Liquidity Auctions, Fixed Rate Tenders, Bailouts & Systemic Risk in the EURO Zone *

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[PRELIMINARY DRAFT]

Abstract

At the end of September 2008, following the bankruptcy of Lehman Brothers, the European Central Bank (ECB) abandoned its usual procedure of allocating short-term funds using an auction and implemented a full-allottment procedure. We show that the data from auctions preceding this change can be used to gain insights about the health of the individual banks and their future recourse to ECB-provided lending. Based on an equilibrium model of bidding, we estimate individual banks' willingness-to-pay for loans, which we link to their cost of funding. We find that banks whose willingness-to-pay for short-term funds kept increasing through the months of 2008 benefited more from the switch: they were allocated relatively more liquidity and at a relatively cheaper rate than before. We also find that the dynamics of the willingness-to-pay during 2008 are correlated with changes in several balance sheet variables, such as write-offs, in the expected direction. Using data on targeted bailouts, we show that banks whose willingness-to-pay increased substantially already in 2007 are much more likely to receive a bailout than those whose willingness-to-pay did not increase or started increasing later as the situation on the financial markets deteriorated further. Using our estimates of cost of funding we propose a new measure of systemic risk based on the propagation of a shock to one bank's cost through the system. We find that the recent bailouts were targeted mostly at the most vulnerable banks according to our measures.

Keywords: multiunit auctions, full allotment, primary market, structural estimation, bailouts, liquidity crisis

JEL Classification: D44, E58, G01

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1 Introduction

The bankruptcy of Lehman Brothers in September 2008 disturbed the already nervous financial markets and led to drops in equity markets and increased uncertainty that had not been experienced in a long time. The reaction of central bankers to the worsening conditions was to inject liquidity into the markets to alleviate the pressure. In the Euro Zone, the European Central Bank (ECB) abandonded its long-lived policy of holding a weekly discriminatory auction, at which banks could bid for liquidity - and instead offered a fixed price. At the posted rate, any bank could obtain a secured loan of its favorite amount. In this paper we examine the behavior exhibited by banks in the period before the Lehman collapse and immediately thereafter and we show that several regularities of the data coming from after the collapse can be predicted based on the earlier data already. We further collect data on actual bailouts of individual banks to this date and provide evidence that the likelihood of a bailout is correlated with our measures of a bank's desperation for liquidity, which is based on a transformation of bids in the ECB's repo auctions. Since we view these results as establishing the validity of using our measures to address the risk level of individual banks, we use our estimates to futher investigate aggregate risk factors and potential systemic risk.

In our previous work (Cassola, Hortaçsu & Kastl forthcoming) we looked at the evolution of banks' behavior during the onset of the financial crisis: from January to December 2007. We argued that the bidding data from the main refinancing operations of the ECB may provide a high-frequency source of information about the financial distress of individual banks when this data is interpreted via a model. We documented a substantial increase in the heterogeneity of the cost of funding among banks. We further argued that interpreting the data through a model is important, since changes in the bidding behavior itself involve also strategic adjustment to the changes in other bidders' behavior (strategies), which in case of a financial turmoil may be quite important. In other words, a bank i may be bidding higher not because its underlying willingness-to-pay increased, for example due to unfavorable development of other banks' perceptions of i's default risk, but because other banks increased their bids and i thus also increased its bid so as to optimally resolve the trade-off between the surplus on the marginal amount of the loan and the probability of winning this marginal amount. We showed that the estimates of the changes in banks' willingness-to-pay coming from the model are consistent with the ex-post observed changes in the usual accounting measures of banks' performance such as cost-to-income ratio or return on equity.

In this paper, we focus on the ECB's change of the liquidity-allocating mechanism. We use this event as an opportunity to test other means of classifying financial health of individual banks, which we view as complementary. In particular, we maintain the intuitive assumption that less financially sound banks have worse position on the interbank market and hence, if they can access funds there at all, they have to pay higher rates. Therefore, other things equal, they would be more likely to ask for larger loans from the central bank relative to their previous demand. We show that classifying bidders based on the differential dynamics of their willingness-to-pay during the months preceding the Lehman collapse does a good job predicting which banks will demand more in fixed rate tenders. More importantly, however, we show that when we look for banks whose reliance on the ECB funding (as measured by the total loans obtained) substantially increased after the switch to the full allotment tenders and whose willingness-to-pay significantly increased during the months preceding the Lehman collapse, we identify a small subset of banks (about a dozen) many of which are currently in severe difficulties, or they previously have been – until a merger or a bailout. We also show that the likelihood of needing some kind of government intervention during the early wave of bailouts following the 2007 financial crisis (in late 2007 and before September 2008) is correlated with the dynamics in the willingness-to-pay for liquidity in the primary market during 2007. We therefore believe that our results provide further support for central banks to use the high-frequency data from liquidity auctions together with economic models of bidding to aid the policy-makers make informed decisions about monetary policy, bailouts or bank regulation.

The remainder of the paper proceeds as follows. In section 2 we provide details on the several data sets that we merge together. We continue in section 3 with the description of the model used to link the bids to the willingness-to-pay. In section 4 we discuss the results of our analysis and we conclude in section 5.

