	0.251	0.111	3.554	0.059
Standard deviation of OR	-3.064	1.140	0.286	-37.831	50.941	0.000
Log(total ON value)	-3.258	1.288	0.256	-1.791	7.414	0.006
Log(total number of lender banks)	-3.412	1.412	0.235	0.064	0.003	0.957
Log(total number of borrower banks)	-3.334	1.349	0.246	-2.172	1.234	0.267
Total lender banks / total borrower banks	-3.450	1.445	0.229	2.327	2.871	0.090
Total liquidity	-3.507	1.493	0.222	-1.827	5.536	0.019
Standard deviation of all OR	-3.513	1.499	0.221	29.390	27.361	0.000
Percentile dispersion of all OR	-3.704	1.667	0.197	26.494	62.759	0.000
BPI	-3.409	1.410	0.235	0.676	0.076	0.783
HHI	-3.448	1.443	0.230	3.807	10.007	0.002
Δ(Log(ON borrows value))	-3.406	1.409	0.235	1.483	19.262	0.000
Δ(Log(ON lender banks count))	-3.363	1.373	0.241	2.577	15.584	0.000
Δ(Log(ON lends value))	3.041	0.522	0.470	-1.166	9.277	0.002
Δ(Log(stock price))	-3.828	1.515	0.218	6.998	0.509	0.476
Δ(EONIA-EUREPO spread)	-3.093	1.162	0.281	-29.841	35.488	0.000
Δ(ON lending rate)	3.104	0.543	0.461	-2.097	0.459	0.498
Δ(Domicile country CDS)	-3.208	1.196	0.274	-0.423	0.309	0.578
Δ(Standard deviation of OR)	-3.368	1.377	0.241	12.769	4.775	0.029
Δ(Log(total ON value))	-3.427	1.426	0.232	-7.529	11.107	0.001
Δ(Log(total number of lender banks))	-3.331	1.347	0.246	-13.265	10.912	0.001
Δ(Log(total number of borrower banks))	-3.360	1.371	0.242	-16.020	14.592	0.000
Δ(Total lender banks / total borrower banks)	-3.411	1.412	0.235	0.948	0.121	0.728
Δ(Total liquidity)	-3.365	1.374	0.241	2.362	2.006	0.157
Δ(Standard deviation of all OR)	-3.503	1.490	0.222	46.224	20.605	0.000
Δ(Percentile dispersion of all OR)	-3.577	1.554	0.213	22.189	22.360	0.000
Δ(BPI)	-3.451	1.445	0.229	11.943	8.856	0.003
Δ(HHI)	-3.337	1.378	0.240	-2.883	3.428	0.064

Table 3 continued

Panel C	H0: AOR causes control variable			H0: CDS causes control variable		
Control variable	Coefficient x 1000	F-statistic	p-Value	Coefficient x 1000	F-statistic	p-Value
Log(ST and LT debt)	-6.596	18.215	0.000	1.104	1.166	0.280
ST debt / total assets	-0.127	0.032	0.857	0.242	0.283	0.594
LT debt / total assets	-0.107	0.036	0.849	0.103	0.077	0.782
Total debt / total assets	-141.555	8.523	0.004	41.987	1.714	0.190
Total debt / common equity	5825.586	0.661	0.416	3098.081	0.427	0.513
Total Liabilities	422014.930	0.694	0.405	73760.709	0.048	0.826
Rating	11.198	1.150	0.284	5.901	0.710	0.399
CDS bid-ask spread	192.594	0.536	0.464	736.208	17.371	0.000
Log(ON borrows value)	-500.855	78.772	0.000	-4.944	0.017	0.896
Log(ON lender banks count)	-87.249	8.901	0.003	-20.534	1.095	0.295
Log(ON lends value)	56.189	0.429	0.513	65.489	1.090	0.297
Log(stock price)	4.104	2.455	0.117	1.096	0.427	0.513
EONIA-EUREPO spread	74.335	380.469	0.000	-4.230	2.756	0.097
ON lending rate	81.458	50.161	0.000	-8.448	1.010	0.315
Domicile country CDS	-33.026	1.822	0.177	230.884	196.401	0.000
Percentile dispersion of OR	8.939	2.550	0.110	5.377	2.048	0.152
Standard deviation of OR	-11.292	13.892	0.000	6.026	8.800	0.003
Log(total ON value)	-79.724	83.281	0.000	15.110	6.636	0.010
Log(total number of lender banks)	39.076	63.322	0.000	5.229	2.516	0.113
Log(total number of borrower banks)	21.153	21.126	0.000	1.257	0.166	0.684
Total lender banks / total borrower banks	29.498	17.510	0.000	12.978	7.524	0.006
Total liquidity	-257.277	480.375	0.000	-22.003	7.820	0.005
Standard deviation of all OR	19.638	107.090	0.000	1.383	1.180	0.277
BPI	-27.072	33.622	0.000	2.972	0.900	0.343
HHI	-2.374	0.041	0.840	10.133	1.644	0.200
Δ(Log(ON borrows value))	39.159	0.516	0.472	1.628	0.002	0.964
Δ(Log(ON lender banks count))	65.246	5.385	0.020	-23.433	1.550	0.213
Δ(Log(ON lends value))	22.635	0.068	0.794	54.058	0.744	0.388
Δ(Log(stock price))	5.040	3.636	0.057	1.260	0.564	0.453
Δ(EONIA-EUREPO spread)	55.535	189.466	0.000	-4.207	2.547	0.111
Δ(ON lending rate)	16.584	2.008	0.157	-7.767	0.859	0.354
Δ(Domicile country CDS)	-35.661	2.084	0.149	200.114	144.136	0.000
Δ(Percentile dispersion of OR)	21.584	13.771	0.000	-3.985	1.043	0.307
Δ(Standard deviation of OR)	7.384	5.739	0.017	0.855	0.173	0.677
Δ(Log(total ON value))	-21.999	7.131	0.008	10.556	3.670	0.055
Δ(Log(total number of lender banks))	26.614	29.525	0.000	4.278	1.704	0.192
Δ(Log(total number of borrower banks))	18.545	15.825	0.000	-1.904	0.371	0.543
Δ(Total lender banks / total borrower banks)	3.380	0.245	0.620	11.395	6.215	0.013
Δ(Total liquidity)	-65.850	36.742	0.000	-24.769	11.939	0.001
Δ(Standard deviation of all OR)	4.084	4.715	0.030	1.515	1.469	0.226
Δ(BPI)	-9.653	4.717	0.030	4.466	2.246	0.134
Δ(HHI)	-44.144	14.655	0.000	12.974	2.816	0.093

