Borradores de ECONOMÍA

Monitoring the Unsecured Interbank Funds Market

Por: Miguel Sarmiento,
Jorge Cely,
Carlos León

Núm. 917
2015

Monitoring the Unsecured Interbank Funds Market♣

Miguel Sarmiento[a*]   Jorge Cely[b]   Carlos León[c]

Abstract

A core goal of regulators and financial authorities is to understand how market prices convey information on the financial health of its participants. From this viewpoint we build an Early-Warning Indicators System (EWIS) that allows for identifying those financial institutions perceived as risky counterparts by the participants of the interbank market. We use micro-level data from bilateral overnight unsecured loans performed in the interbank market between January 2011 and December 2014. The EWIS identifies those participants that systematically pay high prices for liquidity in this market. We employ coverage tests to estimate EWIS' robustness and consistency. We find that financial institutions with an elevated frequency of signals tend to exhibit a net borrower liquidity position in the interbank market, hence suggesting they are facing recurrent liquidity needs. Those institutions also exhibit higher probability of insolvency measured by the Z-score indicator. Thus, our results support the existence of market discipline based on peer-monitoring. Overall, the EWIS may assist financial authorities in focusing their attention and resources on those financial institutions perceived by the market as those closer to distress.

JEL codes: E40; G14; G21

Keywords: Early warning indicators, interbank markets, market discipline, bank risk.

[a] Financial Stability Department, Banco de la República.
[*] Corresponding author, E-mail: nsarmipa@banrep.gov.co; Cra. 7 # 14-78, Bogotá, Colombia. Phone: (+571)3430546.
[b] Financial Stability Department, Banco de la República. E-mail: jcelyfe@banrep.gov.co
[c] Financial Infrastructure Oversight Department, Banco de la República; CentER, Tilburg University. E-mail: cleonrin@banrep.gov.co / carlosleonr@hotmail.com.

1. Introduction

The interbank funds market is one of the main sources of short-term funding among financial institutions world-wide. In spite of most of the interbank operations are overnight or with a very short maturity (2-5 days) counterparty risk plays a major role given that there is no collateral pledged to the loan. Thus, private information on the creditworthiness of interbank participants has been found to be one of the main determinants of the premium charged on interbank loans (Braüning and Fecht, 2012). In normal times the interbank market tends to be a stable source of liquidity, and its participants usually trade funds at rates close to the central bank's policy rate. However, during periods of stress interbank market' participants tend to hoard liquidity, and to lend funds at higher prices because of their concerns on counterparty risk –as evidenced during the global financial crisis (see Afonso, et al 2011; Acharya and Merrouche (2012)).[1] Thus, identifying the behavior of financial institutions and examining disruptions in the interbank market has been a recent concern for central banks and regulators.

From a micro-prudential perspective, a core goal of regulators and financial authorities has been to understand how the market prices convey information on the financial health of its participants. The economic intuition is that when banks are taking too much risk and their creditors can identify those risky banks they tend to demand a higher return on the resources invested in the bank (Flannery, 2001). Hence, a higher risk premium will be observed in the prices that banks are paying for these instruments in the market (i.e. deposits or CDS) which have been used to estimate their default probability (See, Chan-Lau, 2006; Allen et. al, 2011). Accordingly, financial authorities may prioritize and focus their efforts on those financial institutions whose market signals reveal that their peers consider them as more risky. Therefore, market discipline has been recently considered as a key tool to complement financial supervision and regulation, and to enhance financial stability (Plosser, 2014; Yellen, 2015).

Recent evidence shows that banks tend to be good at monitoring their interbank market peers. The seminal work of Furfine (2001) employs interbank interest rates to observe market discipline among participants of the federal funds interbank market. He finds that the interest rate charged on those transactions reflects the credit risk of the borrowing bank. Banks with higher profitability, higher capital ratios, and fewer nonperforming loans are found to pay lower interest rates on federal funds loans. Thus, banks seem to be able to identify risk in their peers and –hence- to effectively monitor each other. Recently, the analytical framework of Furfine (2001) has been extended to incorporate other banks' characteristics. Evidence for European banks shows that banks tend to charge higher prices in unsecured interbank loans to counterparts with higher credit risk, more unbalanced

---

[1] Avoiding counterparty risk and hoarding are unrelated (Gale and Yorulmazer, 2013). In the first case not supplying liquidity to other financial institutions follows concerns on the credit quality of its counterparties, whereas hoarding is due to concerns on its own access to liquidity in the future.

liquidity needs, and fewer access to international markets (Cocco et. al, 2009; Angelini et. al, 2011; Fecht et. al, 2011).

Following this branch of literature we propose an Early-Warning Indicators System (EWIS) based on observed borrowing interest rates charged among interbank participants. We hypothesize that those financial institutions that are willing to pay higher borrowing rates are either facing liquidity risk or being penalized by their counterparts because of their credit risk (as in King, 2008; Heider and Hoerova, 2009; Ashcraft et. al, 2011). Therefore, concurrent with market discipline literature, we examine whether market data allows for identifying "risky" financial institutions, as perceived and priced by their peers in the market.

We use micro-level data from overnight unsecured operations among financial institutions operating in the Colombian interbank market. Our sample comprises non-publicly available data on daily overnight bilateral unsecured transactions among 53 financial institutions from January 2011 to December 2014. The sample is consists of 24,856 overnight interbank loans observed during 974 effective days of operation. We employ conditional, independence and unconditional coverage tests proposed by Christoffersen, (2003) to confirm the robustness of the observed signals. In particular, we test if the share of daily signals over the total number of days of operation is statistically different from a given threshold and if those signals were observed in a recurrent basis (i.e. following days) in a given period. Hence, the EWIS captures those financial institutions that systematically pay high prices for their liquidity in the interbank market.

Results show that some institutions consistently pay high rates for their liquidity in the interbank market. In particular, we find that some participants pay high rates for more than 5 following days and even for more than 20 following days in a period of 60 days of operation. This result suggests that those institutions are exhibiting recurrent liquidity shortages, and that when they borrow liquidity from their counterparts they tend to be charged with high rates (as in Abassi, et. al, 2013).

An interesting result is that institutions that consistently display frequent and statistically significant signals also tend to exhibit a net borrower position in the interbank market, which suggests that they are facing recurrent liquidity needs. Moreover, we find that those institutions also exhibit a lower Z-score which points out that they have a higher probability of becoming insolvent (Lepetit and Strobel, 2013; Demirgüç-Kunt and Huizinga, 2010). Consequently, the EWIS provides evidence on market discipline in the interbank market as risky institutions are found to pay more for their short-term liquidity. Therefore, the EWIS may be a tool to assist financial authorities in focusing their attention and resources on those financial institutions perceived by the market as closer to enter into distress.

2. The Colombian Interbank Market

The Colombian interbank funds market is the unsecured market for liquidity. This is of a bilateral (i.e. over-the-counter) nature, in which participants impose counterparty limits among them based on their credit risk assessments. Despite the interbank market is open to all types of financial institutions, only a handful of large credit institutions use it in a consistent manner (see Martínez and León (2015)). The rationality of this behavior can be explained by the under-provision of liquidity cross-insurance in interbank markets (see Castiglionesi and Wagner (2013)).[2]

In Table 1 we can observe that the interbank rate (TIB) exhibits a similar volatility to the central bank intervention rate (i.e. standard deviation of .72 and .75, respectively) and the mean difference between the two rates is only 1 bps during the period. The mean daily amount traded in the interbank market during the period was COP $493 billion with a maximum of COP $1.348 billion in a day observed in March of 2013.

	TIB (%)	CB (%)	TIB – CB (bps)	Amount (COP billion) [b]
			Overnight rates and volume negotiated in the interbank market [a]	
Mean	4,07	4,06	1	493
Std. Dev.	0,75	0,72	2	202
Min	3,01	3	1	156
Max	5,42	5,25	17	1.348

Table 1. Summary statistics of interbank and central bank rates and volume (2011-2014). [a] Overnight weighted average rates for the interbank market (TIB) and the central bank repo rate (CB), differences between TIB and CB rates are in basis points (bps). [b] Daily mean volume negotiated in the interbank market on an overnight maturity.

