What is a prime bank? A Euribor – OIS spread perspective

by Marco Taboga
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WHAT IS A PRIME BANK?
A EURIBOR – OIS SPREAD PERSPECTIVE

by Marco Taboga *

Abstract

Since the outbreak of the financial crisis in 2007, the level and volatility of Euribor – OIS differentials have increased significantly. According to the extant literature, this variability is mainly explained by credit and liquidity risk premia. I provide evidence that part of the variability might also be explained by ambiguity in the phrasing of the Euribor survey. Participants in the survey are asked at what rate they believe interbank funds to be exchanged between prime banks; given the lack of a clear definition of the concept of prime bank, this question might leave room for subjective judgment. In particular, I find evidence that some variability of Euribor rates might be explained by changes in the survey participants' perception of what a prime bank is. This adds to the difficulties already encountered by previous studies in exactly identifying and measuring the determinants of Euribor rates. I argue that these difficulties are at odds with the clarity, simplicity and replicability that should be required of a widely utilized financial benchmark.

JEL Classification: G1, G2.
Keywords: Euribor rates, Euribor survey, Euribor – OIS spread.

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Introduction$^1$

Since the inception of the financial crisis in 2007, the spreads between Euribor and OIS rates$^2$ have been amongst the most closely followed gauges of tensions in the interbank market (e.g., Taylor and Williams - 2009, De Socio - 2011, Nobili - 2012). In the years before the crisis these spreads had stood at few basis points and had displayed very limited variability, but in 2007 they started moving upwards and have been much higher and more volatile ever since, touching peaks of hundreds of basis points on some occasions.

What do these spreads measure? A consensus has emerged that they embed both credit risk premia, associated to the default probability of borrowers of interbank funds, and liquidity premia, due to the fact that interbank deposits are highly illiquid$^3$. Several empirical studies have confirmed that both these components are relevant and contribute to explaining the time-variation in Euribor-OIS spreads (e.g., Schwarz - 2010, Filipovic and Trolle - 2011).

In this paper I argue that also other factors, that have to do with the way Euribor rates are calculated, might be at play. Euribor rates are averages of survey responses by banks that are asked the following question: what is the interest rate that, to the best of your knowledge, a prime bank would charge another prime bank on an unsecured loan? The keyword in this question is "prime bank". Before the crisis started, the concept of prime bank was probably rather unambiguous: there

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$^2$Or between Libor and OIS rates. In this paper, we concentrate on Euribor rates on euro-denominated deposits.

$^3$It can be very costly, if not impossible, to withdraw funds employed in an interbank deposit before its expiry.
were dozens of large and internationally active banks that enjoyed AAA ratings and had tiny CDS premia (around or below ten basis points); any one of these banks would be easily recognized as a prime bank. During the crisis, however, most of these banks experienced deteriorations in their credit ratings and surges in their credit spreads. Which of them are still to be considered prime? In the absence of a standard definition of prime bank, this is a question that calls for quite a bit of subjective judgement. Therefore, it is conceivable that after 2007 Euribor rates might have been influenced also by changes in the survey respondents’ perception of what a prime bank is. This paper provides empirical evidence in favor of this hypothesis.

Existing studies use either averages (e.g., Michaud and Upper - 2008, McAndrews, Sarkar and Wang - 2008) or quantiles (e.g., Filipovic and Trolle - 2011) of the distribution of banks’ CDS spreads to proxy for the credit risk component of the Euribor-OIS spread. However, if the composition of the set of banks that are considered prime changes through time, it is unlikely that a single proxy of banks’ credit risk will be able to keep track of these changes. Instead, I propose a simple econometric model that allows to capture time-variation in the set of prime banks. Under various specifications, I find that such time-variation is statistically significant, and, by taking it into account, the portion of the Euribor-OIS spread explained by credit risk increases considerably. For example, by allowing for time variation, the $R^2$ of a baseline model including a single measure of credit risk increases from 45 to 73 per cent. Moreover, under certain assumptions, the results from my model can be interpreted as evidence that the definition of prime bank has become more restrictive during my sample period (in particular since 2009, after the first phase of the crisis).
Despite taking a new source of variability into account, I find that proxies of the liquidity premium are still significant explanatory variables for the Euribor-OIS spread. Overall, parsimonious models taking into account both credit risk, the time-variation in its composition, and liquidity risk provide a satisfactory statistical fit, with $R^2$ of up to 80 per cent.

As I thoroughly discuss in the final part of the paper, my findings add further nuances to the existing picture of Euribor rates, and they have potential policy implications, given that these rates are widely utilized financial benchmarks, to which myriads of contracts are indexed. In particular, one might argue that evidence of important elements of ambiguity and subjectivity in the definition of Euribor rates might be at odds with their role of benchmarks, and that further scrutiny by researchers and policy makers is therefore warranted.

The paper is organized as follow: Section 1 reviews the main determinants of the Euribor-OIS spread from a theoretical viewpoint; Section 2 describes the data; Section 3 develops an empirical model and presents its estimates; Section 4 briefly summarizes some robustness checks; Section 5 discusses some caveats; Section 6 concludes and discusses the policy implications of my findings.

1 The Euribor-OIS spread

This section discusses the main determinants of the Euribor-OIS spread.

Euribor rates are benchmark rates used to gauge the cost of unsecured borrowing in the interbank market. On each trading day, the European Banking Federation (EBF) asks a panel of banks what interest rate, to the best of their knowledge, a prime bank would charge another prime bank on an unsecured loan.
Euribor rates are then computed as averages of individual bank’s responses. The interbank loans to which Euribor rates are referred have fixed length, ranging from 1 week to 12 months.