Table 4

Bank-level regression results

This table reports the relevant VAR coefficient and Granger causality test results when the VAR is done in the bank-level. The results for individual banks are ordered according to the smallest p value.

	H0: AOR causes CDS				H0: CDS causes AOR		
p-Rank	Coefficient x 1000	F-statistic	p-Value	p-Rank	Coefficient x 1000	F-statistic	p-Value
1	110.760	13.698	0.000	1	35.606	8.332	0.004
2	372.613	7.429	0.006	2	55.102	6.163	0.013
3	75.387	6.920	0.009	3	-130.982	5.386	0.020
4	128.269	5.389	0.020	4	-90.493	5.176	0.023
5	87.611	4.310	0.038	5	-41.044	4.554	0.033
6	67.202	4.207	0.040	6	29.751	3.877	0.049
7	75.919	3.940	0.047	7	-47.836	3.816	0.051
8	-86.430	3.827	0.050	8	127.897	3.534	0.060
9	82.601	3.699	0.054	9	57.719	3.381	0.066
10	55.346	3.085	0.079	10	24.063	2.799	0.094
11	38.686	2.939	0.086	11	42.559	2.771	0.096
12	32.510	2.733	0.098	12	-33.058	2.648	0.104
13	-382.449	2.718	0.099	13	56.278	2.491	0.115
14	65.675	2.636	0.104	14	-68.243	2.379	0.123
15	55.715	2.424	0.120	15	36.041	2.347	0.126
16	-130.802	2.341	0.126	16	-76.272	2.243	0.134
17	96.839	2.312	0.128	17	-41.434	1.851	0.174
18	84.412	2.174	0.140	18	-14.406	1.817	0.178
19	52.598	2.051	0.152	19	29.446	1.675	0.196
20	64.554	1.986	0.159	20	30.805	1.429	0.232
21	-49.441	1.824	0.177	21	-23.695	1.284	0.257
22	29.668	1.740	0.187	22	-54.598	1.258	0.262
23	-26.708	1.688	0.194	23	-21.899	0.960	0.327
24	22.456	1.658	0.198	24	43.315	0.926	0.336
25	90.747	1.644	0.200	25	42.942	0.792	0.373
26	94.060	1.621	0.203	26	-8.913	0.779	0.377
27	-79.022	1.611	0.204	27	-14.819	0.727	0.394
28	65.401	1.432	0.231	28	-78.386	0.714	0.398
29	431.689	1.343	0.246	29	42.974	0.704	0.401
30	68.778	1.285	0.257	30	-103.492	0.670	0.413