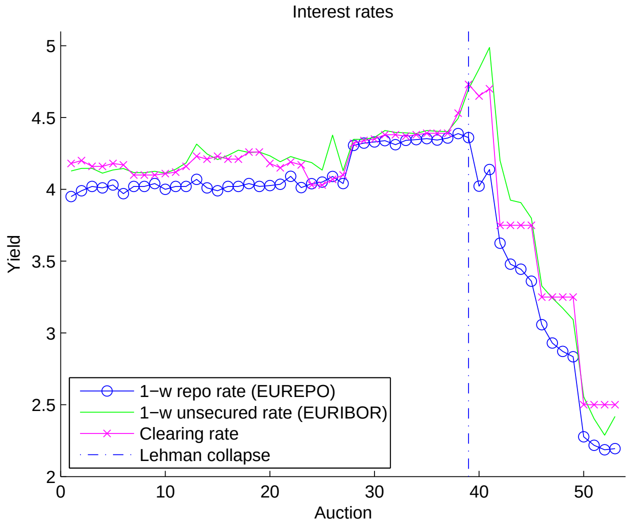


Figure 1: Interest Rates during 2008

2 Data

Figure 1 depicts the evolution of the secured and unsecured interest rates during the period of our study. It shows that the financial markets were experiencing fairly quiet times during summer 2008 until mid September, when Lehman Brothers declared bankruptcy. Subsequently, central banks reacted by lowering the key interest rates and substantially adjusting the monetary policy. In case of the ECB, the main refinancing operations were conducted as discriminatory auctions until early October 2008 and as full allottment (or a fixed price mechanism) thereafter. Our main data set consists of all bids in the main refinancing operations and long term refinancing operations of the ECB during 2008. In total there were 41 auctions in the MROs and 19 auctions in the LTROs before the switch to the full allottment took place in mid-October. This switch was a direct consequence of the turmoil in the financial markets that culminated in the collapse of Lehman Brothers. The last standard discriminatory auction took place in the MROs on 10/7/2008, and on 10/8/2008 in the LTROs. The data from the MRO auctions is summarized in Table 1. There are several evident trends. In the period post May 2008, there were many more participants in the MRO auctions than before (414 verus 284), which may be suggestive of banks experienceing increasing difficulties in securing funding in the secondary market. The larger average number of steps may suggest that the uncertainty about where the auction would clear increased. The bids, however, changed on average rather little – the mean spread over the reference interest rate, EONIA, stayed around 15 basis points. We also obtained data on banks' demands (and allocations) in 12 fixed rate tenders that were offered by the ECB following the collapse of Lehman Borthers. Initially, the offered rate was set at 3.75, and further reduced to 3.25 and finally in late 2008 to 2.5. Notice that the total amount loaned in the fixed rate tenders was about 50

Apart from observing the bidding behavior and quantity demanded at fixed rate tenders, we also obtained data on banks' usage of the standing facilities of the ECB during 2008. The first is the marginal lending facility, at which a bank can obtain a loan against collateral at a fixed rate. This rate was set at 100 basis points above the policy rate (the minimum bid rate set in the auctions). The counterpart of the marginal lending facility is the deposit facility, at which any bank can deposit its extra cash at a fixed rate, which is 100 basis points below the policy rate. After the collapse of Lehman Brothers, these premia were reduced to 50 basis points. This data is summarized in figure 3 with the left y-axis corresponding to loans and the right y-axis to deposits. Before the switch to fixed rate tenders, banks used the marginal lending facility 136 times with an average loan (conditional on taking a loan) of $1,328$ million euros. After the switch, banks turned to the facility 295 times asking for an average loan of $1,249$ million euros. Before the switch there were 418 deposits, with the mean deposit of $1,285$ million euros. After the switch, there were $5,194$ deposits, with the mean being $2,207$ million - almost double of the earlier average amount! During the three weeks following the collapse of Lehman Brothers, but before the switch to the fixed rate tenders, there were 69 loans from the marginal lending facility, with an average amount of $2,195$ million euro - over 5 times the average amount before that (435 million). Similarly, an average deposit (conditional on depositing a positive amount) before Lehman collapse amounted to 706 million, while it doubled during the two weeks following the Lehman collapse to 1458 million, and increased even more after the switch to the full allotment to $2,208$ million as mentioned above.

To obtain information on balance sheets of individual banks we also linked our data with Bankscope. We successfully linked the data for 390 European banks. We used these data to obtain information on 40 balance sheet variables, which we list in the appendix. We use data from 2005-

Table 1: Data Summary: Before and After May 2008

Summary Statistics				
	Mean		Std Dev	
	Before	After	Before	After
Bidders	284.2	414	28.92	58.46
Submitted steps	2.10	2.66	1.44	1.98
Price bid	4.18	4.37	0.07	0.21
Price bid spread[a]	0.17	0.15	0.07	0.22
Quantity bid[b]	0.005	0.003	0.01	0.01
Issued Amount (billion €)	173.94	147.48	2.49	2.60

[a] Spread against EONIA rate.
[b] Bid expressed as a fraction of the issued amount.