OIS (Overnight Indexed Swap) rates are the interest rates applied to swap contracts where one counterparty receives a variable payment indexed to the interest rate on overnight unsecured interbank deposits and the other counterparty receives the fixed OIS rate. Also OIS contracts can have different lengths, usually ranging from 1 week to 2 years. In this paper, attention will be restricted to EONIA swaps, i.e. OIS contracts indexed to EONIA. The latter is a weighted average, also calculated by the EBF, of all overnight unsecured lending transactions undertaken in the interbank market, initiated within the euro area by the contributing banks.

When we compute the spread between a Euribor rate and an OIS rate referred to the same maturity (fixed, for concreteness, at 12 months), we make an implicit comparison between two alternative strategies that are available to a bank willing to lend funds on the interbank market:

1. **One-shot strategy (OS).** Funds are lent for 12 months to one bank at the 12-month Euribor rate, which is fixed today for all the length of the loan.

2. **Roll-over strategy (RO).** For 12 months, on each day funds are lent until the next day at the overnight rate. The borrower bank is not necessarily the same on each day. Furthermore, the variable sequence of overnight interest payments is exchanged with a fixed payment through an OIS contract. The OIS contract is signed on the first day, so that the amount of the fixed payment (the 12-month OIS rate) is established in advance for the whole period.
These two strategies look very similar: they both involve lending unsecured funds on the interbank market for 12 months and both yield a fixed interest payment at the end of the period. At a superficial look, these two strategies might seem identical and one might be led to think that the Euribor rate and the OIS rate should coincide, so as to prevent arbitrages. However, there are subtle differences that can justify a spread between the two rates. These differences are mainly determined by the different exposure to credit risk and by the different liquidity of the two investment strategies.

Both Euribor and EONIA (OIS contracts are indexed to the latter) are interest rates on interbank deposits where the bank receiving the deposit is a prime bank, i.e. a bank of outstanding credit quality. Despite this fact, strategy OS is more exposed to credit risk than strategy RO. The reason is the following:

1. with strategy OS, the borrower bank is a prime bank at the beginning of the loan, but it is possible that its credit quality will deteriorate before the end of the loan; therefore, during the length of the loan, the lender might become exposed to a level of credit risk that is higher than the level of credit risk of a prime bank;

2. with strategy RO, on each day a new overnight loan is made to a prime bank (not necessarily the same on each day); as a consequence, the lender is always exposed to a level of credit risk that is equal to the level of credit risk of a prime bank.

The only way in which strategy RO can generate a credit loss is if one of the borrower banks transitions overnight from the status of prime bank to default status. While this is possible in principle, this possibility is deemed so remote that
strategy RO is usually considered free of credit risk. Thus, it is implicitly assumed that before defaulting a bank will transition from the status of prime bank to a less creditworthy status and that this transition will take at least one day\textsuperscript{4}.

Strategies OS and RO are also characterized by a different degree of liquidity. Strategy RO can be interrupted on any given day and the funds that are employed in it can be diverted to other uses, without incurring any cost. On the contrary, it can be very costly, if at all possible, to interrupt strategy OS and free the funds that are employed in it. The reason is that, by its very nature, an interbank time deposit cannot be withdrawn before its expiration; the only way to do so is to bargain with the borrower bank and agree with it upon an early withdrawal penalty. In case the borrower is short of funds, it might not agree at all on the early withdrawal.

Thus, strategy OS is much less liquid than strategy RO. This greater illiquidity can command a premium, increasing the Euribor rate with respect to the OIS rate. This premium is likely to be higher in times of scarce funding liquidity, when banks attach the most value to the possibility of freeing financial resources quickly and cheaply if needed (e.g., Brunnermeier and Pedersen - 2009; Acharya and Skeie - 2011).

As the reader might have noticed, up to this point of the discussion I have used, somewhat imprecisely, the term "Euribor rate" as a synonym for "interest rate on an unsecured interbank loan". However, Euribor is an average of the interest rates that Euribor survey respondents think are applied to interbank loans between prime banks. Therefore, the Euribor-OIS spread does not reflect the credit and

\textsuperscript{4}See Morini (2009) and Mercurio (2009) for a discussion of the assumption that EONIA and OIS rates are risk-free.
liquidity risks of a specific interbank loan, in which the identity of the borrower is known, but rather an average of opinions about a generic interbank loan, whose counterparties are rather vaguely defined as "prime". Hence, it is conceivable that changes in the respondents' perception of what a prime bank is might be a further and autonomous source of variation in the Euribor-OIS spread. In other words, it is not possible to rule out that *ceteris paribus*, that is, absent any variation in credit and liquidity risk premia, the spread might vary just as a consequence of the ambiguity inherent in the definition of the Euribor rate. To my knowledge, there are no attempts in the extant literature to quantify and test for the existence of this further source of variation. The empirical part of this paper tries to fill this gap.

2 Data and descriptive statistics

My dataset includes daily data on the 1-year Euribor rate, the 1-year Eonia Swap rate\(^5\) and 1-year CDS premia of individual banks, from January 1st 2006 to February 29th 2012. I focus on the 1-year maturity, because this allows for an exact maturity match between the Euribor-OIS spread and the CDS spreads.