Table 4 continued

	H0: AOR causes CDS				H0: CDS causes AOR			
p-Rank	Coefficient x 1000	F-statistic	p-Value		p-Rank	Coefficient x 1000	F-statistic	p-Value
31	-31.571	1.067	0.302		31	-14.631	0.658	0.417
32	172.220	0.995	0.319		32	15.179	0.648	0.421
33	18.302	0.992	0.319		33	16.522	0.617	0.432
34	-70.781	0.946	0.331		34	-33.065	0.554	0.457
35	24.448	0.849	0.357		35	-21.016	0.543	0.461
36	34.031	0.838	0.360		36	-13.678	0.442	0.506
37	92.200	0.834	0.361		37	10.742	0.393	0.531
38	25.913	0.654	0.419		38	-9.801	0.327	0.567
39	81.292	0.649	0.421		39	7.348	0.322	0.570
40	-26.536	0.603	0.437		40	20.759	0.319	0.572
41	-87.507	0.543	0.461		41	-17.485	0.317	0.573
42	35.836	0.524	0.469		42	-37.646	0.277	0.599
43	-60.873	0.476	0.490		43	11.135	0.249	0.618
44	28.327	0.398	0.528		44	-49.777	0.229	0.632
45	40.389	0.336	0.562		45	-7.769	0.135	0.714
46	-30.815	0.320	0.571		46	-9.787	0.109	0.741
47	21.834	0.277	0.599		47	50.103	0.106	0.744
48	23.548	0.272	0.602		48	7.971	0.095	0.758
49	-53.926	0.252	0.616		49	-8.238	0.074	0.785
50	13.410	0.229	0.632		50	-6.156	0.063	0.801
51	26.259	0.180	0.671		51	11.312	0.055	0.814
52	-11.099	0.179	0.672		52	-17.695	0.047	0.828
53	20.117	0.173	0.678		53	-5.038	0.047	0.829
54	19.826	0.170	0.680		54	-5.214	0.032	0.859
55	6.762	0.126	0.722		55	6.182	0.014	0.906
56	6.621	0.065	0.799		56	3.289	0.005	0.943
57	-6.238	0.034	0.853		57	-2.393	0.005	0.944
58	-3.720	0.019	0.890		58	-1.801	0.002	0.963
59	2.245	0.011	0.918		59	1.921	0.002	0.969
60	-2.012	0.003	0.957		60	-0.426	0.001	0.981

Table 5

Further characteristics of the lag-lead relationship

This table reports the results of panel VAR regressions for CDS (iTraxx subtracted), AOR (EONIA subtracted) and interactions of AOR with variety of dummy variables. In Panel A the dummy variable depends only on the day of the observation and not on the bank. In Panels B to D the panel the dummy categorizes observations each day according to the median of the variable relevant for that dummy that day. For example, if on 2010/05/14 the median CDS for observations is 144.00, then the "Higher CDS" dummy on that day is 1 for those banks whose CDS is above 144.00 that day. For the case of one dummy variable DUM, the relevant component of VAR equations is written as $\Delta \boldsymbol{CDS_t} = \boldsymbol{\beta_1}\, \Delta \boldsymbol{CDS_{t-1}} + \boldsymbol{\beta_2} \Delta \boldsymbol{AOR_{t-1}} + \boldsymbol{\beta_3}\, \Delta \boldsymbol{AOR_{t-1}} \times \boldsymbol{DUM_{t-1}} + \boldsymbol{\beta_0}$. Only the results related to this equation for CDS are shown. The constant coefficients $\boldsymbol{\beta_0}$ and coefficients of CDS $\boldsymbol{\beta_1}$are all small and statistically insignificant and have been omitted for brevity. In all cases the R-sq is about 0.0010 and the number of observations is 46,729 (44,398 if credit rating is used). In parentheses are the standard errors. Superscripts ***,**,* indicate p-value less than 0.001, 0.01 and 0.05, respectively.

Panel A	(1)	(2)	(3)	(4)	(5)	(6)
Lagged variable	ΔCDS	ΔCDS	ΔCDS	ΔCDS	ΔCDS	ΔCDS
ΔAOR	0.0476***	0.0641***	0.0178	0.0035	0.0309***	-0.0090
	(0.0071)	(0.0085)	(0.0112)	(0.0102)	(0.0089)	(0.0114)
Pre Lehman (15.9.2008)	-0.0053	-	-	-	-	-
	(0.0358)					
Post Lehman (before 2010)	-	-0.0491***	-	-	-	-
		(0.0146)				
Sovereign Debt Crisis (2010 onwards)	-	-	0.0476***	-	-	-
			(0.0143)			
High iTraxx	-	-	-	0.0806***	-	0.0778***
				(0.0139)		(0.0139)
High money market excess liquidity	-	-	-	-	0.0414**	0.0351*
					(0.0141)	(0.0142)

Panel B	(1)	(2)	(3)	(4)	(5)	(6)
Lagged variable	ΔCDS	ΔCDS	ΔCDS	ΔCDS	ΔCDS	ΔCDS
ΔAOR	0.0284*	0.0327**	0.0254**	0.0307***	0.0194	0.0236*
	(0.0111)	(0.0106)	(0.0091)	(0.0092)	(0.0123)	(0.0096)
Higher CDS	0.0312*	-	-	-	0.0067	-
	(0.0142)				(0.0165)	
Higher AOR	-	0.0258	-	-	0.0046	-
		(0.0141)			(0.0160)	
Worse rating	-	-	0.0517***	-	0.0424*	0.0453*
			(0.0140)		(0.0187)	(0.0179)
Domicile in GIIPS	-	-	-	0.0386**	0.0075	0.0104
				(0.0140)	(0.0187)	(0.0179)