Table 2: Data Summary: Fixed Rate Tenders

Summary Statistics of Fixed Rate Tenders			
	Mean	Median	Std Dev
Allocated amount per bank	391.5	398.6	68.95
Allocated amount per bank (fraction of total amount)	0.001	0.001	0.0002
SD of allocated amount (within auction)	1,337.5	1,452.4	275.3
Rate	3.17	3.25	0.54
Participants	747.1	769.5	86.24
Issued Amount (billion €)	290.8	311.2	52.0

2010. We believe that the variables we selected should be representative of the balance sheets of the individual banks.

We also use reports of European Commission on government interventions in individual banks (EC 2011). For 629 banks that appear in our data from liquidity auctions from 2007 and 2008, we identified 20 banks that received targeted government support at least once. Table 3 shows that 50% of these banks in fact received help in multiple rounds. The most notorious recepients of government funds were the Anglo Irish Bank Corporation, which was eventually nationalized, and the IKB Deutsche Industriebank, which after a generous government injection was almost fully privatized in August 2008. From the other 18 banks, 1 more is from Ireland, 8 are German, 2 are from Austria, Belgium and Netherlands, and 1 bank comes from France, Greece and Slovenia. The bailouts can be categorized into several waves. The first wave, which included 5 bailouts, occured before the collapse of Lehman Brothers between February 2008 and September 2008. After the

Table 3: Data Summary: Bailouts

Summary Statistics of Bailouts		
# of Bailouts	# of Banks	Average Size (in mil €)
0	609	
1	10	3,327
2	7	18,397
3	1	4,425
4	1	5,825
5	0	
6	1	7,359

subsequent change of the ECB's liquidity providing mechanism from auctions to fixed rate tenders the second wave followed with 14 bailouts before May 2009. Later, there were additional 17 bailouts before July 2011.

We now move on to discuss the model we use to interpret these data.

3 Model

Our modeling will focus on two aspects. First, we use an equilibrium model of bidding in a discriminatory auction to link the bids in the liquidity auctions to the implied willingness-to-pay for repo loans. As we described in Cassola et al. (forthcoming) this measure provides us with information on prices (interest rates) that a given bank would have to pay to secure liquidity from other sources on the interbank market. Since there likely are various important factors, which affect the evolution of banks' willingness-to-pay for liquidity from week to week and which are unobserved to the econometrician, we will use an estimation method, which uses data only from one auction at a time.

Since we are also interested in providing predictions on the behavior and state of financial sector as a whole, we will also use a model to address the issue of the systemic and aggregate risk. In particular, using the estimated willingness-to-pay from the first part, our goal is to recover the unobserved aggregate risk factors. Our data allows us to idetify these by making use of the correlation patterns across banks. Finally, we attempt to link these factors to common ownership across banks, geographical location and common evolution of various balance sheet items.

3.1 Link between the willingness to pay for liquidity and the cost of funding

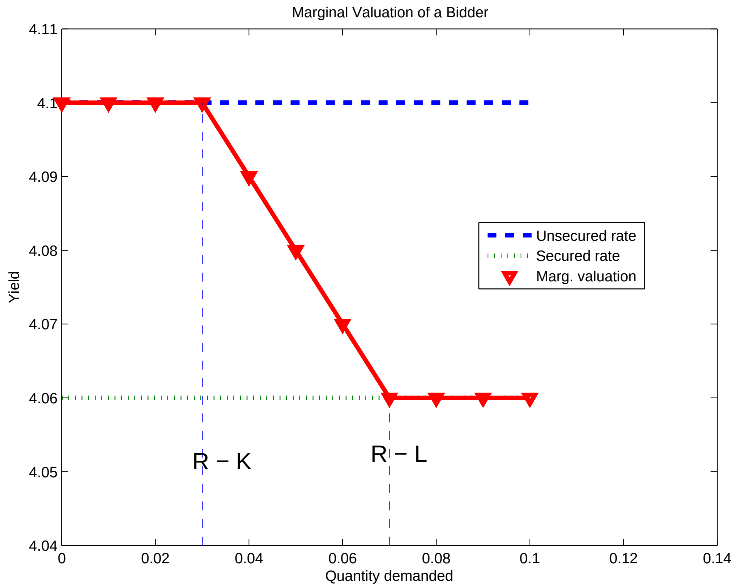
Since the main goal of this article is not to provide tools and methodology for estimating this type of models, we refer the reader to our earlier work for more detailed discussion and analysis. The discriminatory auction version of Wilson's model with private values has been studied in Hortaçsu & McAdams (2010) in the context of Turkish treasury bill auctions. Kastl (2011) and Kastl (2012) extend this model to an empirically relevant setting, in which bidders are restricted to use step functions with limited number of steps as their bidding strategies. The estimation of this extended model (which is also utilized in this paper) and the relevant asymptotic behavior of the resulting estimates are described in detail in Hortaçsu & Kastl (2012). Our main model of a discriminatory auction is based on the classic Wilson's (1979) paper on share auctions. There is a unit perfectly divisible good to be sold and bidders submit bids for shares of this good. We do not want to view bidders' values as coming from a vacuum, however. As in Cassola et al. (forthcoming) we link the marginal values to the secondary market secured and unsecured interest rates as follows. Suppose bank i has a liquidity need (possibly due to a reserve requirement, to improve its balance sheet, or to close a funding gap) of R_i. This must be fulfilled through three alternative channels: 1) ECB primary auctions, 2) unsecured interbank lending, which is done through over-the-counter deals, or 3) secured interbank lending, which is also done over-the-counter. W assume that these methods are substitutes, but access to them is limited based on collateral availability. In particular, bank i has L_i units of "liquid", high-quality collateral acceptable by secured interbank lending counterparties at a zero "haircut" rate. The bank also has $K_i - L_i$ units of securities that are acceptable by the ECB and perhaps by other counterparties as collateral, but are subject to haircuts. The haircuts applied to this set of securities effectively increase the interest rate at which the bank can borrow against these securities; these rates are bounded below by the "secured" interbank lending rate, s_i, that the bank faces (which assumes the use of highest quality, i.e. zero haircut collateral), and bounded above by the "unsecured" interbank lending rate, u_i, which requires no collateral. The marginal value for obtaining liquidity in the auctions run by the ECB can therefore be represented as in Figure 2, where we assume the bank's total collateralized borrowing capacity, K_i, to be less than its liquidity need R_i. The bank's willingness-to-pay for the first $R_i - K_i$ euros of funding, thus, is equal to its unsecured funding rate, u_i. Between the $R_i - K_i$ and $R_i - L_i$, the bank faces different haircut rates depending on its portfolio of securities it can post as collateral. The last L_i euros of funding can be obtained from the "secured" interbank market, thus the bank's willingness-to-pay for these units is s_i. Notice that for banks that submit fairly rich bid curves (i.e., with multiple steps), the above reasoning would allow us to obtain a bank-specific unsecured versus secured spread, $u_i - s_i$. Assuming collateral is liquid, this spread should contain the rival bank's perceptions of bank i's default risk.