Figure 1 depicts the trend of the interbank rate compared with the central bank rate during the 2011-2014 period. It is observed that the interbank rate closely follows the central banks rate (CB); this is expected because the interbank rate is the target rate for the implementation of the monetary policy of the central bank (see evidence in Cardozo et al., 2011; González et al., 2013). However, we also observe some periods in which the interbank rate exceeds the central bank rate, especially during the tightening of the monetary policy in 2011and 2014. We also observe that the volume of interbank loans

---

[2] However, as reported by León et al. (2014), a hierarchical architecture similar to a core-periphery structure in which some large credit act as money-center institutions or super-spreaders of the central bank liquidity. Such architecture may alleviate inefficiencies from liquidity cross-underinsurance. See also Cepera et. al. (2013) for an evaluation of the role of lending relationships in the Colombian interbank market.

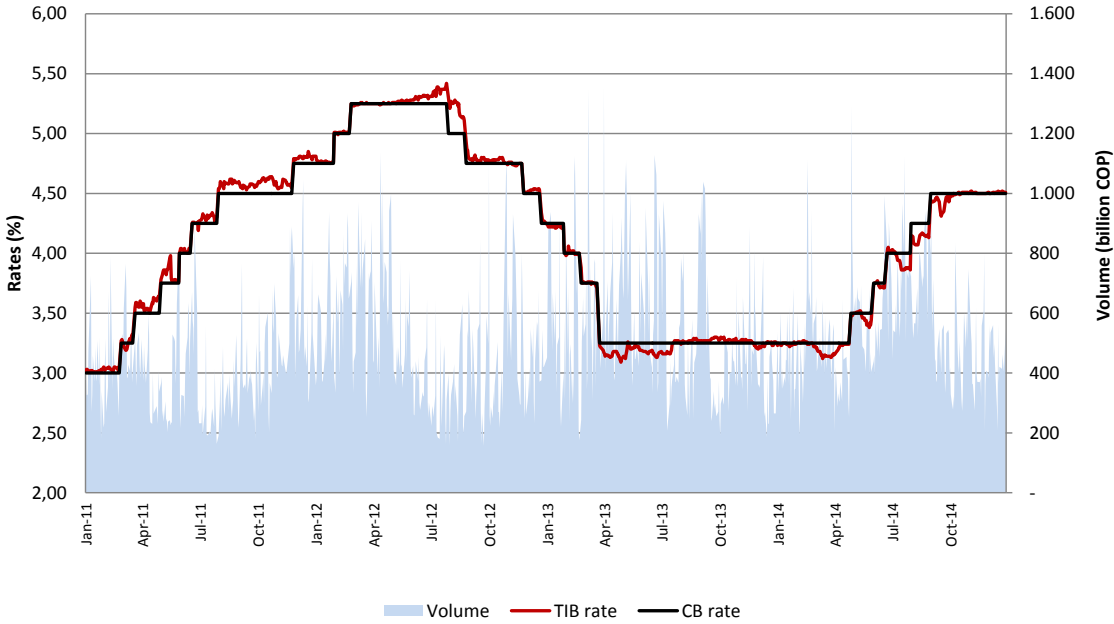varies greatly during the period (right axis) reflecting the liquidity shocks that banks usually face[3].

Figure 1. Overnight rate (%) and daily volume negotiated in the interbank market (COP billion), 2011-2014. Overnight interbank rate (TIB) and central bank rate (CB). Average daily amount traded in the interbank market (Right axis).

2.1. Interbank rate volatility

We employ three alternative benchmarks to analyze the interbank rate volatility by using the intraday rates, daily rates and 5-day rates. This approach allows us to identify structural changes in the dispersion of the interest rates in order to identify the high prices of liquidity paid by the participants of the interbank market. Table 2 describes the main statistics of the interbank rate under the three alternative measures. It is observed that the mean values tend to be very close under the three measures of the interest rate. As expected, intra-day volatility tends to be higher than both 5-day and daily volatility.

---

[3] In the literature, these shocks have been associated with unexpected withdraws from their depositors, assets management, and investment opportunities that conditioning both their liquidity excess and needs (Ashcraft et. al. 2011)

| Interbank market rates (%)			
	Intra-day	Daily	5-day
Mean	4,051	4,066	4,063
Std. dev.	0,748	0,740	0,737
Kurtosis	1,720	1,728	1,640
Skewness	0,152	0,098	0,076
No. of obs.	24.856	799	794

Table 2. Summary statistics of the overnight interest rates in the interbank market. Intra-day stands for the interest rates during the day. Daily corresponds to the average weighted interest rate of each day. 5-day corresponds to the 5-day moving average of the interest rate.

In order to examine the evolution of the interbank rate volatility during the period we visualize the deviations of observed interbank interest rates charged between financial institutions from the three selected measures of volatility. In Figure 2 (panel I) we compare the deviations of the observed rates standardized with the standard deviation estimated on the entire period. This approach allows identifying structural changes in the dispersion of the interest rates. Visual inspection reveals that there are operations that are priced above the rest, especially since October 2011. This already suggests that some participants are charged with interest rates well above the mean rates in the interbank market (i.e. the blue bars located above the green bars in Figure 2, panel I).

In Figure 2 (panel II and III) we compare the deviations of the observed rates standardized with intraday and 5-day volatility, respectively. Under this approach rates' dispersion is higher than that observed when standardizing with the entire period's standard deviation. Likewise, the presence of participants charged with interest rates well above the mean rates is more evident: the dispersion of observed interest rates reaches 5-standard deviation with ease. If those prices correspond to specific participants and are observed in a recurrent basis, we can argue that they are exhibiting recurrent liquidity needs because of a higher risk-taking in other markets (i.e. deposits or credit markets). Thus, private information on the risk-taking of those financial institutions will be reflected in their prices for liquidity loans (as in Furfine, 2001; Cocco et. al, 2009).

Therefore, this result could be indicating that some participants have been consistently charged with higher rates evidencing peer monitoring among interbank participants. Further, the 5-day volatility seems to account for the recent behavior of the market while smooth out the intra-day volatility. In the next section we consider the 5-day volatility as our preferred measure to compare the high prices for liquidity. Nevertheless, as a robustness of our results, we also compute the prices by using the other two measures of volatility.

(I) Daily volatility
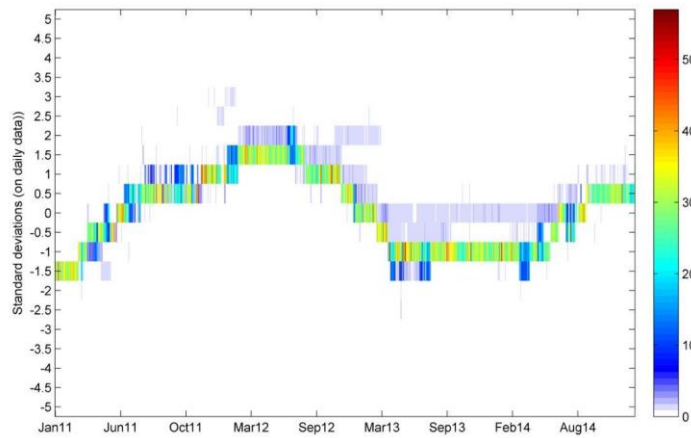
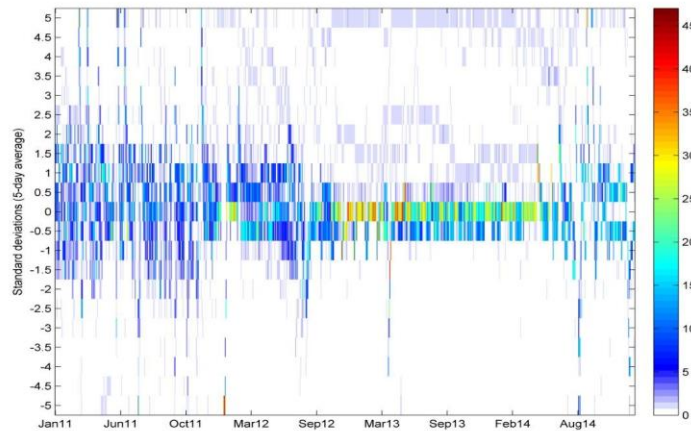## (II) Intra-day volatility
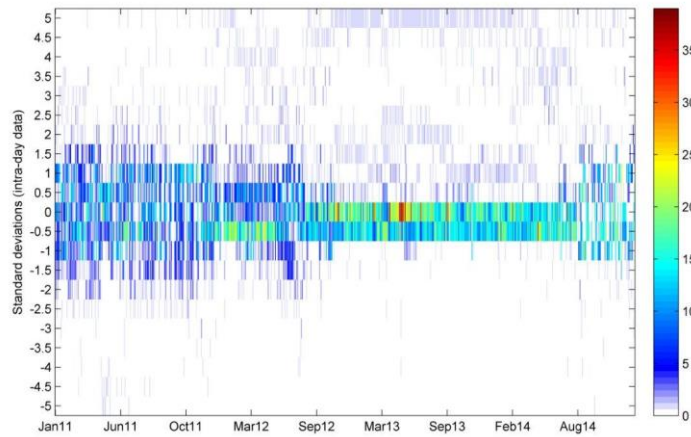
(III) 5-day volatility