As a proxy of liquidity premium, I use the yield spread between off-the-run and on-the-run US Treasuries (e.g., Fontaine and Garcia - 2012). This is computed as the difference between the redemption yield of the Merril Lynch US Treasuries off-the-run 9.5-11.0 Index and the redemption yield of the Merril Lynch US Treasury Current 10 Year Index.

My sample of banks includes 27 banks\(^6\). I use individual CDS spreads to

\(^5\)For brevity, the Eonia Swap rate is referred to as OIS rate in the rest of the paper.
\(^6\)These banks are the banks included in the Euribor panel for which time series of 1-year CDS
construct quartiles and deciles of the distribution of CDS spreads, which I use in my empirical analysis. Each quantile is a time series whose value at a given date is equal to the corresponding quantile of the cross-sectional distribution of the CDS spreads of the banks included in my sample at that date.

The first thing to be noticed is that both the Euribor-OIS spread (see Figure 1) and the CDS quantiles (see Figure 2) remained almost flat and at a very low level until June 2007. After that date both their level and their volatility increased. Also, the cross-sectional distribution of CDS spreads became much more dispersed. As I mentioned in the Introduction, before the inception of the crisis almost all banks in my sample had tiny CDS premia and would easily qualify for the status of prime bank. However, their differences increased afterwards, as highlighted by the increased dispersion of CDS spreads, and this arguably complicated the task of defining and identifying what a prime bank is.

In my empirical analysis, I do not use the data between January 2006 and June 2007, because of the almost total absence of variability in these data and because of the structural break that happened after June 2007.

Table 1 reports the results of a battery of univariate regressions of the Euribor-OIS spread on the CDS deciles. From these results, it is apparent that different deciles have different explanatory power. The maximum explanatory power is provided by the fourth decile, which explains approximately 46% of the variability of the Euribor-OIS spread. Also, by subdividing the sample in two sub-samples, I find that the explanatory power changes considerably across sub-samples. The spreads are available. They are: Erste Group, Raiffeisen, Dexia, KBC, Nordea, BNP Paribas, Société Générale, Natixis, Crédit Agricole, Bayerische Landesbank, Deutsche Bank, Commerzbank, Norddeutsche Landesbank, Intesa San Paolo, Monte Paschi, Unicredit, UBI Banca, ING Bank, BBVA, Santander, Barclays, Danske, Svenska, UBS, Citigroup, JP Morgan, Bank of Tokyo Mitsubishi.
maximum $R^2$ found for the sub-period going from June 2007 to June 2009 is 33% (provided by the fifth decile), while the maximum $R^2$ for the sub-period going from July 2009 to February 2012 is 91% (provided by the fourth decile); this can be seen as evidence that the credit risk component was predominant during the latter sub-period (see also Figure 3).

3 Regression analysis

3.1 The framework

Denote the 1-year Euribor-OIS spread at time $t$ by $SPREAD_t$. The analysis in this section is based on the following linear decomposition, which is motivated by the discussion in Section 1:

$$SPREAD_t = CR_t + LIQ_t + O_t$$  (1)

where $CR_t$ is the portion of the spread at time $t$ that is explained by credit risk, $LIQ_t$ is the portion explained by liquidity premia and $O_t$ is a residual (whose mean is not necessarily zero) that might capture other factors affecting the spread, such as pricing errors or non-linear pricing factors.

I propose a stylized representation of the credit risk component $CR_t$. Denote by $N$ the number of banks that are active on the interbank market, by $J$ the number of respondents to the survey, and by $CDS_{t,i}$ the CDS spread of bank $i$ at time $t$. Suppose the $j$-th respondent’s assessment of credit risk, denoted by $CR_{t,j}$,

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1 June 2009 is often considered a break-date marking the end of the sub-prime crisis (e.g., De Socio - 2011, Acharya and Mora - 2011).
is made by averaging the CDS spreads of the banks she considers prime:

\[ CR_{t,j} = \sum_{i \in P_{t,j}} w_{t,i,j} CDS_{t,i} \]  \hspace{1cm} (2)

where \( w_{t,i,j} \) is the weight given to bank \( i \) by respondent \( j \) at time \( t \), and \( P_{t,j} \) is the set of banks considered prime by respondent \( j \) at time \( t \). Without loss of generality equation (2) can be written as

\[ CR_{t,j} = \sum_{i=1}^{N} w_{t,i,j} CDS_{t,i} \]  \hspace{1cm} (3)

where \( w_{t,i,j} = 0 \) when \( i \notin P_{t,j} \).

Since Euribor is computed by averaging individual survey responses, the credit risk component of Euribor is a weighted average of the respondents’ individual assessments of credit risk:

\[ CR_t = \sum_{j=1}^{J} w_j CR_{t,j} = \sum_{j=1}^{J} w_j \sum_{i=1}^{N} w_{t,i,j} CDS_{t,i} = \sum_{i=1}^{N} CDS_{t,i} \sum_{j=1}^{J} w_j w_{t,i,j} \]

where \( w_j \) is the weight assigned to respondent \( j \). This can be rewritten as

\[ CR_t = \sum_{i=1}^{N} w_{t,i} CDS_{t,i} \]  \hspace{1cm} (4)

where \( w_{t,i} = \sum_{j=1}^{J} w_j w_{t,i,j} \). In other words, the weights assigned to individual CDS spreads are determined by: (i) the weights given to individual survey responses when computing Euribor; (ii) the weights assigned by the single respondents to take into account the uncertainty in identifying a representative prime bank; (iii)
a combination of the previous two.