To recover the willingness-to-pay from the bids submitted in the discriminatory auctions we assume that banks play a Bayesian Nash Equilibrium which we will describe below. We assume that banks willingness-to-pay is private and conditionally independent, i.e., that we are in an environment with conditionally independent private values. This means that conditional on all public information available before a given auction, each bank's willingness-to-pay is a function only of its own information and is independent of any rivals' information. While both independence and private values are clearly restrictive assumptions, we showed in our previous work and will further show here that the estimates produced by such model pass several ex-post tests. We therefore view these estimates as a useful source of information about the situation of individual banks during the crisis. As an example of the ex-post tests that we have in mind here, our estimates of the changes in a bank's willingness-to-pay are correlated with changes in several accounting measures of performance between 2006 and 2007, i.e., at the onset of the financial crisis, such as return on equity or cost-to-income ratio. Our goal here is to focus on the time period when the crisis is already under way and use these new estimates to provide predictions about recourse to fixed rate tenders and future need for government intervention.

3.2 Equilibrium

We now move on to formally describe our model of a discriminatory auction, which we will use to find marginal values that would rationalize the observed bids. We assume that there are N (potential) bidders, where N is commonly known. Q denotes the amount of liquidity offered for sale by the central bank, i.e., the good to be divided between the bidders, and we assume Q is

Figure 2: Marginal Value for Liquidity in ECB Auctions



perfectly divisible. Q is itself a random variable since the ECB augments the supply based on current situation after the bids have been submitted. We assume that the distribution of Q is common knowledge among the bidders. Each bidder receives a private (possibly multidimensional) signal, θ_i, which is the only private information about the underlying value of the auctioned goods. The joint distribution of the signals will be denoted by $F(\theta_1, ..., \theta_N)$. As mentioned above, we assume (conditionally) independent private values (CIPV) paradigm.[1] In this case the θ_i's are distributed independently across bidders, and bidders' values do not depend on private information of other bidders, i.e., the marginal valuation function has the form $v_i(q, \theta_i)$.

Assumption 1 *Bidder i's signal* θ_i *is drawn from a common support* $[0,1]^M$*, according to an atomless marginal d.f.* $F_i(\theta_i)$*.*

Assumption 2 $v_i(q, \theta_i)$ *is measurable and bounded, strictly increasing in (each component of)* θ_i $\forall q$ *and weakly decreasing in* q $\forall \theta_i$*.*

[1] Bindseil, Nyborg & Strebulaev (2009) provide some econometric evidence that private values might be appropriate in case of repo auctions.

$V_i(q,\theta_i)$ denotes the gross utility: $V_i(q,\theta_i) = \int_0^q v_i(u,\theta_i)\,du$. Bidders' pure strategies are mappings from private signals to bid functions: $\sigma_i : \Theta_i \to \mathcal{Y}$. Since in most divisible good auctions in practice, including the liquidity auctions of the ECB, the bidders' choice of bidding strategies is restricted to non-increasing step functions with an upper bound on the number of steps, $K = 10$, we impose the following assumption:

Assumption 3 *Each player $i = 1, ..., N$ has an action set:*

$$A_i = \left\{ \begin{array}{c} \left(\vec{b}, \vec{q}, K_i\right) : \dim\left(\vec{b}\right) = \dim\left(\vec{q}\right) = K_i \in \{0, ..., 10\}, \\ b_{ik} \in B = [0,\infty),\ q_{ik} \in [0,Q],\ b_{ik} > b_{ik+1}, q_{ik} < q_{ik+1} \end{array} \right\}$$

Therefore the set $\mathcal{Y}$ includes all non-decreasing step functions with at most 10 steps, $y : \mathbb{R}_+ \to [0,Q]$, where $y_i(p) = \sum_{k=1}^{K} q_{ik} I\left(p \in (b_{ik+1}, b_{ik}]\right)$ where I is an indicator function. A bid function for type θ_i specifies for each price p, how big a share $y_i(p|\theta_i)$ of the securities offered in the auction (type θ_i of) bidder i demands.