Figure 2. Standardized dispersion of overnight interbank interest rates (2011-2014). This figure depicts the dispersion of observed interest rates between financial institutions, standardized with three different measures of volatility. The intensity (i.e. color) corresponds to the number of observed loans.

3. Methodology

We propose a EWIS that is intended to identify those financial institutions paying higher prices for their liquidity in the interbank market. The proposed methodology has two stages. Firstly, we compare individual and market weighted average interest rates. Then, we define some thresholds for "high" interest rates based on the standard deviation of interbank rates during the last 5 days of operations. Afterwards, we compute the signals for each participant of the interbank market as those exceeding those thresholds. Secondly, we perform unconditional, independence and conditional tests to gauge the robustness of the signals; these tests allow identifying the signals that are statistically different from a given threshold and that also tend to be recurrent during a given period.

3.1. The Early-Warning Indicators System (EWIS)

We are interested in identifying those operations that are systematically traded at high prices among participants of the interbank market. For the identification strategy we compute the weighted average interest rate of overnight loans per day for each financial institution and compare it against the overnight (market-wide) interest rate plus a spread based on the recent (i.e. 5-day) market volatility.

Formally, in equation (1) the interest rate for a financial institution i is computed as the volume-weighted average of the borrowing interest rates (r_{it}) of all overnight loans (l_{it}) per day. That is the weighted average interest rate:

$$r_{it} = \frac{\sum_{l=1}^{L}(1 + r_{it}) * l_{it}}{\sum_{l=1}^{L} l_{it}} \tag{1}$$

Then, in (2) we define the market interest rate as the sum of the weighted average interest rate for all financial institution j that borrow overnight liquidity in the interbank market at day t i.e. the average overnight (market-wide) interest rate:

$$r_{jt} = \sum_{i=1}^{J} r_{it} / q_{it} \tag{2}$$

We define three warning levels based on the number of standard deviations at which financial institutions' rates are contracted. We use the mean standard deviation of the previous 5 days of the market rate (σr_{jt-5}) as a benchmark to compare with the observed interest rate of each institution for every day t. As we mentioned before, we choose the 5-day volatility because it accounts for the recent behavior of the market. In addition, our

minimum threshold for a significant signal of a frequent borrowing cost ranges from 5 to 20 days. Hence, we are using a volatility measure that is consistent with our time framework analysis.

The three warning levels or signals are defined in conditions (3) to (5). We set the warning level I in (3) for those institutions with average borrowing interest rates above the market interest rate plus 1.0 and below 1.5 times σr_{jt-5}. Accordingly, in condition (4) the level II accounts for those with average interest rates greater than the market interest rate plus 1.5 and below 2.0 times σr_{jt-5}. Finally, in (5) average interest rates greater than the market interest rate plus 2.0 times σr_{jt-5} are located in warning level III:

Level I $$ r_{jt} + 1.0(\sigma r_{jt-5}) \quad < \quad r_{it} \quad \leq \quad r_{jt} + 1.5(\sigma r_{jt-5}) \tag{3}$$

Level II $$ r_{jt} + 1.5(\sigma r_{jt-5}) \quad < \quad r_{it} \quad \leq \quad r_{jt} + 2.0(\sigma r_{jt-5}) \tag{4}$$

Level III $$ r_{it} \quad > \quad r_{jt} + 2.0(\sigma r_{jt-5}) \tag{5}$$

We set those different warning levels in order to assess to what extent financial institutions are paying higher prices for liquidity in the interbank market, and to be able to discriminate among them. The key element for this identification strategy is to disentangle if those high prices for liquidity correspond to a few institutions (counterparty risk) or to several institutions (aggregated liquidity risk). If the latter result is observed we may infer that high prices are reflecting market sentiment rather than credit rationing for individual counterparty risk (Iori et. al, 2012).

4. Results

We compute the overnight average interest rate for each institution as in (1) and the market rate as in (2), then, we classify the rates within the three warning levels by using the conditions defined in (3) to (5). The sample comprises 10.589 observations for 974 days from January 2011 to December 2014. Note that an observation is defined as the average weighted borrowing rate of all the loans that a participant received in a given day t. In order to test for robustness we also compute the signals by using the other two measures of volatility. This strategy allows us to observe how sensitive the signals are when we use different measures of volatility.

Table 3 shows the number of signals by using the three different volatility measures. We observe that the number of signals is greater under the 5-day volatility than when we

employ the intra-day and daily volatility measures. This result is due to the 5-day volatility being lower (less volatile) than the other two measures (as reported in Table 2), which is because of it accounts for the recent history of the market and smooth the impact of the intraday behavior of the interest rates.

As expected, the lower the volatility the higher the signals exhibited. The number of signals as a proportion of the number of operations is the same when we employ the intraday and 5-day volatility measures (11%); whilst it is greater when we compute the signals under the daily standard deviation for the full period (16%). The number of signals in each of the warning levels differs but the share over the total number of signals remains relatively stable across the three measures of volatility. We may observe that around 30% of the signals are placed in level I, 13% in level II, and 60% in level III. This result shows that the signals are robust to alternative measures of volatility. Also, results show that the fraction of operations with high rates (level III) is the most frequent in our sample –excluding those not generating any signal. We are particularly interested in identifying who are the participants with those costly loans.

Level / Market	Daily		Intra-day		5-day	
	No.	%	No.	%	No.	%
Level I	495	29%	282	25%	308	27%
Level II	216	12%	138	12%	146	13%
Level III	1024	59%	724	63%	707	61%
Total signals	1735	100%	1144	100%	1161	100%
Total operations	10589	16%	10589	11%	10589	11%

Table 3. Frequency of EWIS for the interbank market under alternative measures of volatility (2011-2014). Daily corresponds to the standard deviation during the full period. Intra-day volatility is the standard deviation for each day. 5-day volatility is the moving average of the standard deviation during the previous 5 days.

Figure 3 depicts the observed interest rates classified under the three warning levels (signals) and includes the interbank market rate (computed as in (2)) and the central bank rate in order to identify how large the spread of those operations is. As expected, most of interbank operations (green dots) were agreed at rates close to the central bank rate, below +1.0 5-day standard deviation from the market rate. As reported in Table 2, the average gap between interbank and the central bank rates was 1 bps, and the standard deviation was 2 bps. This result is in line with evidence from other interbank markets as they are the target

market for the implementation of the monetary (see, BIS (2009) and Friedman and Kuttner (2011)).