Panel C	(1)	(2)	(3)	(4)	(5)	(6)
Lagged variable	ΔCDS	ΔCDS	ΔCDS	ΔCDS	ΔCDS	ΔCDS
ΔAOR	0.0177	-0.0023	0.0245**	0.0250**	-0.0342*	0.0007
	(0.0105)	(0.0046)	(0.0093)	(0.0097)	(0.0147)	(0.0117)
Higher BPI	0.0528***	-	-	-	0.0326*	0.0471***
	(0.0139)				(0.0146)	(0.0141)
Higher HHI	-	0.0677***	-	-	0.0604***	-
		(0.0147)			(0.0152)	
Smaller bank	-	-	0.0507***	-	0.0409	0.0448**
			(0.0139)		(0.0214)	(0.0140)
Larger CDS bid-ask spread	-	-	-	0.0459***	0.0089	-
				(0.0138)	(0.0215)	

Table 5 continued

Panel D	(1)	(2)	(3)	(4)	(5)	(6)
Lagged variable	ΔCDS	ΔCDS	ΔCDS	ΔCDS	ΔCDS	ΔCDS
ΔAOR	-0.0350*	0.0019	0.0030	0.0042	0.0070	0.0188
	(0.0156)	(0.0118)	(0.0118)	(0.0114)	(0.0115)	(0.0098)
Higher CDS	-0.0003	-	-	-	-	-
	(0.0165)					
Worse rating	0.0326	0.0320	-	0.0430**	-	0.0336*
	(0.0220)	(0.0210)		(0.0143)		(0.0170)
Domicile in GIIPS	-0.0034	-	-	-	0.0310*	-
	(0.0196)				(0.0141)	
Higher BPI	0.0305*	0.0438**	0.0460**	0.0443**	0.0479***	-
	(0.0147)	(0.0142)	(0.0142)	(0.0142)	(0.0141)	
Higher HHI	0.0604***	-	-	-	-	-
	(0.0152)					
Smaller bank	0.0409	-	-	-	-	0.0317
	(0.0217)					(0.0169)
Larger CDS bid-ask spread	-0.0123	0.0147	0.0378**	-	-	-
	(0.0270)	(0.0206)	(0.0141)			

Panel E	(1)	(2)	(3)	(4)	(5)	(6)
Lagged variable	ΔCDS	ΔCDS	ΔCDS	ΔCDS	ΔCDS	ΔCDS
ΔAOR	-0.0334*	0.0254**	0.0307***	0.0177	0.0021	0.0245
	(0.0147)	(0.0091)	(0.0092)	(0.0105)	(0.0120)	(0.0093)
Worse rating	0.0005	-0.0258	-	-	-	-
	(0.0272)	(0.0191)				
Domicile in GIIPS	-0.0200	-	-0.0350	-	-	-
	(0.0271)		(0.0189)			
Higher BPI	-0.0098	-	-	-0.0187	-	-
	(0.0209)			(0.0173)		
Higher HHI	0.0497*	-	-	-	0.0106	-
	(0.0207)				(0.0173)	
Smaller bank	0.0244	-	-	-	-	-0.0195
	(0.0279)					(0.0182)
Worse rating x Higher iTraxx	0.0250	0.1288***	-	-	-	-
	(0.0389)	(0.0217)				
Domicile in GIIPS x Higher iTraxx	0.0154	-	0.1238***	-	-	-
	(0.0382)		(0.0214)			
Higher BPI x Higher iTraxx	0.0728***	-	-	0.1299***	-	-
	(0.0237)			(0.0185)		
Higher HHI x Higher iTraxx	0.0250	-	-	-	0.1055***	-
	(0.0249)				(0.0170)	
Smaller bank x Higher iTraxx	0.0328	-	-	-	-	0.1236***
	(0.0359)					(0.0208)

Table 6

Interactions

This table reports the relevant panel VAR coefficients and Granger causality tests that AOR and/or interaction term, which is a product of AOR and another variable, Granger causes CDS. We perform the VAR for each interaction term separately. The relevant VAR component reads $\Delta CDS_t = \beta_1 \Delta CDS_{t-1} + \beta_2 \Delta AOR_{t-1} + \beta_3\ \Delta AOR_{t-1} \times VA_{t-1} + \beta_0$ where VA is the other variable in the interaction term.