Finally, since bidders use step functions, a situation may arise in which multiple prices would clear the market. If that is the case, we assume consistently with our application that the auctioneer selects the most favorable price from his perspective, i.e., the highest price. In case of excess demand at the market clearing price, we assume consistently with our application that demands are rationed pro-rata on-the-margin.

The natural solution concept in this framework with private information is the Bayesian Nash Equilibrium. The expected utility of type θ_i of bidder i who employs a strategy $y_i(\cdot|\theta_i)$ in a discriminatory auction given that other bidders are using $\{y_j(\cdot|\cdot)\}_{j \neq i}$ can be written as:

$$EU_i(\theta_i) = E_{Q,\theta_{-i}|\theta_i} \left[\begin{array}{c} \int_0^{q_i^c(Q,\theta,\mathbf{y}(\cdot|\theta))} v_i(u,\theta_i)\,du \\ -\sum_{k=1}^{K} \mathbf{1}\left(q_i^c(Q,\theta,\mathbf{y}(\cdot|\theta)) > q_k\right)(q_k - q_{k-1})\, b_k \\ -\sum_{k=1}^{K} \mathbf{1}\left(q_k \geq q_i^c(Q,\theta,\mathbf{y}(\cdot|\theta)) > q_{k-1}\right)\left(q_i^c(Q,\theta,\mathbf{y}(\cdot|\theta)) - q_{k-1}\right) b_k \end{array} \right] \quad (1)$$

where $q_i^c(Q,\theta,\mathbf{y}(\cdot|\theta))$ is the (market clearing) quantity bidder i obtains if the state (bidders' private information and the supply quantity) is (θ, Q) and bidders bid according to strategies specified in the vector $\mathbf{y}(\cdot|\theta) = [y_1(\cdot|\theta_1), ..., y_N(\cdot|\theta_N)]$, and similarly $P^c(Q,\mathbf{s},\mathbf{y}(\cdot|\theta))$ will denote the market clearing price associated with state (θ, Q), which turns out to be the random variable that is most crucial to the analysis. The first term in (1) is the gross utility the type θ_i enjoys from his allocation, the second term is the total payment for all units allocated at steps at which the type θ_i was not rationed and the final term is the payment for units allocated during rationing. A Bayesian Nash Equilibrium in this setting is thus a collection of functions such that almost every type θ_i of bidder i is choosing his bid function so as to maximize his expected utility: $y_i(\cdot|\theta_i) \in \arg\max EU_i(\theta_i)$ for a.e. θ_i and all bidders i. Part (i) of the following proposition proved in Kastl (2012) provides necessary conditions characterizing the equilibrium in discriminatory auctions with private values when marginal valuation function is continuous in q. Since continuity of the marginal valuation function might be questionable at the last step (in particular for bidders who submit just one step), we make use of the necessary conditions for optimality with respect to the bid (part (ii)).

Proposition 1 *Under assumptions 1-3 in any Bayesian Nash Equilibrium of a Discriminatory Auction, for almost all θ_i, with a bidder of type θ_i submitting $K_i(\theta_i) \leq 10$ steps, every step k in the equilibrium bid function $y_i(\cdot|\theta_i)$ has to satisfy:*
(i) $\forall k < K_i(\theta_i)$ such that $v(q, \theta_i)$ is continuous in a neighborhood of q_k for a.e. θ_i:

$$v(q_k, \theta_i) = b_k + \frac{\Pr(b_{k+1} \geq P^c)}{\Pr(b_k > P^c > b_{k+1})}(b_k - b_{k+1}) \tag{2}$$

and at $K_i(\theta_i)$:

$$b_K = v(\overline{q}, \theta_i)$$

where $\overline{q} = \sup_{(Q,\theta_{-i})} q_i^c(Q, \theta, \mathbf{y}(\cdot|\theta))$, i.e., the largest quantity allocated to bidder i in equilibrium.
(ii) $\forall k \leq K_i(\theta_i)$ such that $v(q, \theta_i)$ is a step function in q at step k such that $v(q, \theta_i) = v_k$ $\forall q \in (q_{k-1}, q_k]$ for a.e. θ_i and signals are independently distributed:

$$v_k = b_k + \frac{\Pr(b_k > P^c)}{\frac{\partial \Pr(b_k > P^c)}{\partial b_k}} \tag{3}$$

In practice, we use equation (2) to identify the marginal values at all but last step, and we use equation (3) at the last step.[2] Note that as $K \to \infty$, (2) and (3) coincide in the limit.[3]Kastl (2012) further proves that there exists an equilibrium of a discriminatory auction in distributional strategies in this constrained game when signals are not too dependent.