Interestingly, when we compare individual rates in the warning levels we find that there is a sizeable set of operations traded at particularly high rates (i.e. level III, in red dots) during most of the studied period. In fact, the number of signals located in level I (yellow dots) and II (orange dots) is lower than those observed in level III (as reported in Table 3). If those loans located in the warning level III correspond to a few institutions, we may infer that interbank participants are punishing those institutions in the market via high prices incorporated in the liquidity they lend to them. On the contrary, if those signals correspond to several participants we may infer that there is high volatility affecting the prices for liquidity or aggregated liquidity risk (as in Iori, et. al, 2012).
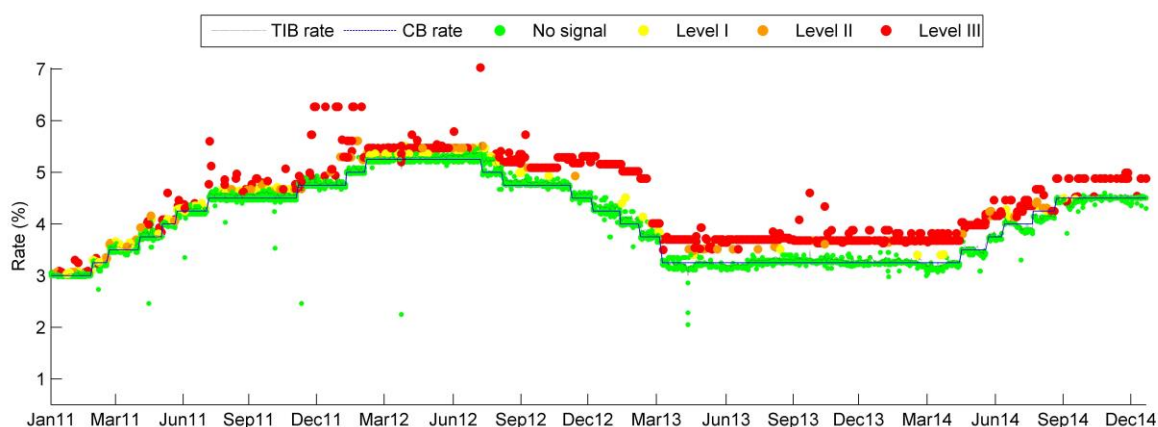

Figure 3. Early warning indicators for the interbank market (2011-2014). This figure depicts daily frequency of EWIS for the interbank market, between 2011 and 2014, along with the market rate (TIB) and the central bank repo rate (CB). The green dots are those participants with rates below the market rate plus 1.0 standard deviation (i.e. observations with no signal). The yellow, orange and red dots correspond to those daily operations with rates between 1.0 and 1.5, between 1.5 and 2.0, and more than 2.0 times the 5-day volatility from the market interest rate, respectively.

In Table 4 we show the frequency of the signals by year in order to identify if there are changes in the share of signals over the period. The total number of signals was 1,161, accounting for 11% of the number of operations, from which 61% of those signals were located at the warning level III. Overall, the number of signals decreased along the period from 351 in 2011 to 244 in 2014. The number of signals in level I during 2011 was 218 (i.e. 62% of total signals), whereas it was 60, 11, and 19 (20%, 4%, and 8%) respectively. For level II the number of signals from 2011 to 2014 was 58 (17%), 42 (14%), 20 (8%), and 26 (11%), respectively. For level III the number of signals from 2011 to 2014 was 75 (21%),

11

202 (66%), 231 (88%), and 199 (82%), respectively. It is noteworthy that the number of signals in level III reached 88% and 82% in 2013 and 2014, respectively.

Level / Market	2011		2012		2013		2014		2011-2014	
	No.	%	No.	%	No.	%	No.	%	No.	%
Level I	218	62%	60	20%	11	4%	19	8%	308	27%
Level II	58	17%	42	14%	20	8%	26	11%	146	13%
Level III	75	21%	202	66%	231	88%	199	82%	707	61%
Total signals	**351**	**100%**	**304**	**100%**	**262**	**100%**	**244**	**100%**	**1161**	**100%**
Total operations	**2852**	**12%**	**2774**	**11%**	**2656**	**10%**	**2307**	**11%**	**10589**	**11%**

Table 4. Frequency of EWIS in the interbank market (2011-2014). This table shows the frequency of EWIS classified by the three warning levels between 2011 and 2014. Level I accounts for the number of operations with interest rates above one standard deviation over the market interest rate. Level II and III correspond to the number of operations with interest rates between 1.5 and 2.0 standard deviations, and above 2.0 standard deviations over the market interest rate, respectively.

It is rather surprising that the number of level III signals exceeds those of level I and II. Our initial guess is that interbank interest rates distribute as a typical continuous distribution, with the frequency of observations monotonically decreasing in a smooth manner as they depart from the mean. However, if level III are more numerous than level I and II this may signal that the distribution of interest rates is not continuous.

Figure 4 displays the distribution of interbank interest rates. We calculated the spread of each financial institution's interest rate with respect to the interbank average interest rate (TIB), classify them by their standardized difference with respect to TIB (i.e. no signal, level I, level II, level III), and plotted their frequency distribution. It is rather evident the non-continuity of the overall distribution, with level III describing some sort of different distribution. This is related with the fact that 63% of all the signals during the period were located al level III confirming the bimodal distribution of the signals we found.

It is arguable that the entire distribution may be bimodal, in which two different types of participants coexist: a set of financial institutions able to borrow at rates close to the average interest rate (e.g. no signal and low level signal), and a set able to borrow at rates that consistently exceed the average interest rate (i.e. level III signal). Thus, the EWIS seems able to capture those financial institutions paying higher prices. But the key element is to identify who are those institutions, and to determine if those high prices were recurrent for a well-defined set of financial institutions, or if they correspond to particular episodes along the assessed period that indistinctly affected all financial institutions.
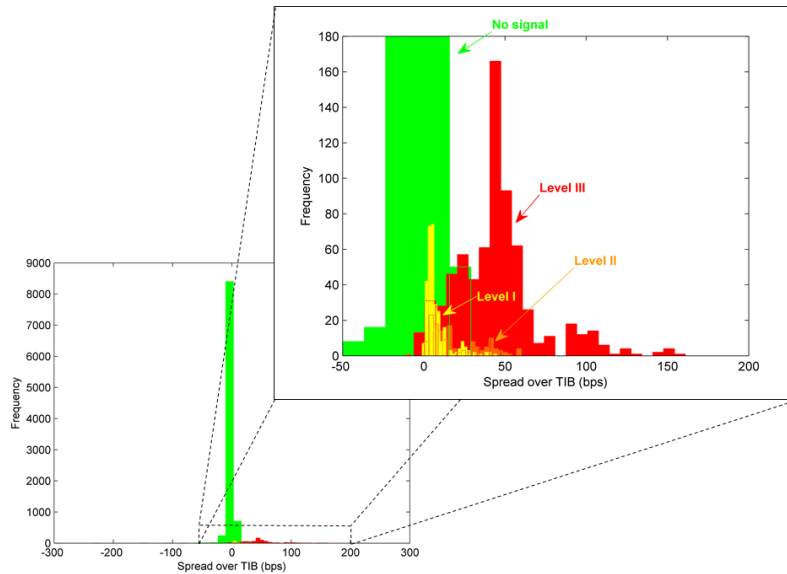
Figure 4. Distribution of the spreads by early warning levels in the interbank market. This figure shows the distribution of interbank interest rates spreads with respect to the market rate. Level I (in yellow) accounts for the number of operations with interest rates above one standard deviation over the market interest rate. Level II (in orange) and III (in red) correspond to the number of operations with interest rates between 1.5 and 2.0 standard deviations, and above 2.0 standard deviations over the market interest rate, respectively.

4.1. Identifying the riskier participants of the interbank market

In the previous section we found that some institutions paid high prices for their liquidity in the interbank market. Moreover, visual inspection of the distribution of interest rates (Figure 3) even advocates for the existence of two distinct sets of financial institutions, each accessing a different level of price for liquidity. Now, we want to identify who are those institutions and if paying high prices tend to be a recurrent behavior in the market.

In this sense, EWIS is useful to the extent that it can alert financial authorities of anomalies within financial institutions operating in the market. Thus, we are interested in identifying those financial institutions that exhibited an important proportion of signals in the interbank market. In particular, we want to know if the share of signals is statistically significant from a given threshold and to identify those participants exhibiting this behavior in a recurrent basis. The unconditional, independence and conditional tests proposed by Christoffersen (2003) allow us to incorporate these properties for the EWIS[4].

---

[4] Murcia (2012) applied a similar test to identify high prices paid by participants of central bank's repo operations.

4.1.1. Unconditional coverage testing

We are interested in identifying those financial institutions that exhibit an important number of signals in the interbank market. Thus, the first test compares the proportion of observed signals by each financial institution with respect to an admissible threshold. We want to test if the fraction of signals exhibited by a participant is significantly different from a given threshold. This is known as an unconditional coverage test.