	H0: AOR causes CDS			H0: Interaction term causes CDS		
Interaction term	Coefficient x 1000	F-statistic	p-Value	Coefficient x 1000	F-statistic	p-Value
ΔAOR x Rating	-103.063	59.901	0.000	25.378	175.425	0.000
ΔAOR x BPI	47.902	30.696	0.000	-4.579	0.009	0.923
ΔAOR x HHI	43.093	8.584	0.003	7.348	0.110	0.740
ΔAOR x Total Assets	69.293	42.955	0.000	0.000	8.285	0.004
ΔAOR x CDS bid-ask spread	46.811	42.055	0.000	0.011	0.083	0.773
ΔAOR x AOR	49.485	50.343	0.000	47.601	5.685	0.017
ΔAOR x CDS	-9.298	1.385	0.239	26.150	217.819	0.000

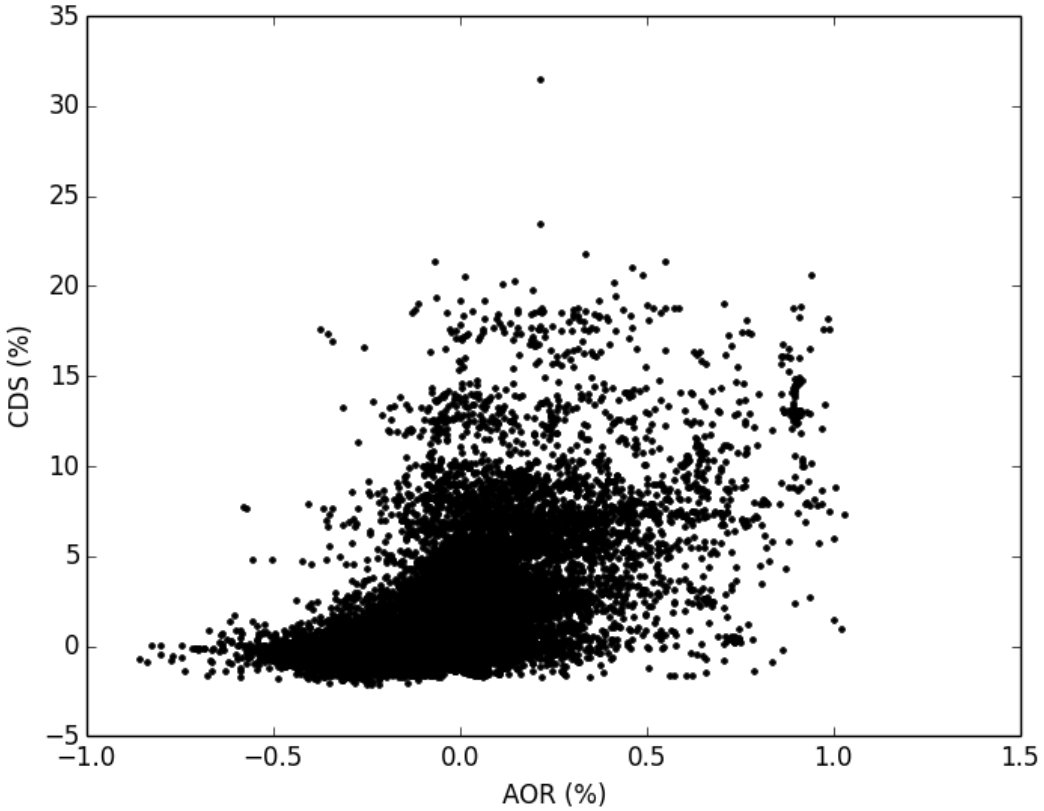

Figure 1. Scatter plot of the daily AOR and CDS observations. Each point corresponds to one of the 53,987 daily observations. A linear least square fit of the data reads CDS = 7.79 (0.06) AOR + 1.54 (0.01) with standard errors in the parentheses and explained variance R-sq = 0.26.