As far as the liquidity premium is concerned, I assume that it can be represented as a linear function of $K$ variables:

$$LIQ_t = \alpha^l + \sum_{j=1}^{K} \beta_j^l LIQ_{j,t}$$

(5)

where $LIQ_{j,t}$ is the $j$-th liquidity variable. I also assume that the first $L$ variables (with $0 \leq L \leq K$) are observable.

Note that I have assumed that the liquidity premium is independent of the borrower’s identity. This is justified by the observation that liquidity is a characteristic of the financial instrument under analysis (i.e. an interbank time deposit) and not of the counterparties of the contract.

Substituting equation (4) and (5) into equation (1) yields

$$SPREAD_t = \alpha + \sum_{i=1}^{N} w_{t,i} CDS_{t,i} + \sum_{j=1}^{L} \beta_j^l LIQ_{j,t} + \varepsilon_t$$

(6)

where $\varepsilon_t$ is a zero-mean error and I have defined

$$\alpha = \alpha^l + E \left[ \sum_{j=L+1}^{K} \beta_j^l LIQ_{j,t} + O_t \right]$$

$$\varepsilon_t = \sum_{j=L+1}^{K} \beta_j^l LIQ_{j,t} + O_t - E \left[ \sum_{j=L+1}^{K} \beta_j^l LIQ_{j,t} + O_t \right]$$

The collinearity and the high numerosity of the time series of individual CDS spreads prevent direct estimation of Equation (6). Therefore, I adopt a procedure that is commonly utilized in the finance literature (e.g., Longstaff and Rajan - 2008): I postulate a factor structure for the individual CDS spreads. In particular,
I assume that

\[ CDS_{t,i} = b_i CDS_t + u_{it} \tag{7} \]

where \( CDS_t \) is a common factor, \( b_i \) are factor loadings and \( u_{it} \) are idiosyncratic shocks orthogonal to the common factor.

Substituting equation (7) into equation (6), one obtains

\[ SPREAD_t = \alpha^f + \omega_t CDS_t + \sum_{j=1}^{L} \beta^j LQ_{j,t} + \eta_t \tag{8} \]

where

\begin{align*}
\omega_t &= \sum_{i=1}^{N} w_{t,i} b_i \tag{9} \\
\alpha^f &= \alpha + E \left[ \sum_{i=1}^{N} w_{t,i} u_{it} \right] \\
\eta_t &= \varepsilon_t + \sum_{i=1}^{N} w_{t,i} u_{it} - E \left[ \sum_{i=1}^{N} w_{t,i} u_{it} \right]
\end{align*}

Several studies\(^8\) have utilized fixed-weight averages of individual banks’ CDS premia to proxy for credit risk premia. In my framework, this is equivalent to estimating a restricted version of equation (8) in which the coefficient on the common factor is time-invariant, i.e.,

\[ \omega_t = \overline{\omega}, \ \forall t \tag{10} \]

\(^8\)For example, Michaud and Upper (2008) and Eisenschmidt and Tapking (2009) use a fixed average of individual banks’ CDS spreads; McAndrews, Sarkar and Wang (2008) use the JP Morgan Banking Sector CDS index; Filipovic and Trolle (2011) use the median of individual CDS premia, which can also be proved to be a restriction of our time-varying specification and is rejected in our regressions.
which, in turn, is equivalent to

\[ w_{t,i} = \overline{w}_i, \quad \forall t \]

Restriction (10) is legitimate only if respondents do not change their assessment of the group of banks to be considered prime for the purposes of the Euribor survey. Also note that time-variation in \( \omega_t \) could be caused by time-variation in factors loadings \( b_i \) (see equation 9). This is ruled out by the tests conducted in Subsection 4.2.

I use two different methods to model time-variation in the coefficient \( \omega_t \):

1. Time dummies:

\[ \omega_t = \beta_0^d + \sum_{q=1}^{Q} \beta_q^d d_{q,t} \]

where \( \beta_0^d, \ldots, \beta_Q^d \) are regression coefficients and \( d_{1,t}, \ldots, d_{Q,t} \) are \( Q \) time dummies used to subdivide the sample into sub-periods of equal length:

\[ d_{q,t} = \begin{cases} 1 & \text{if } t \leq \left\lfloor \frac{qT}{Q+1} \right\rfloor \\ 0 & \text{otherwise} \end{cases} \] (11)

where \( T \) is the last observation in the sample.

2. Polynomials:

\[ \omega_t = \beta_0^p + \sum_{r=1}^{R} \beta_r^p \left( \frac{t}{T} \right)^r \]

where \( \beta_0^p, \ldots, \beta_R^p \) are regression coefficients, \( R \) is the order of the polynomial and again \( T \) is the last observation in the sample.

Depending on which of the two methods is used, restriction (10) can be tested
by running tests of the hypotheses that the coefficients \( \beta_1^d, \ldots, \beta_Q^d \) and \( \beta_1^p, \ldots, \beta_R^p \) are equal to zero.

### 3.2 The results

This section describes the main results of the regression analysis. Further results and robustness checks are discussed in Section 4.

In all the regressions commented here the common factor \( CDS_t \) is equal to the 4-th decile of the cross-sectional distribution of CDS spreads. This is the decile that provides the best fit in univariate regressions (see Section 2). It can be interpreted as the median of the distribution obtained by discarding the worst two deciles of the original distribution. I also use only one liquidity variable, the yield spread between off-the-run and on-the-run US Treasuries. The hypothesis that the liquidity variable is orthogonal to the common factor can not be rejected at conventional levels of confidence in my sample (the estimated correlation coefficient between the two variables is \( -0.05 \), with a \( p \)-value of 0.88).