Formally, we define a threshold, α, that is the proportion of signals from the total number of observations T in the period. The signals are those defined in conditions (3) to (5) in section 3.2. Overall, we hypothesize that if participants of the interbank market are good at monitoring their peers they should tend to exert market discipline by charging those counterparts with less probability of repayment with higher prices for liquidity (as in Cocco et. al, 2009; King, 2008; Angelini et. al, 2009). Thus, we want to test if the fraction of signals, π, is significantly different from the expected fraction α. To test it, Christoffersen (2003) employs the likelihood of an *i.i.d* Bernoulli (π) hit sequence, as follows:

$$L(\pi) = \prod_{t=1}^{T}(1-\pi)^{1-Ht}\pi^{Ht} = (1-\pi)^{T0}\pi^{T1} \qquad (6)$$

In (6), if a participant registers a signal it takes the value of 1 in the sequence H_t. Thus, $H_{t=1}$ is the sequence across T days indicating when past violations occurred (i.e. when signals are observed in each institution). The total number of days with signal is given by T_1, while the total number of days free from signal is T_0. Using observed data (Table 4), we can easily estimate π from the ratio between the number of days with signals and the total number of observations; that is, $\pi^* = T_1 / T$. Plugging the maximum likelihood (ML) estimates in the likelihood function (6) gives the optimized likelihood as:

$$LR_{uc} = -2\ln\left[(1-\alpha)^{T0}\alpha^{T1} / \{(1-T_1/T)^{T0}(T_1/T)^{T1}\}\right] \sim \chi^2 \qquad (7)$$

Hence, in case we reject the null hypothesis that $\pi = \alpha$, we are checking that the assessed institution exhibits a fraction of signals that is statistically greater than the threshold α.

4.1.2. Independence testing

We employ the independence testing for identifying those institutions presenting signals that are no independent; that is, signals that tend to be persistent over time. Thus, we can identify those participants of the interbank market that tend to pay higher prices recurrently. To do this, we can employ a Markov sequence with transition probability matrix that relates our signals ($H_{t=0}$ and $H_{t=1}$) as dependent over time:

$$\Pi_1 = \begin{bmatrix} 1 - \pi01 & \pi01 \\ 1 - \pi11 & \pi11 \end{bmatrix} \tag{8}$$

These transition probabilities simply mean that conditional on today being a state with no signal ($H_{t=0}$), then the probability of tomorrow being a state with signal ($H_{t=1}$) is given by π_{01}. The probability of tomorrow being a state with signal ($H_{t=1}$) given today is also a state with signal ($H_{t=1}$) is given by π_{11}. As only two outcomes are possible (zero and one), the two probabilities π_{01} and π_{11} describe the entire process. The probability of a non-signal state ($H_{t=0}$) following a non-signal state ($H_{t=0}$) is given by $1 - \pi_{01}$, and the probability of a non-signal state ($H_{t=0}$) following a signal state ($H_{t=1}$) is $1 - \pi_{11}$.

If we have a sample of T observations, then we can write the likelihood function of the first-order Markov process as (See, Christoffersen, 2003):

$$L(\Pi_1) = (1 - \pi_{01})^{T_{00}} \, \pi_{01}^{\ T_{01}} \, (1 - \pi_{11})^{T_{10}} \, \pi_{11}^{\ T_{11}} \tag{9}$$

Thus, we can check the independence hypothesis that $\pi_{01} = \pi_{11}$ using the likelihood ratio test:

$$LR_{ind} = -2\ln\,[\,L(\pi^*)\,/\,L(\Pi^*_1)\,] \sim \chi^2 \tag{10}$$

Where $L(\pi^*)$ is the likelihood under the alternative hypothesis form the LR_{uc} test in (7). If we reject the null hypothesis for a particular institution it is possible to argue that it exhibits signals that are not independent among them. In other words, is safe to say that this institution registers signals than tend to be recurrent (i.e. to cluster) over time. This is an important characteristic of the signals because we are interested in identifying riskier institutions in the interbank market based on the prices they paid in the market, and on the recurrence those prices are charged with.

4.1.3. Conditional coverage testing

Ultimately, we care about simultaneously testing if the number of signals is above the threshold, and if they signals are independent. Thus, we can identify those institutions that simultaneously pay high prices in a recurrent fashion. For this type of evaluation we can employ the conditional coverage test proposed by Christoffersen, (2003), which jointly checks for independence and correct coverage:

$$LR_{cc} = -2\ln [L(\alpha)/ L(\Pi^*_1)] \sim \chi^2 \qquad (11)$$

The test in (11) corresponds to testing that $\pi_{01} = \pi_{11} = \alpha$. Notice that the LR_{cc} test takes the likelihood from the null hypothesis in the LR_{uc} and combines it with the likelihood from the alternative hypothesis in the LR_{ind} test[5].

4.2.   Estimating the statistical significance of the signals

To implement the abovementioned tests we need to define the period of evaluation (T) and the threshold of admissible signals (α). These are crucial elements of the tests for the accurate identification of those institutions that may be considered as riskier. From equations (1) to (5) we obtain the days with signal (T_1) and free from signal (T_0) for each participant during the period. We need to define the number of days for the test (T) in order to compute the fraction of days with signals ($\pi^* = T_1/T$.) The unconditional test (LR_{uc}) defined in (7) requires choosing a threshold α, which is the proportion of signals we consider as "normal" during a given period of time. Because of we are using daily observations on overnight loans in the interbank market the signals are expressed as the number of days an institution pays a high price for its overnight liquidity. Thus, α represents a number of admissible days a participant of the market pays a high price for its liquidity.

In order to incorporate the recent behavior of the markets we test the signals in a quarterly basis. The test on quarterly samples usually accounts for 60 days of operation ($T = 60$). In this sample a participant with more than α days exhibiting signals will be identified by the test. For robustness we select different thresholds, 20, 10 and 5 days, which corresponds to levels of α equal to 0.33, .016 and 0.08, respectively, for periods of 60 days. This means that a participant with more than 5 days paying a high price (i.e. with signals) in a period of 60 days will be identified as risky. By using more thresholds we can check how robust our results are under alternative specifications.

As argued, the frequency in which the signals are observed is also relevant in this analysis. For instance, an institution exhibiting 10 signals along a 60-days period is different (i.e. less risky) from one who exhibits 10 signals in 10 days of the period of 60 days. Under both scenarios the LR_{uc} test will identify these institutions given that the proportion of signals is greater that the threshold of five days i.e. $\pi^* > \alpha^5$. But clearly, the latter participant entails a more risky behavior than the former. Therefore, to account for this type of behavior in the

---

[5] Christoffersen (2003) shows that the joint test of conditional coverage can be computed by simply summing the two individual tests for unconditional and independence. The author also remarks that in large samples, the distribution of the tests defined in (7), (10) and (11) follows a χ2 with one degree of freedom.

identification of the institutions we apply the independence test (LR$_{ind}$) presented in (10). This test allows us to identify if an institution exhibits recurrent signals during the period[6]. Applying both tests simultaneously (as in (11)) will result in that only those institutions with a significant amount of recurrent signals will be identified as part of the ranking of risky institutions.

As with any statistical test we need to choose a significance level. The significance level depends on whether the number of observations and violations are relevant in the sample. We have 10,589 observations (T) and 1,161 signals (T_1) so we have 11% of the sample observations to test for, which brings us an appropriated set of observations and violations of these types of tests. We choose a significance level of 10% for the tests, which entails a critical value of 2.7055 from the χ^2 distribution.

4.3.   Results on coverage testing

We apply unconditional, independence and conditional tests under the thresholds of 5, 10 and 20 days (i.e. α^5, α^{10} and α^{20}) to gauge the robustness of our results under different thresholds. To compare the results we rank the participants by the share of signals registered during the full period. We present for each of them the number of signals by level and the quarters with signals above each of the selected thresholds.