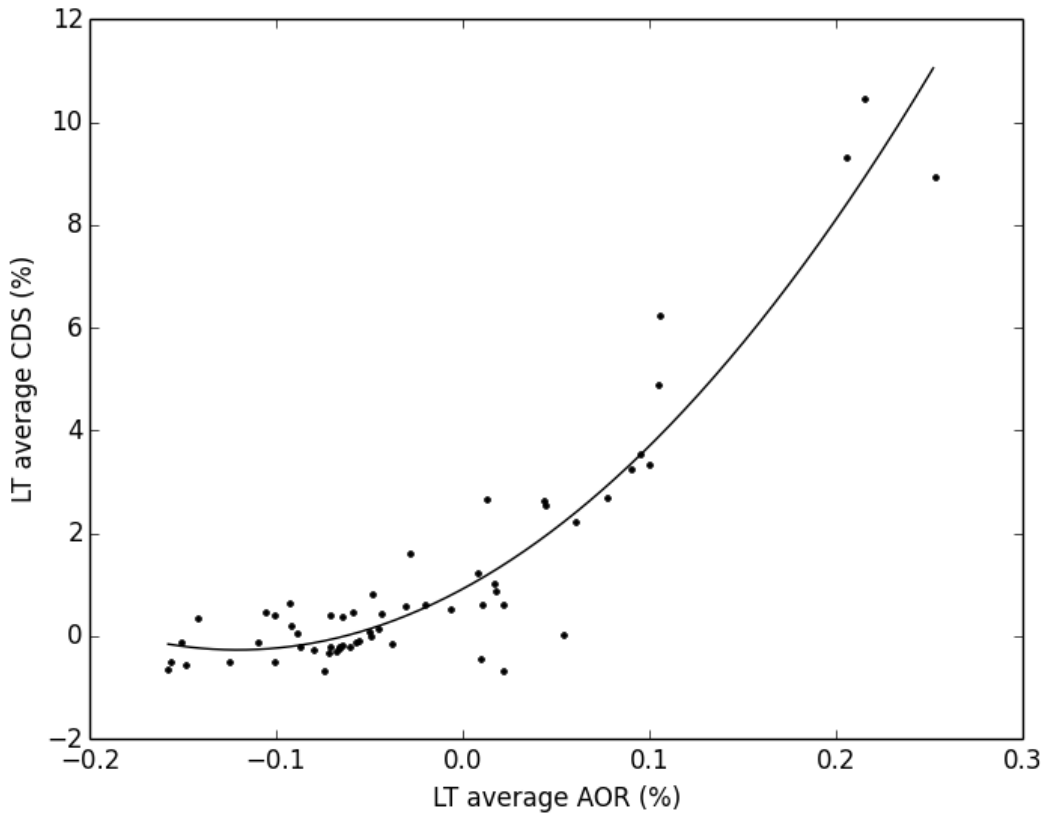

Figure 2. Long-term average of AOR and CDS. Each point corresponds to one of the 60 banks and the data is averaged over the whole period from begin of June 2008 to end of June 2013. The parabola is an OLS fit with equation CDS = 19.56 (1.26) AOR + 81.30 (9.52) AOR^2 + 0.93 (0.14) with standard errors in the parentheses and the explanatory power (R-squared) equal to 0.89.

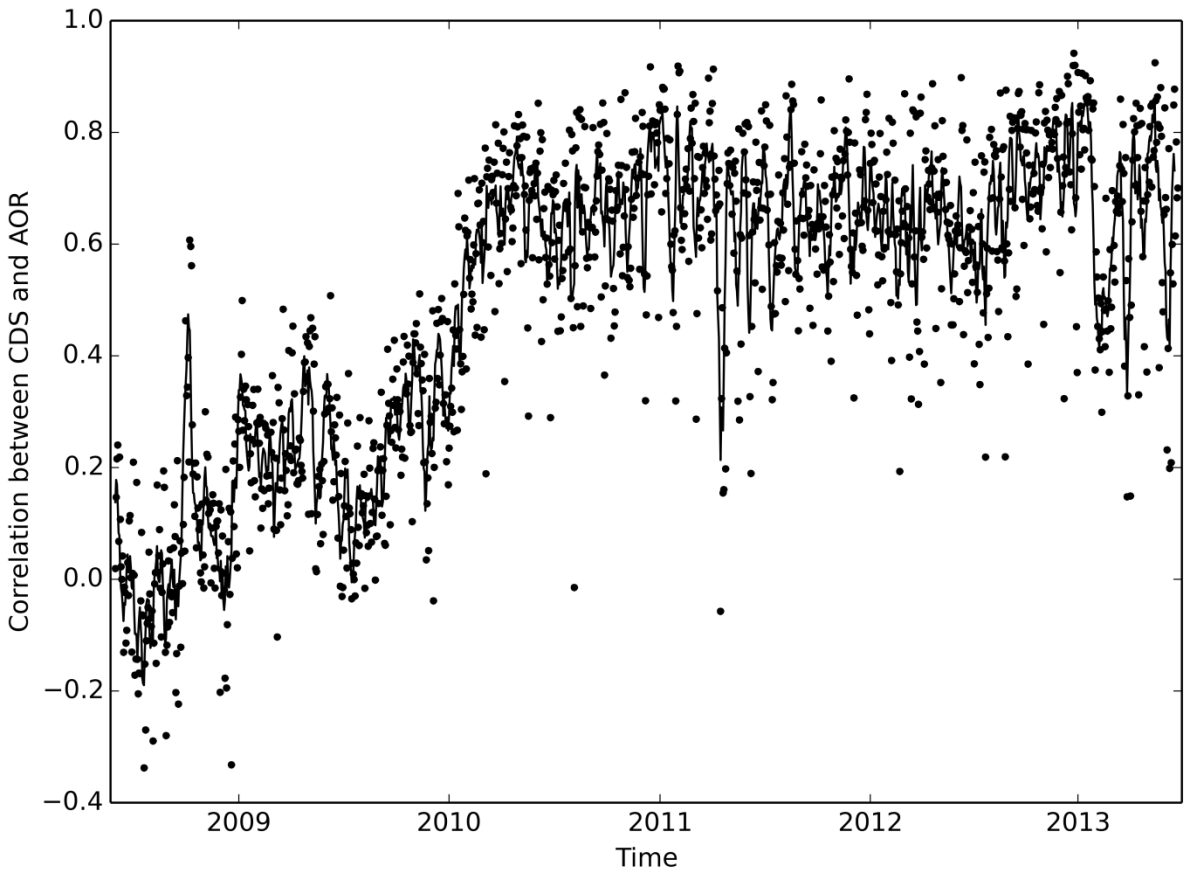

Figure 3. The cross-sectional correlation between CDS and AOR. The dots are the daily cross-sectional correlation values. For illustrational purposes the line shows 5 day moving average. The correlation is calculated across those of the 60 panel banks that participate in the money market in the corresponding business day. The short-term variation of the correlation is thus partially attributed to different sample in different days.