Table 2 reports the results of a first set of regressions in which time-variation of \( \omega_t \) is modeled with time dummies. I use two time-dummies: \( d_1 \) is equal to 1 during the first third of the sample and equal to 0 afterwards; \( d_2 \) is equal to 1 during the first two thirds of the sample and equal to 0 afterwards. When interacted with the common factor, both dummies are highly significant and they remain significant also when I include/exclude other regressors (see Table 2 for details). For example, if the same two dummies are interacted also with the constant, this does not make the interaction with the common factor less significant.

Table 3 reports the estimates of the regressions in which time-variation of \( \omega_t \)
is modeled with polynomials. I interact two functions of time with the common factor: \((t/T)\) and \((t/T)^2\). Also in this case I find that the time-variation in \(\omega_t\) is highly significant and robust to inclusion/exclusion of other regressors.

Given the framework presented in the previous section, the fact that restriction (10) is strongly rejected with both methods can be interpreted as evidence in favor of the hypothesis that respondents might change their assessment of the group of banks to be considered prime for the purposes of the Euribor survey.

Figure 4 plots the pattern of \(\omega_t\) as estimated by two of the regressions (one with dummies and one with polynomials). The two methods yield qualitatively similar results: in the last two thirds of the sample, that is, since 2009, \(\omega_t\) was much smaller than in the first third. Under the assumption that more creditworthy banks have smaller factor loadings \(b_i\), the observed decrease in \(\omega_t\) can be interpreted as evidence that the definition of prime bank has become more restrictive over time (more weight has been given to more creditworthy banks in Equation 4). Another interpretation is that adverse selection phenomena might have decreased the average quality of borrowers during the first phase of the crisis (Heider, Hoerova and Holtausen - 2009).

It is also worth mentioning that the fit of the regressions noticeably increases if one allows for time-variation in \(\omega_t\). For example, the \(R^2\) increases from 45% to 73% by adding the two time dummies to a univariate model including only the common factor (Table 2). With polynomials, the increase in \(R^2\) is smaller.

Finally, the liquidity variable is always highly significant, irrespective of the modelling strategy, and its inclusion/exclusion from the set of regressors does not significantly change the results concerning the common factor and its time-variation.
4 Robustness checks and technical details

This section briefly summarizes some technical details of the regressions and some robustness checks I have made.

4.1 Standard errors

Standard errors of coefficient estimates have been computed using autocorrelation and heteroskedasticity consistent estimators, with a bandwidth of 250 periods and a Bartlett kernel. Using different bandwidths (50, 100, 500 periods) and different kernels (Parzen, quadratic spectral) causes only small changes in estimated standard errors.

4.2 Time-invariance of the factor loadings

My interpretation of the time-variation in $\omega_t$ is valid only as long as factor loadings $b_i$ are time-invariant. This can clearly be seen from equation (9). To test the constancy of the factor loadings I have run some $\chi^2$-tests. Denote by $f$ the $T \times 1$ vectors of values of the common factor, by $d_1$ and $d_2$ the $T \times 1$ vectors of values of the two time-dummies (equation 11), by $U$ the $T \times N$ matrix of errors from the factor model (equation 7), by $\hat{U}$ their de-meaned OLS estimates, and by $i$ a $1 \times N$ vector of ones. Define the following matrix:

$$G = [ \hat{U} \circ [(d_1 \circ f) \ i] \ \hat{U} \circ [(d_2 \circ f) \ i] ]$$
where $\circ$ denotes the Hadamard product. Under the null hypothesis of no time-
variation in the factor loadings, $d_1 \circ f$ and $d_2 \circ f$ are orthogonal to $\hat{U}$, i.e.,

$$E[G_t] = 0$$ (12)

where $G_t$ denotes the $t$-th row of $G$. Denote by $\bar{G}_T$ the sample average of $G_t$ and
by $\hat{V}_G$ a consistent estimate of its long-run covariance matrix. The orthogonality condition (12) can be tested by performing a $\chi^2$-test based on the following statistic:

$$\chi^2 (2N) = \bar{G}_T \left( \frac{1}{T} \hat{V}_G \right)^{-1} \bar{G}_T^\top$$

which, asymptotically, has a Chi-square distribution with $2N$ degrees of freedom.

Estimating $\hat{V}_G$ with the same bandwidth and kernel used to estimate my main regressions (see Subsection 4.1), I obtain a value of the $\chi^2$ statistic equal to 3.05.

According to the asymptotic distribution, this corresponds to a $p$-value of 1. Sus-
pecting a possible lack of power of the test, due to inadequacy of the asymptotic
approximation, I also use two different bootstrap procedures\(^9\) to derive two esti-
mates of the exact distribution of the $\chi^2$ statistic. Based on these estimates, the
$p$-values I obtain are equal to 0.64 and 0.56. Substituting time-dummies with time-

\(^9\)In the first bootstrap procedure: 1) CDS spreads are used to estimate a VAR(1); 2) VAR
errors are bootstrapped; 3) initial values of the CDS, estimated coefficients and bootstrapped
errors are used to produced simulated time series of CDS spreads; 4) the common factor is
computed using simulated CDS spreads; 5) the value of the statistic is calculated. In the second
bootstrap: 1) a SUR system is estimated, where the CDS spreads are the dependent variables
and the common factor is the independent variable; 2) estimated errors from the SUR are used
to estimate a VAR(1); 2) VAR errors are bootstrapped; 3) initial values of the SUR errors,
estimated coefficients and bootstrapped VAR errors are used to produce simulated time series
of SUR errors; 4) simulated SUR errors are plugged into the estimated SUR system to produce
simulated time series of CDS spreads; 5) the value of the statistic is calculated. Note that, in
both cases, the data generating processes are strictly stationary and the associated SUR systems
have time-invariant coefficients. In each of the two bootstraps 250 draws are performed.
polynomials, the same procedure yields $p$-values equal to 0.66 and 0.63. I conclude that the tests do not reject the null hypothesis of time-invariance at conventional levels of confidence.