In Table 5 we present the 10 institutions with a share of signals greater than 1% during the period. We rank the participants by the share of signals, which is the quantity of signals over the total number of operations ($\pi^* = T_1/T$). We observe that 10 institutions accounted for 80% of the total signals presented during the period (927), and they also account for 33% of the operations in the interbank market. For these 10 institutions most of the signals were located at level III, followed by level II and level I, accounting for 91%, 75%, and 57% of the total signals, respectively.

We find that 7 of these 10 institutions registered at least one quarter with signals for more than 5 days, which were also recurrent (i.e. signals following signals). It means that for these 7 institutions we find statistically significant signals under the conditional and independence tests for the α^5 threshold. As expected, institutions with a greater share of signals tend to exhibit more periods of warning (i.e. quarters with statistically significance signals). Under the 10-days threshold (α^{10}) six participants registered quarters with recurrent signals, whereas under the 20-days threshold (α^{20}) only three of them (FI101, FI99 and FI100). These three institutions, FI101, FI99, and FI100, have a statistically significant amount of signals. Moreover, for several quarters more than one third of the days in which they borrow liquidity from the market they were charged with high rates (i.e.

---

[6] In particular, if a signal is following other signal it accounts for one event under the LR$_{ind}$ test. When two of these events are registered the participant is identified in the ranking.

signals greater than the α^{20} threshold). The share of signals for these institutions was 98%, 93%, and 47%, respectively; this suggests that these participants consistently paid high prices for their liquidity in the interbank market. In addition, those prices were mainly located at the level III of warning, indicating a larger premium charged from their counterparts.

Financial Institution (FI)	Early Warning Signals by level and FIs [a]						Number of quarters with signals above the threshold and recurrent [b]		
	Level I	Level II	Level III	Total (T_1)	Total Op. (T)	Share % (π^*)	# of Q > α^5	# of Q > α^{10}	# of Q > α^{20}
FI 101	0	2	76	78	80	98%	2	2	2
FI 99	31	61	498	590	635	93%	10	10	10
FI 100	7	11	23	41	88	47%	2	2	2
FI 49	16	3	13	32	90	36%	1	1	0
FI 51	41	2	2	45	322	14%	1	1	0
FI 63	26	5	4	35	316	11%	1	1	0
FI 10	26	7	3	36	411	9%	1	0	0
FI 23	9	5	6	20	254	8%	0	0	0
FI 20	10	7	9	26	351	7%	0	0	0
FI 36	11	7	6	24	974	2%	0	0	0
Total of the 10 FIs	177	110	640	927	3521	26%	18	17	14
Share 10 FIs (%)	57%	75%	91%	80%	33%	..	100%	100%	100%
Total 54 FIs	308	146	707	1161	10589	11%	18	17	14

Table 5. Top 10 financial institutions with the higher frequency of EWI in the interbank market (2011-2014)
[a] Number of signals by level for each financial institution during the period. [b] Number of quarters (Q) in which an institution exhibited signals with statistical significance for each threshold (α) of 5, 10 and 20 days. Significance level at 10% for the tests with a critical value of 2.7055 from the $\chi 2$ distribution.

Figure 5 presents the evolution of the observed prices and signals for the above-mentioned financial institutions. We can observe that paying higher prices for liquidity was a frequent behavior for these financial institutions. The fact that the signals were consistently observed for these participants suggests that regulators should closely monitor their behavior in the market. To complement our results we present some characteristics of these participants in the next section.
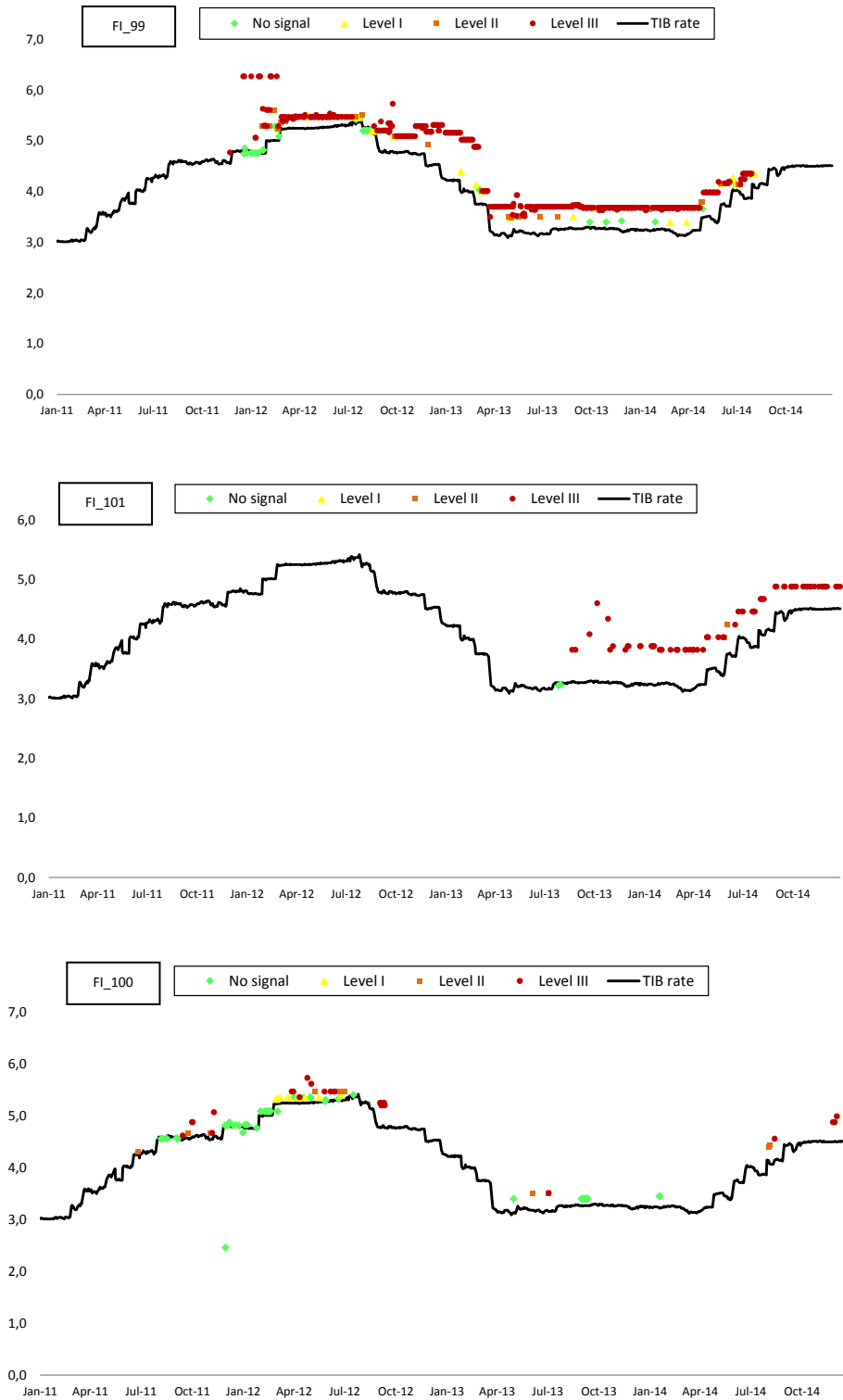
Figure 5. Early warning indicators of selected financial institutions (2011-2014). This figure depicts daily frequency of EWIS in the interbank market for institutions FI_99, FI_101 and FI_100, between 2011 and 2014, along with the market rate (TIB). The green dots are those operations with rates below the market rate plus 1.0 standard deviation (i.e. observations with no signal). The yellow, orange and red dots correspond to those operations with rates between 1.0 and 1.5, between 1.5 and 2.0, and more than 2.0 times the 5-day volatility from the market interest rate, respectively.

4.3.1. Insolvency risk, liquidity position and the EWIS

In this section we present some features of the participants identified with higher frequency of signals. For each institution in the top ten of the signals we compute the average spread over the interbank rate and the average net position in the interbank market during the period. These variables help us to understand how large the price of liquidly is for these institutions compared with their peers in the interbank market, and if they have recurrent liquidity needs that force them to pay those high prices. In particular, participants with frequent net borrower position may exhibit unbalanced liquidity positions, or they may tend to rely more on wholesale funding to operate. This behavior has been associated with bank fragility (Demirgüç-Kunt and Huizinga, 2010).