Equation (2) provides us with the link between the observable data (bids) and the variables of interest: banks' willingness-to-pay. This inversion of bids is a common approach in the empirical auction literature at least since Guerre, Perrigne & Vuong (2000). In order to invert bids using equation (2) we need to estimate the distribution of the market clearing price, P^c, which is bidder-specific, because it depends on the submitted bid.

To do that we employ the resampling method introduced in Hortaçsu & McAdams (2010) and further developed in Kastl (2011) and Hortaçsu & Kastl (2012). In order to perform this step we impose the assumption of (within group) independence and ex-ante (within group) symmetry among banks, where we allow two groups of banks: the ones who our indicators designate as experiencing significant changes in the statistic of interest (such as in the mean willingness-to-pay) and those that do not. One of our goals in this paper is to investigate whether defining the two groups based on different statistic will yield to robust classification. The resampling procedure allows us to simulate the distribution of market clearing price using bids submitted only within one particular auction. By repeatedly drawing with replacement $N - 1$ bids from the observed sample, we can simulate a state of the world, a particular realization of the residual supply, which interestected with the submitted bid delivers a particular realization of the market clearing price. Repeating the procedure yields an empirical distribution of the market clearing prices and thus allows us to evaluate the probabilities in equation (2). In Cassola et al. (forthcoming) we showed that with uncertainty about the available supply our estimator is consistent as the number of bidders within an auction goes to infinity.

We use this method to estimate the willingness-to-pay of each bank that participates in a given auction. Since most banks participate quite frequently (and the major one participate virtually always), we thus obtain a time series of willingness-to-pay for every bank, which rationalizes its

[2]Using (3) at all steps leads to qualitatively very similar results, but the estimates turn out to be less precise due to the necessity to numerically estimate the derivative of the distribution of the market clearing price.

[3]The formal argument is in Kastl (2012).

bids in the MRO auctions. We project this data onto various sets of covariates related to riskiness of individual banks.

3.3 Aggregate and Systemic Risk

An important question when studying the financial system involves how to quantify the systemic risk, i.e., risk that a failure of a financial institution would translate into difficulties for the whole financial system. Brunnermeier & Oehmke (2013) and Haubrich & Lo (2013) provide an overview of the recent approaches to measuring systemic risk. Acharya, Pedersen, Philippon & Richardson (2010) provide a simple theoretical framework, in which they propose to measure the systemic risk by an institution's marginal contribution to the shortfall of capital in the financial system that can be expected in a crisis. Their analysis focuses on cross-sectional differences. Brownlees & Engle (2010) instead propose to measure the systemic risk by the expected shortage of capital of an institution given its degree of leverage. Duffie (forthcoming) proposes a method based on asking largest banks about how they would be impacted under various potential scenarios. Farhi & Tirole (2012) provide a simple model of the financial system, where the correlated liquidity shocks may (optimally) result in systemic bailouts. Due to strategic complementarities all banks prefer to engage in maturity mismatch behavior rather than to be the only one to not play along, which in turn results in government bailout when a crisis arises. Adrian & Brunnermeier (2011), in a paper that is the closest to ours, propose a way how to empirically assess the degree of systemic risk associated with a bank, which relies on marginal contribution of each bank to the "value at risk" conditional on that bank being under distress relative to its median state.[4] Yet another alternative could be based on a model of financial contagion as in Aït-Sahalia, Cacho-Diaz & Laeven (2011). Here we will propose an alternative approach to quantification of aggregate risk and also a new way how to measure the systemic risk. Our approach is based on the dynamics of the willingness-to-pay. In particular, we are interested in recovering the correlation patterns both within the cross-section and over time. The intuition for our approach is the following: Suppose bank i poses a greater risk for the financial system than bank j, but both are important large banks. Further suppose that bank i suffers an adverse shock to its balance sheet in period t, which translates into higher

[4] Schwarcz (2011) offers an interesting perspective on systemic risk and its measurement from the point of the law.

cost of funding on the interbank market. This in turn implies an increase in the willingness-to-pay for liquidity obtained in the main refinancing operations from the ECB for bank i. Suppose a similar scenario occurs with bank j, but in period t'. Since i's contribution to systemic is higher by assumption, we should expect other banks' willingness-to-pay for liquidity in the MROs to increase shortly after the adverse shock to i's balance sheet. It should increase more than following the shock to j's balance sheet. Obviously, an important caveat is that for banks that have healthy balance sheets and rely mostly on loans secured by high quality collateral, the willingness-to-pay for liquidity does not necessarily have to increase after such shocks. To address this caveat, we make use of the simple model of the composition of the willingness-to-pay as depicted in figure 2. In particular, for banks submitting multiple steps in an auction, which large banks typically do, our method allows us to obtain an estimate of the spread $u_i - s_i$. Our goal is therefore to identify banks whose significant changes in the quantity weighted willingness-to-pay and in the spread $u_i - s_i$ propagate further into the system. In other words, whether such changes are followed by similar changes in the spreads for other banks.

Ideally, we would like to use information on exposure of individual banks to risk associated with bank i. Unfortunately, such data is currently not available to us. Instead, we will use panel data techniques in order to try to infer these exposures from the joint correlation patterns in the funding costs. We first recover the network structure using the least absolute shrinkage operator (LASSO), which produces a sparse matrix of links between banks. Subsequently, using this network structure we employ various measures of importance in a network and panel data techniques to develop our measure of systemic risk.