### 4.3 Differences vs levels

Some of the variables in my regressions are highly persistent: the autoregressive coefficient estimated from an $AR(1)$ model is equal to 0.997 for the Euribor-OIS spread, to 0.994 for the CDS common factor, and to 0.983 for the liquidity variable. Running augmented Dickey-Fuller tests of the null hypothesis of non-stationarity, I obtain $p$-values of 0.29, 0.19 and 0.18, respectively. The results from these tests can hardly be taken as strong evidence against stationarity, for at least two reasons. First, tests of the null of non-stationarity tend to have low power (e.g., Kwiatkowski et al. - 1992, Nelson and Plosser - 1982). Second, these tests provide valid inferences only if structural breaks are absent (e.g., Perron - 1989) and if errors are reasonably homoskedastic (e.g., Kim and Schmidt - 1993). These conditions are not met by my data: I find significant GARCH effects in my series ($p$-values smaller than 0.01), and I obtain several rejections of stability from structural break tests.

If the series were not only integrated, but also cointegrated, my OLS estimates would remain consistent (actually super-consistent, hence with smaller standard errors - Phillips and Durlauf - 1986). Johansen’s cointegration tests do not give clear cut results for my series: depending on the assumptions and on the statistic used to test the null hypothesis of no cointegration, I obtain $p$-values ranging from 0.12 to 0.04. I have chosen not to carry out my analysis in a cointegra-
tion framework, both because of the lack of strong evidence of cointegration, and because testing for time-invariance (equation 10) would pose severe econometric challenges\footnote{The development of econometric frameworks that allow to simultaneously take into account both cointegration and the presence of structural breaks is still in its infancy. Existing frameworks require to make aprioristic assumptions about at least one of these two features (e.g., Kejriwal and Perron - 2010).}.

One might still be concerned about the case in which variables are I(1), but not cointegrated. In this case, my OLS estimates could give rise to spurious results. To address this concern, I repeated the analysis using first differences, computed on a monthly basis\footnote{I compute differences on a monthly, rather than daily, basis, to avoid potential problems caused by stale CDS quotes and by the fact that closing prices of instruments traded on different markets might be recorded at different daytimes.}. Although the fit of the regressions decreases considerably, the results from this supplementary analysis are not qualitatively different from those presented in the main empirical section.

4.4 Other common factors

I have used the 4-th decile of the cross-sectional distribution of CDS spreads as a common factor. Other choices, like the 3-rd and 5-th decile or the mean of the distribution do not change significantly my results.

4.5 Other liquidity variables

In the main empirical section I have used a unique proxy of the liquidity premium: the yield spread between off-the-run and on-the-run US Treasuries. As a robustness check, I have used also other measures of the liquidity premium. Among these:

1. moving averages of the daily returns on the Credit Suisse Illiquidity Premium
Liquid Index, a total return index of a diversified investment strategy aimed at profiting from the liquidity premium embedded in illiquid assets;

2. the difference between the asset swap spreads of Ginnie Mae 30-year Mortgage Backed Securities and 30-year US Treasuries.

While coefficient estimates change, the time-variation in $\omega_t$ remains significant.

4.6 Different specifications of $\omega_t$

I increased the number of dummies and polynomial terms beyond three. The additional terms are sometimes significant, but they increase the fit of the regressions only slightly. They also do not affect the joint significance of the time-variation in $\omega_t$. I also tried other functional forms (e.g.: trigonometric functions) and still found significant time-variation.

5 Caveats

In this section, I briefly summarize some caveats that suggest caution in interpreting the results of my analysis, and that may also provide cues for further research:

- **Credit risk premia.** I have assumed that CDS spreads are a pure measure of credit risk premium. However, some authors (e.g., Buhler and Trapp - 2009) argue that CDS spreads might embed other components, unrelated to credit risk, such as premia due to the illiquidity of CDS contracts. As the profession has not yet reached an agreement on the theoretical foundations and methodologies to measure these additional components of CDS spreads,
I have not explored this issue, but I recognize that it could have an impact on my results.

- **Liquidity risk premia.** I have used several measures of the liquidity risk premium, but none that is specific to the markets of the European Monetary Union (EMU). This could be a drawback insofar as some form of geographical segmentation could be preventing a uniform pricing of liquidity risk across markets and financial instruments. While this possibility is not to be excluded, I have encountered some obstacles to constructing a simple and reliable measure of the liquidity risk premium specific to the EMU. For example, measures based on the yield differential between KfW bonds and German government bonds (e.g., Schwarz - 2010) seem to be quite unstable and dependent on the term structure models used to compute the differential. For this reason, I have decided to keep using the proxies of the liquidity risk premium discussed above.

- **1-year maturity.** My analysis has focused on the 1-year maturity because it allows for a transparent matching with CDS quotes. However, contracts with this maturity represent only a small fraction of total unsecured interbank lending (see ECB - 2012). It is possible that working with shorter and more liquid maturities would yield different results.