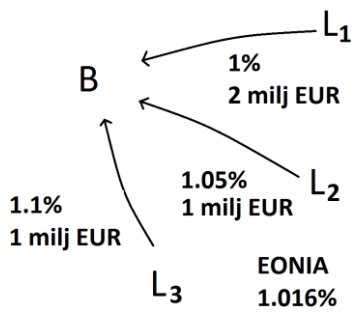

Figure 4. Illustration of how the Average Overnight Rate (AOR) is calculated. We apply uniform weights and subtract the EONIA so that the resulting AOR is (1%+1.05%+1.1%)/3-1.016% = 0.034%.

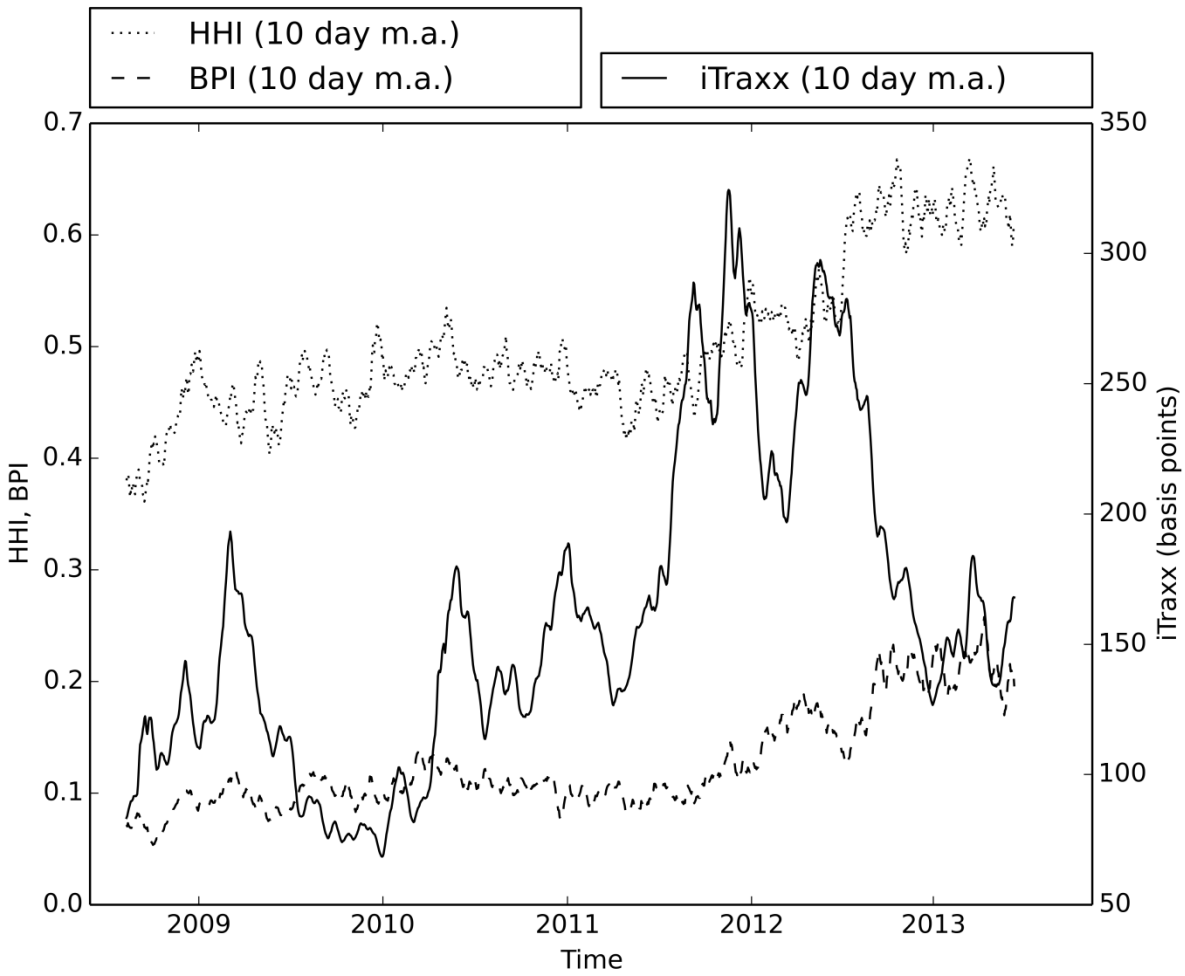

Figure 5. Average Herfindahl-Hirschmann Index (HHI), average Borrower Preference Index (BPI) and iTraxx Europe Financial subindex. HHI and BPI are calculated as average HHI or BPI of the observations in our panel for each day. Not all 60 banks participate in the market each day. For ease of illustration, 10 day moving average is shown. Daily values (not moving average) are used for calculation of the correlations below. The correlation between HHI and BPI is 0.78. With effect from 11th July 2012, the ECB Deposit facility rate has been 0.00 % and the HHI and BPI indices show more concentrated borrowing due to change in the incentives of market participants. If this latter period is left out, the correlation between BPI (HHI) and iTraxx is 0.44 (0.43) otherwise 0.29 (0.34).