Our measure of insolvency risk is the Z-score indicator, which corresponds to the inverse probability of insolvency (Roy, 1952; Altman, 1968). This indicator has been broadly used in the banking literature as a measure of the distance-to-insolvency, which is able to capture the risk-taking behavior of a financial institution (Tabak, et. al, 2012)[7]. The Z-score is defined as the number of standard deviations that an institution's rate of return on assets (ROA) has to fall for the institution to become insolvent. Formally, the Z-score is constructed as the sum of the mean rate of return on assets (μ_{roa}) and the mean equity-to-assets ratio (car) divided by the standard deviation of the return on assets: $z\text{-}score_t = (\mu_{roa} + car_t) / \sigma_{roa}$.

There are several ways to compute this indicator. We use the approach of Lepetit and Strobel (2013), in which the mean and standard deviation estimates, μ_{roa} and σ_{roa}, are calculated over the full sample $[1 \dots T]$, and combine these with current t values of the equity ratio (car_t). We compute the Z-score by using monthly balance-sheet information for all the participants of the interbank market during the period 2011-2014. We find a negative correlation between the share of signals and the Z-score with a slope of -0.24 (Figure 6). This result indicates that a larger proportion of signals can be associated with a greater probability of insolvency (i.e lower Z-score).

Table 6 depicts the liquidity position in the interbank market and the insolvency risk (Z-score) for the top ten participants with higher share of signals in the interbank market. We observe that these participants registered on average a net borrower position, indicating that they may are using this market as a recurrent source of funding, which can be risky, especially for commercial banks given that they are expected to rely more on deposits than on wholesale funding.

---

[7] The Z-score measure was initially proposed by Roy (1952) who shown that the probability that current losses would exceed capital is less than or equal to $1/z^2$, so that higher level of z implies lower upper bound of insolvency probability. Altman (1968) tested the Z-score for the corporate sector. After that the Z-score was tested for the banking industry by Hannan and Hanweck (1988) and Boyd et. al. (1993). Since then many studies have been using the Z-score as a measure of bank's risk-taking (see Laeven and Levine (2009), Demirgüç-Kunt and Huizinga (2010), Houston et al. (2010), and Bertay et al. (2013), among others).
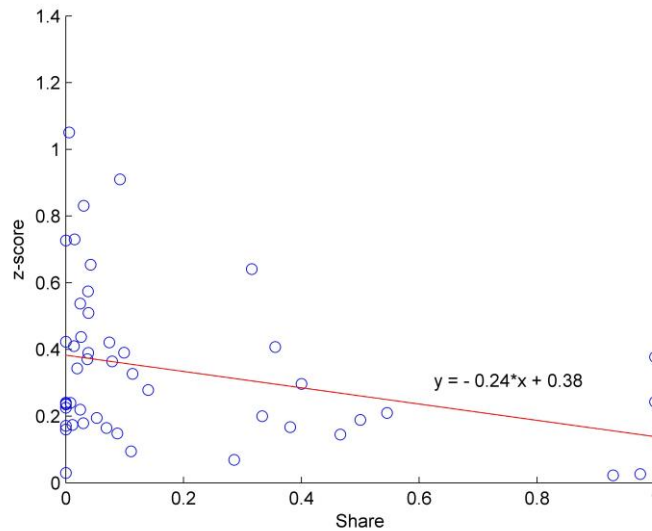
Figure 6. Relationship between the total share of signals and the Z-score for participants of the interbank market for the period 2011- 2014.

Financial Institution (FI)	Total signals[a]	Total Operations[b]	Share %[c]	Spread (bp)[d]	Net position[e]	Z-score[f]	Share in the system[g]
FI 101***	78	80	98%	23	-27	0,027	0,01%
FI 99***	590	635	93%	37	-2.422	0,023	0,01%
FI 100***	41	88	47%	63	-95	0,145	0,00%
FI 49**	32	90	36%	33	-124	0,408	0,06%
FI 51**	45	322	14%	-23	2.831	0,278	2,46%
FI 63**	35	316	11%	31	-4.442	0,095	0,09%
FI 10*	36	411	9%	17	10.423	0,148	3,71%
FI 23	20	254	8%	8	-988	0,364	0,17%
FI 20	26	351	7%	10	-1.134	0,421	2,45%
FI 36	24	974	2%	-3	-147.355	0,22	1,82%
Total of the 10 FIs	927	3521	26%	20	-14.333	0,213	10,79%
Share 10 FIs (%)	80%	33%	..	..	..		
Total 54 FIs	1161	10589	11%	3	-1.350	0,339	100%

Table 6. Liquidity position and insolvency risk for the 10 financial institutions with the higher frequency of EWI in the interbank market (2011-2014) [a] Total number of signals during the period. [b] Total number of days of operation. [c] The share of signals over the operations. [d] Average difference between the borrowing rate and the interbank market rate in basis points (bps). [e] Average net position in the interbank market computed as the difference between the amount of funds lent and borrowed in Millions of COP per day. [f] The Z-score refers to the inverse probability of insolvency, the lower its value the larger the probability of insolvency. [g] Average share of institution's assets in the total assets of the 54 participants during the period. ***, **, * denote that the institutions presented at least one period with significant signals under the thresholds of α^{20}, α^{10} and α^{5}, respectively.

These institutions also tend to exhibit a positive spread over the interbank market rate. On average, the spread paid by these institutions was 20 bps, which exceeds the mean spread paid for all the participants in this market (i.e. 3 bps). Thus, we find evidence that the participants exhibiting the higher frequency of signals are consistently net borrowers in the interbank market, which may reflect recurrent liquidity needs. This result coincides with Fecht et al. (2011) in the sense that those institutions with higher liquidity needs are found to pay higher prices for their liquidity.

Regarding Z-score, we find that the ten participants with higher share of signals also tend to exhibit lower levels of Z-score (.213) compared with the mean level of all the participants (.339) indicating a higher risk-taking in those institutions compared with the rest of participants. For this group of participants insolvency risk is higher, and it can be associated with the higher price for liquidity they pay in the market. This evidence supports the role of lenders' private information in the interbank market (see Braüning and Fecht (2012), Cocco et al. (2009)).

As we mentioned before, we identify three interesting cases in the interbank market (institutions FI99, FI101, and FI100), with statistically significant signals under the α^{20} threshold. These institutions have several characteristics in common. On average they paid a spread over the interbank market rate of 37 bps, 23 bps, and 63 bps, respectively, and also exhibited a borrower net position in this market. The Z-score for these institutions was .023, .027 and .145 which means that they faced a reduction in their financial robustness during this period. These levels of the Z-score are below the mean level of the top ten riskier participants (.213). Therefore, we may point out that these institutions' diminished robustness overlaps with their counterparts consistently charging them with high prices for liquidity. It is worth noting that the contribution of those financial institutions to the total assets of the 54 participating institutions is less than 0.02%.

5. Final remarks

We propose an EWIS that is able to identify those participants of the interbank market who consistently pay high prices for their liquidity. We assess to what extent financial institutions are paying higher prices for liquidity in the interbank market. As a few institutions with particular features are those which pay high prices for liquidity in a consistent manner, we find that credit rationing for individual counterparty risk is the main factor behind our results.

We confirm that a high frequency of signals is associated with a net borrowing position in the interbank market, and with a high probability of insolvency. In our case, institutions with high frequency of signals experienced episodes of diminished financial robustness as well, but their contribution to financial systems' assets is rather low. Thus, we provide

evidence on market discipline based on peer-monitoring for the unsecured interbank market, in which riskier counterparts are consistently charged with higher prices for their liquidity.

The EWIS can be used for regulators to monitor the behavior of the participants of the money market. The main policy recommendation of this paper is that financial institutions with a significant amount of EWI should be more carefully monitored by the supervisors, and eventually asked to reduce their overall level of risk.

A more comprehensive model to understand the determinants of the spreads over the market rates of the interbank market is needed. We find some evidence supporting that the net position in the interbank market and the risk of insolvency are important institution-specific characteristics associated with a growing share of signals (i.e. high and recurrent liquidity prices). However, there are other relevant characteristics such as size, credit risk, aggregated money market liquidity position, and lending relationships, among others that influence the price of liquidity in the interbank market. In addition, market characteristics such as money market rates, the central bank liquidity and the structure of the network are also key determinants to account for.