- **Panel of banks.** I include a bank in my CDS indices only if: 1) it belongs to the Euribor panel; 2) a continuous time series of its CDS spreads is readily available. Following these two criteria, I might have excluded some banks that actively participate in the interbank market and are considered prime. To the extent that these exclusions could significantly affect the computation
of my CDS indices, they could also have an impact on the results of my analysis.

6 Conclusions and policy implications

Euribor rates are amongst the most important financial benchmarks in the world. Besides being a primary indicator of the cost of interbank funding, they are the reference rates for highly traded derivative contracts, such as interest rate swaps, and myriads of other financial contracts, including variable rate mortgages commonly offered by commercial banks to the retail market. In recent years, also some governments have issued bonds whose interest payments are indexed to Euribor (e.g., the CCTs-eu issued by the Italian Treasury).

The utter importance of these benchmark rates has stimulated much research work aimed at understanding their behavior and their determinants. Before the inception of the crisis in 2007, Euribor rates were considered almost risk-free. However, they have since begun incorporating large credit and liquidity risk premia whose exact quantification is still an open issue, despite being the subject of a rich strand of the recent financial literature.

This paper has highlighted an aspect that had been neglected by previous papers, but that also adds to the difficulties of understanding the behavior of Euribor rates. These rates are obtained by averaging the responses to a survey in which the participants are asked at what interest rates they believe interbank loans to be taking place between prime banks. Before the crisis, this question arguably left little room for subjective judgment, because most large and internationally active banks enjoyed AAA ratings, had tiny CDS premia and could, without almost
any doubt, be considered "prime". By contrast, after the crisis most of these banks experienced sharp deteriorations in their credit ratings and surges in their CDS premia. Which of them are still to be considered prime? The answer to this question might have become highly subjective, introducing a severe ambiguity in the definition and calculation of Euribor rates\textsuperscript{12}. My paper has provided empirical evidence that this might indeed be the case. In other words, the data seem to point to the fact that part of the variability of Euribor rates might be explained by changes in the survey respondents’ perception of what a prime bank is.

With all the caveats required when drawing policy inferences from simple empirical analyses, the evidence provided by this paper, along with the evidence provided by previous studies, suggests that Euribor rates, in their current definition, might have lost some of the characteristics that should be possessed by a widely utilized financial benchmark, namely clarity, simplicity and replicability. Given the sheer amount of financial contracts indexed to these rates, this problem certainly warrants further scrutiny by both researchers and policy makers.

\textsuperscript{12}Looking at transaction-level data from the e-Mid market, I also found that: 1) before the crisis, it was relatively straightforward to check the correspondence between Euribor rates and rates applied to actual interbank deposits, because several transactions could be observed everyday; 2) after the crisis started, almost no transactions regarding unsecured deposits with a duration of 3 months or more were recorded on the e-Mid market, thereby making it impossible to check whether Euribor rates match actual rates applied to interbank loans. See Angelini, Nobili and Piccillo (2011) for a description of the e-Mid dataset.
References


7 Appendix

Figure 1 - 1-year Euribor-OIS spread
Figure 2 - Cross-sectional distribution of 1-year banks’ CDS spreads
Figure 3 - 1-year Euribor-OIS spread and 1-year banks’ CDS spreads
Figure 4 - The credit risk component of the Euribor-OIS spread

Estimated time-variation$^{13}$

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$^{13}$Estimated time variation in the exposure of the Euribor rate to the credit risk factor (coefficient $\omega_t$ in Equation 8). Mod(d,2) refers to Model 2 in Table 2 (time dummies), while Mod(t,2) refers to Model 2 in Table 3 (time polynomials).
Table 1 - Univariate regressions\textsuperscript{14}

Dependent variable: Euribor-OIS spread

<table>
<thead>
<tr>
<th>Explanatory v.</th>
<th>Slope</th>
<th>$R^2$</th>
<th>Slope</th>
<th>$R^2$</th>
<th>Slope</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>CDS 1st decile</td>
<td>0.90</td>
<td>0.45</td>
<td>0.76</td>
<td>0.30</td>
<td>1.14</td>
<td>0.85</td>
</tr>
<tr>
<td>CDS 2nd decile</td>
<td>0.72</td>
<td>0.44</td>
<td>0.69</td>
<td>0.30</td>
<td>0.84</td>
<td>0.83</td>
</tr>
<tr>
<td>CDS 3rd decile</td>
<td>0.64</td>
<td>0.46</td>
<td>0.65</td>
<td>0.31</td>
<td>0.73</td>
<td>0.90</td>
</tr>
<tr>
<td>CDS 4th decile</td>
<td>0.55</td>
<td>0.46*</td>
<td>0.62</td>
<td>0.31</td>
<td>0.62</td>
<td>0.91*</td>
</tr>
<tr>
<td>CDS 5th decile</td>
<td>0.50</td>
<td>0.43</td>
<td>0.59</td>
<td>0.33*</td>
<td>0.57</td>
<td>0.90</td>
</tr>
<tr>
<td>CDS 6th decile</td>
<td>0.45</td>
<td>0.43</td>
<td>0.53</td>
<td>0.33</td>
<td>0.52</td>
<td>0.90</td>
</tr>
<tr>
<td>CDS 7th decile</td>
<td>0.37</td>
<td>0.42</td>
<td>0.42</td>
<td>0.31</td>
<td>0.44</td>
<td>0.89</td>
</tr>
<tr>
<td>CDS 8th decile</td>
<td>0.26</td>
<td>0.38</td>
<td>0.24</td>
<td>0.23</td>
<td>0.33</td>
<td>0.87</td>
</tr>
<tr>
<td>CDS 9th decile</td>
<td>0.19</td>
<td>0.40</td>
<td>0.19</td>
<td>0.26</td>
<td>0.22</td>
<td>0.86</td>
</tr>
</tbody>
</table>