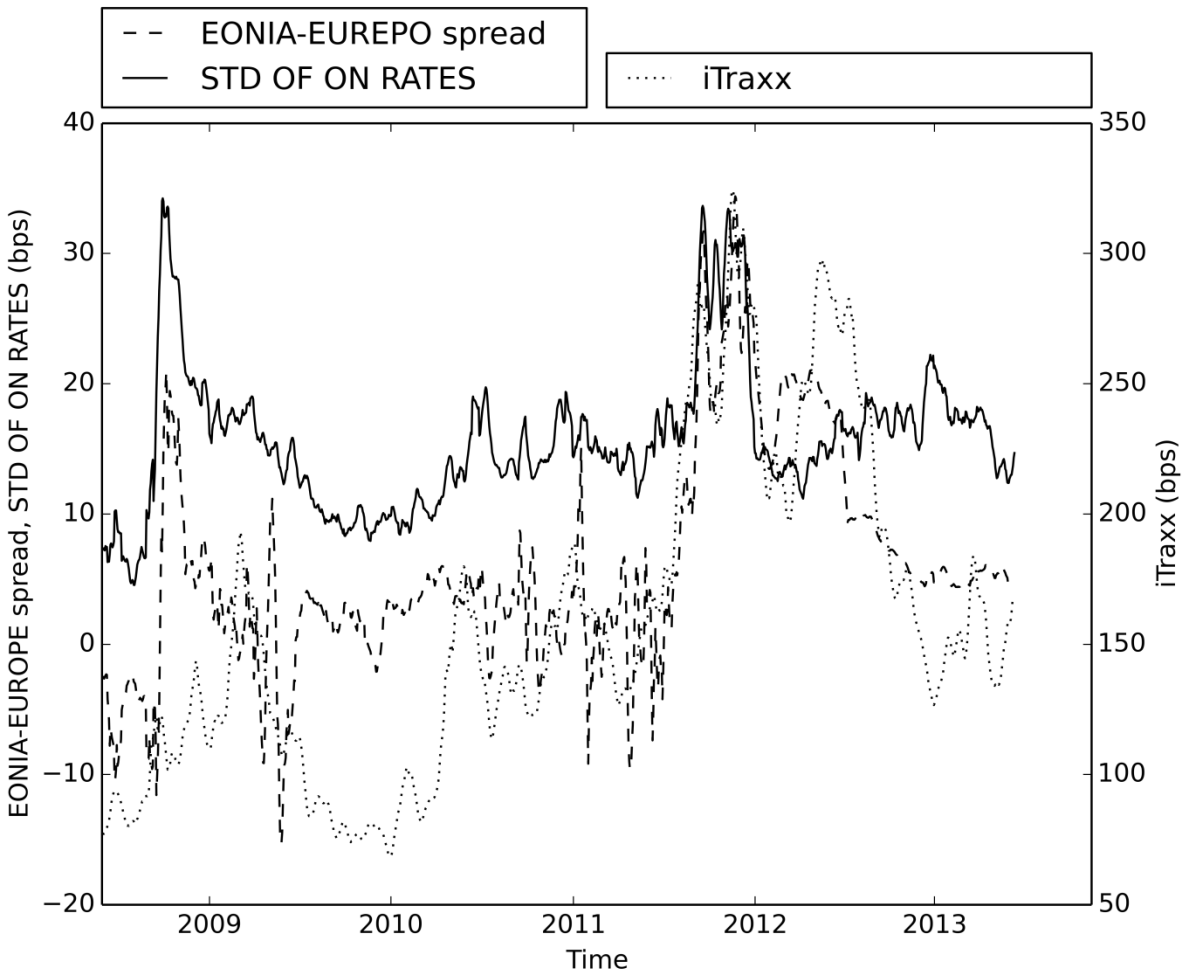

Figure 6. EONIA-EUREPO spread (EONIA-EUREPO), Standard deviation of overnight rates (SD) and iTraxx Europe Financial index. EONIA-EUREPO spread is the spread between uncollateralized and collateralized overnight loans. Standard deviation of overnight rates is calculated daily from the all the observed overnight loans (not restricted to the 60 banks). For illustrational purposes, 10 day moving average is shown. Daily values (not moving average) are used for calculation below. A linear regression of iTraxx on the rate data gives *iTraxx* = 302.401 (14.18) *EONIA-EUREPO* + 264.41 (23.50) *SD* + 98.37 (3.67) with standard errors in the parentheses and the explained variance of regression R-sq = 0.42.

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