4 Results

We begin our discussion of the main results by describing the situation on the European financial markets that led to the eventual departure from the auction mechanism in October 2008. The developments in the main liquidity markets following the collapse of Lehman Brothers are a classic example of full market shutdown. After discussing the switch to the fixed rate tenders, we will provide further evidence that our estimates of the funding costs (or willingness to pay) from the banks' bids in the liquidity auctions are informative about the health of the individual banks and we use these estimates to investigate which types of banks benefitted the most from the abandoning of the auction procedure. We also show that during the later part of the crisis, as one might expect, one could also use the increase in the reliance on the liquidity provided by the central bank as an indicator of financial difficulty of a particular institution. Finally, we will discuss our systemic risk measure.

4.1 Switch to Fixed Rate Tenders

Before the switch to fixed rate tenders in October 2008, banks had two possibilities to obtain liquidity from the ECB. Either use the marginal lending facility and pay a 100 basis points premium over the policy rate to obtain loan of any size (subject to having suitable collateral available) or participate in the discriminatory auction and bid weakly above the policy rate and potentially obtain a repo loan at a cheaper rate depending on the bids of its rivals. Figure 3 shows that banks seldomly used either the deposit facility or the marginal lending facility before the collapse of Lehman Brothers. Even during the late 2007, well into the crisis, the amount borrowed rarely exceeded 5 billion Euros and the amount deposited hovered around few billions. This picture changed dramatically, however, after the switch to full allotment: the amounts parked at the deposit facility fluctuated week-to-week peaking at over 300 billion Euros after Lehman's collapse and in the summers of 2009, 2010 and 2011. Why did the ECB switch to the full allotment mechanism and why has the ECB not returned to the discriminatory auctions since then?

Figure 7 depicts the aggregate bids in the auctions under the main refinancing operations that were held in 2008 prior to the switch to the full allotment mechanism. Each solid (blue) curve corresponds to one auction of 1-week repo loans prior to September 15th, 2008 - when Lehman filed for bankruptcy protection. The lowest line-dotted (red) curve corresponds to the aggregate bid on 9/23/2008 and it clearly shows that the market has become quite nervous, since the bids expressed as spreads over the overnight rate increased by about 10-20 basis points. The two highest curves correspond to the last two discriminatory auctions held on 9/30/2008 and 10/7/2008. The amount of funds auctioned on those dates substantially exceeded the amount that the ECB determined was

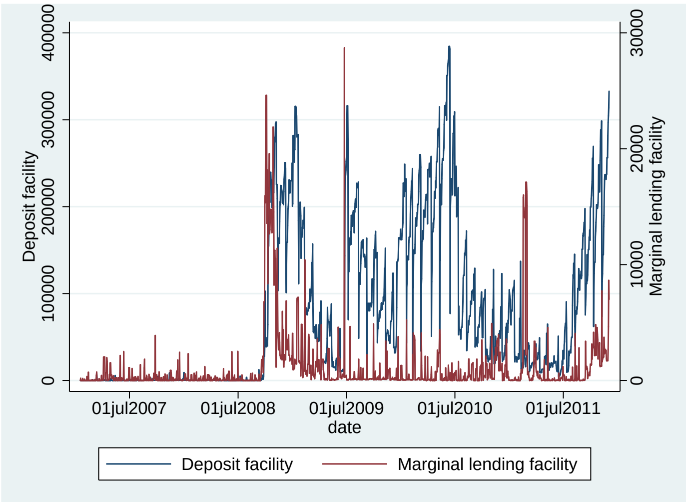


Figure 3: Usage of Deposit and Lending Facilities

necessary for every bank to be able to satisfy its reserve requirement, i.e., the benchmark amount that the ECB announces on the day of the auction and that, in the usual times, constitutes a very good proxy of the actual supply. In fact, on 9/30/2008, there was more liquidity on the market than needed even before the auction itself by about 40 billion Euro! Nevertheless, additional 190 billion Euro were allocated in the auction. Similarly, on 10/7 only about 40 billion Euro were needed in the market and yet 250 billion were auctioned. These amounts clearly signaled that banks were exceedingly nervous about being able to access sufficient liquidity. Moreover, the marginal rate (the market clearing price) in these auctions exceeded EONIA by close to 100 basis points! Since ECB's policy is to steer this overnight rate, these two auctions suggested that during that time period there was very little difference for banks between using the marginal lending facility (i.e., pay a posted price of the policy rate + 100 basis points) and participating in the auctions. It would thus seem that switching to fixed rate tenders might have been a prudent decision at that time. This conclusion may further be supported by it avoiding the so-called "stigma" that is associated with a bank's reliance on the marginal lending facility. The existence of such stigma is directly evidenced by that fact that in two auctions after the Lehman collapse bids were submitted that exceed the policy rate by more than 100 basis points. This is, however, the price at which loans can be obtained at the marginal lending facility and hence banks valued liquidity obtained from the MRO more than that obtained at the standing facility.