\textsuperscript{14}Results from univariate regressions where the dependent variable is the Euribor-OIS spread and the independent variables are a constant and a decile of the cross-sectional distribution of CDS spreads (each row corresponds to a different decile). The labels in the uppermost row correspond to different sample periods. Slope is the estimated coefficient of the CDS decile. An asterisk marks the regression that, for a given sample period, provides the best fit.
Table 2 - Multivariate regressions\textsuperscript{15}

Dependent variable: Euribor-OIS spread

<table>
<thead>
<tr>
<th></th>
<th>Mod 1</th>
<th>Mod 2</th>
<th>Mod 3</th>
<th>Mod4</th>
<th>Mod5</th>
</tr>
</thead>
<tbody>
<tr>
<td>$c$</td>
<td>41.45 (0.00)</td>
<td>26.5 (0.00)</td>
<td>27.9 (0.00)</td>
<td>24.9 (0.00)</td>
<td>27.4 (0.00)</td>
</tr>
<tr>
<td>$CDS$</td>
<td>0.55 (0.00)</td>
<td>0.62 (0.00)</td>
<td>0.68 (0.00)</td>
<td>0.63 (0.00)</td>
<td>0.69 (0.00)</td>
</tr>
<tr>
<td>$CDS \cdot d_1$</td>
<td>0.90 (0.00)</td>
<td>0.62 (0.00)</td>
<td>0.95 (0.01)</td>
<td>0.84 (0.00)</td>
<td></td>
</tr>
<tr>
<td>$CDS \cdot d_2$</td>
<td>-0.07 (0.03)</td>
<td>-0.35 (0.02)</td>
<td>-0.12 (0.03)</td>
<td>-0.53 (0.00)</td>
<td></td>
</tr>
<tr>
<td>$liq_{on/off}$</td>
<td></td>
<td>1.83 (0.02)</td>
<td></td>
<td>2.03 (0.01)</td>
<td></td>
</tr>
<tr>
<td>$c \cdot d_1$</td>
<td></td>
<td>-4.30 (0.50)</td>
<td>-20.6 (0.02)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$c \cdot d_2$</td>
<td></td>
<td>5.31 (0.21)</td>
<td>15.0 (0.06)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.45</td>
<td>0.73</td>
<td>0.79</td>
<td>0.73</td>
<td>0.80</td>
</tr>
</tbody>
</table>

\textsuperscript{15}The leftmost column contains the regressors: $c$ is a constant, $CDS$ is the common factor (the 4th decile of the distribution of CDS spreads), $d_1$ and $d_2$ are two time dummies, $liq_{on/off}$ is the yield spread between on-the-run and off-the-run US Treasuries. Different models (one for each column) are obtained from different choices of the explanatory variables to include in the linear regression. p-values in parentheses.
Table 3 - Multivariate regressions\textsuperscript{16}

Dependent variable: Euribor-OIS spread

<table>
<thead>
<tr>
<th></th>
<th>Mod 1</th>
<th>Mod 2</th>
<th>Mod 3</th>
<th>Mod 4</th>
<th>Mod5</th>
</tr>
</thead>
<tbody>
<tr>
<td>$c$</td>
<td>41.5 (0.00)</td>
<td>35.9 (0.00)</td>
<td>39.0 (0.00)</td>
<td>8.69 (0.44)</td>
<td>5.40 (0.62)</td>
</tr>
<tr>
<td>$CDS$</td>
<td>0.55 (0.00)</td>
<td>1.84 (0.00)</td>
<td>0.43 (0.17)</td>
<td>2.24 (0.00)</td>
<td>1.01 (0.00)</td>
</tr>
<tr>
<td>$CDS \cdot (t/T)$</td>
<td>-4.24 (0.01)</td>
<td>-1.34 (0.03)</td>
<td>-6.62 (0.01)</td>
<td>-4.30 (0.00)</td>
<td></td>
</tr>
<tr>
<td>$CDS \cdot (t/T)^2$</td>
<td>3.08 (0.02)</td>
<td>1.70 (0.00)</td>
<td>5.20 (0.01)</td>
<td>4.09 (0.00)</td>
<td></td>
</tr>
<tr>
<td>$\text{liq}_{\text{on/off}}$</td>
<td>2.98 (0.01)</td>
<td>3.26 (0.00)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$c \cdot (t/T)$</td>
<td>192 (0.10)</td>
<td>175 (0.08)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$c \cdot (t/T)^2$</td>
<td>-184 (0.16)</td>
<td>-129 (0.21)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

$R^2$ | 0.45 | 0.58 | 0.71 | 0.61 | 0.76 |

\textsuperscript{16}The leftmost column contains the regressors: $c$ is a constant, $CDS$ is the common factor (the 4th decile of the distribution of CDS spreads), $t$ is time, $T$ is the last observation in the sample, $\text{liq}_{\text{on/off}}$ is the yield spread between on-the-run and off-the-run US Treasuries. Different models (one for each column) are obtained from different choices of the explanatory variables to include in the linear regression. p-values in parentheses.
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