Furthermore, it is not only important to develop a more extensive framework in order to incorporate these characteristics, but also using both unsecured and secured money market prices. This is important because recent evidence suggests that market discipline prevails regardless of the use of collateral in the secured money market. For instance, based on data for the U.S. secured market, King (2008) and Gorton and Metrick (2012) find that secured borrowing costs also exhibit cross-section differences that are related to counterparty risk. For the Colombian case, Martínez and León (2015) find that borrowing costs vary across financial institutions despite they all use rather homogeneous and low credit risk collaterals (i.e. sovereign's local securities denominated in local currency).

Finally, we stress the relevance of promoting market discipline to enhance monitoring among financial institutions. As envisaged by Plosser (2014) and Yellen (2015), promoting market discipline is a key goal for policy makers around the globe to safeguard financial stability.

References

Abbassi, P., Fecht, F., & Weber, P. (2013). "How stressed are banks in the interbank market?". *Deutsche Bundesbank Discussion Paper*, 40/2013.

Acharya, V.V. & Merrouche, O. (2012). "Precautionary Hoarding of Liquidity and Inter-Bank Markets: Evidence from the Sub-prime Crisis". *Review of Finance, 17 (1)*, 107-160.

Afonso, G., Kovner, A., & Schoar, A. (2011). "Stressed, not frozen: the Federal Funds Market anmd the financial crisis". *The Journal of Finance*, *4*, 1109-1139.

Angelini, P., Nobili, A., & Picillo M.C. (2011). "The interbank market after August 2007: what has changed and why?". *Journal of Money, Credit, and Banking, Vol. 43 (5)*, 923–958.

Ashcraft, A., McAndrews, J. & Skeie, D. (2011). "Precautionary Reserves and the Interbank Market". *Journal of Money, Credit, and Banking, Vol 3(7)*, 311-348.

Allen, J., Hortaçsu, A., & Kastl, J. (2011). "Analyzing Default Risk and Liquidity Demand during a Financial Crisis: The Case of Canada". *Bank of Canada Working Paper, 2011-17*, August.

Altman, E., (1968). "Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy". *Journal of Finance 23 (4)*, 589-609 .

Braüning, F. & Fecht, F. (2012). "Relationship lending in the interbank market and the price of liquidity". *Deutsche Bundesbank Discussion Paper, 22/2012*.

Bertay, A., Demirgüc-Kunt, A., & Huizinga, H. (2013). "Do we need big banks? Evidence on performance, strategy and market discipline". *Journal of Financial Intermediation, 22*, 532-558.

BIS (2009). "Monetary Policy Frameworks and Central Bank Market Operations", Markets Committee Compendium, Bank for International Settlements, May, Basel.

Boyd, J.H., Graham, S.L., & Hewitt, R.S., (1993). "Bank holding company mergers with nonbank financial firms: Effects on the risk of failure". *Journal of Banking & Finance* 17, 43-63.

Castiglionesi, F. & Wagner, W. (2013). "On the efficiency of bilateral interbank insurance". *Journal of Financial Intermediation, 22*, 177-200.

Cardozo, P., Huertas, C., Parra, J., & Patiño, L. (2011). "Mercado interbancario colombiano y manejo de liquidez del Banco de la República". *Borradores de Economía, 673*, Banco de la República.

Capera, L., Lemus, J., & Estrada, D. (2013). "Relaciones crediticias y riesgo de contagio en el mercado interbancario no colateralizado colombiano", Temas de Estabilidad Financiera, No.77, Banco de la República, June.

Chan-Lau, J.A. (2006). "Market-Based Estimation of Default Probabilities and Its Application to Financial Market Surveillance" *IMF Working Paper, WP/06/104*, International Monetary Fund, April.

Christoffersen, P.F. (2003). *Elements of Financial Risk Management*, Elsevier. U.S.

Cocco, J., Gomes, F., & Martins, N. (2009). "Lending Relationships in the Interbank Market". *Journal of Financial Intermediation, 18 (1)*, 24-48.

Demirgüç-Kunt, A. & Huizinga, H. (2010). "Bank Activity and Funding Strategies: The Impact on Risk and Returns." *Journal of Financial Economics 98 (3),*626–50.

Fecht, F., Nyborg, K. G., & Rocholl, J. (2011). "The price of liquidity: The effects of market conditions and bank characteristics". *Journal of Financial Economics, 102(2)*, 344 – 362.

Flannery, M.J. (2001). "The Faces of Market Discipline." *Journal of Financial Services Research, 20*, 107-119.

Friedman, B.M. & Kuttner, K.N. (2011). "Implementation of Monetary Policy: How Do Central Banks Set Interest Rates?" in *Handbook of Monetary Economics*, (Friedman, B.M. and M. Woodford Eds), Vol 3, 1345–1438, Elsevier.

Furfine, C. (2001). "Banks Monitoring Banks: Evidence from the Overnight Federal Funds Market". *Journal of Business*, *74 (1)*, 33-58.

Gale, D. & Yorulmazer, T. (2013). "Liquidity hoarding". *Theoretical Economics*, *8*, 291-324.

González, C., Silva, L., Vargas, C., & Velasco, A.M. (2013). "Uncertainty in the money supply mechanism and interbank markets in Colombia". *Borradores de Economía, 790*, Banco de la República.

Gorton, G. & Metrick, A. (2012). "Securitized banking and the run on repo". *Journal of Financial Economics, 104*, 425-451.

Hannan, T.H., & Hanweck, G.A., (1988). "Bank insolvency risk and the market for large certificates of deposit". *Journal of Money, Credit and Banking, 20*, 203–211.

Heider, F & Hoerova, H. (2009). "Interbank Lending, Credit Risk Premia and Collateral", *International Journal of Central Banking, Vol. 5*, 1-39.

Houston, J.F., Lin, C., Lin, P., & Ma, Y. (2010). "Creditor rights, information sharing, and bank risk taking". *Journal of Financial Economics, 96*, 485–512.

Iori, G., Kapar, B. & Olmo, J. (2012). "The Cross-Section of Interbank Rates: A Nonparametric Empirical Investigation". *Report No. 12/03*, City University London.

King, T. (2008). "Discipline and liquidity in the interbank market". *Journal of Money, Credit and Banking, 40 (2-3)*, 295-317.

Laeven, L., & Levine, R. (2009). "Bank governance, regulation and risk taking". *Journal of Financial Economics*, 93, 259–275.

León, C., Machado, C. & Sarmiento, M. (2015). "Identifying Central Bank Liquidity Super-Spreaders in Interbank Funds Networks". *CentER Discussion Paper, 2015-052*, Tilburg University, November.

Lepetit, L. & Strobel, F. (2013). "Bank Insolvency Risk and Time-Varying Z-Score Measures". *Journal of International Financial Markets, Institutions and Money 25*, 73–87

Martínez, C. & León, C. (2015). "The Cost of Collateralized Borrowing in the Colombian Money Market: Does Connectedness Matter?". *Journal of Financial Stability, (forthcoming)*.

Murcia A. (2012). "Indicadores de Riesgo utilizando Información de Mercado de Operaciones de Repos de Expansión por parte del Banco de la República". Unpublished technical report, Banco de la República.

Plosser, C.I. (2014). "Simplicity, Transparency, and Market Discipline in Regulatory Reform" *Speech for the Conference "Enhancing Prudential Standards in Financial Regulations*, Federal Reserve Bank of Philadelphia, the Wharton Financial Institutions Center, and the Journal of Financial Services Research Philadelphia, PA April 8, 2014.

Roy, A.D. (1952). " Safety first and the holding of assets". *Econometrica,* 20, 431-449.

Tabak, B.M, Fazio, D.M., & Cajueiro, D.O. (2012). "The relationship between banking market competition and risk-taking: Do size and capitalization matter?". *Journal of Banking & Finance 36*, 3366–3381.

Yellen, Y.L. (2015). "Supervision and Regulation", *Testimony by Ms Janet L Yellen, Chair of the Board of Governors of the Federal Reserve System, before the Committee on Financial Services*, US House of Representatives, Washington DC, 4 November 2015.