Switching to fixed rate tenders had a very different impact on different banks. For example, a bank that had financial difficulties before the switch would have faced higher borrowing rates in the interbank market and thus would have come to the auctions with a higher willingness-to-pay already. This in turn might suggest that such a bank would also bid more aggressively and hence its benefit (relative to some other financially sound institution) from switching to a posted price mechanism where the price is equal to the policy rate would be higher. To verify this assertion, we run two regressions. The dependent variable in the first is the difference in quantity-weighted average allotment rate in the fixed rate tenders and in the auctions. The regressor is the change in mean (within a bank, across auctions) quantity-weighted willingness-to-pay post- and pre- May.[5] For the second regression, the regressor is instead the change in the corresponding in mean bid. Column (1) and (2) of Table 4 indeed show that this correlation is significant and negative both for differences in marginal values and bids, respectively. Figure 4 shows this graphically. This suggests that banks that were bidding more aggressively (respectively, for which we estimated a higher willingness-to-pay) closer to the end of the sample also benefited the most from the switch: they paid a relatively lower rate than before. If bank i's willingness-to-pay increased by 100 basis points during 2008, i would have saved about 20 basis on its loans after the full allotment relative to its payment in an auction.

The relationship between savings resulting from fixed rate tenders and more aggressive bidding or relatively higher marginal values in the previous auctions is perhaps not surprising. The external validity test of the estimates produced by our model is, however, related to the changes in the allocated quantity. On average, Figure 5 shows that there is high persistence of reliance on ECB funding: the main regression line is close to the 45 degree line. It illustrates that this persistence holds across the board. Even when we condition on a banking group (defined more or less as a group of banks with common ownership structure), the size of the loan allocated in the MRO auctions is highly correlated with the loans obtained in the fixed rate tender. There are a few banking groups, however, that started obtaining significantly larger loans after the switch to fixed rate tenders than before. In particular, a bank that is experiencing tighter conditions in the secondary market should

[5]We chose May since it is the middle of our sample.

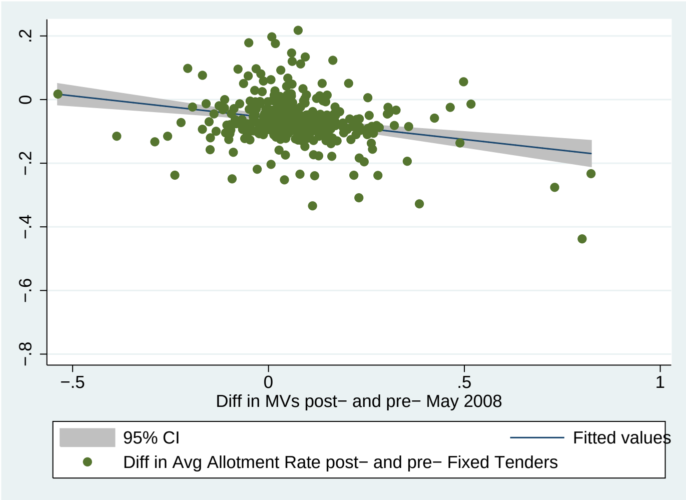


Figure 4: Regression of Δ Avg Rate Paid for a Repo Loan on Δ Marginal Values

also obtain relatively higher amount of loans once the cheap financing at the policy rate becomes available than a bank that has a relatively easier access to funds from other banks. Columns (3) and (4) of Table 4 show that the changes in average loan size between the auctions and fixed rate tenders are significantly correlated with the changes in the estimated willingness-to-pay (Column (3)), but not with the change in the bids (Column (4)).

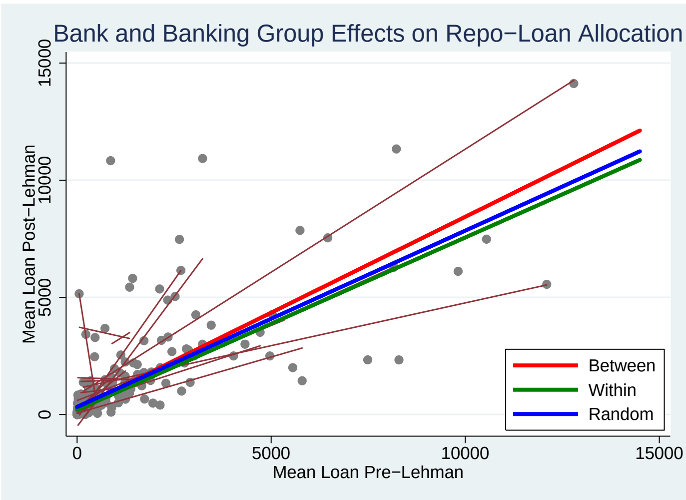


Figure 5: Size of repo loans from the ECB (in million €)

Figure 6 depicts the average fraction of the supply allocated to a winning bank, where we

Table 4: Changes in Willingness-to-Pay, Bids, Rates Paid and Allocations in Auctions and Fixed Rate Tenders

	Avg Rate Paid		Avg Allocated Amount	
	(1)	(2)	(3)	(4)
Willingness-to-Pay	-0.203**		636.2*	
	(0.08)		(332.4)	
Bids		-0.370***		492.7
		(0.09)		(387.8)
R^2	0.014	0.035	0.008	0.004
N	439	439	439	439

[a] Each column corresponds to a separate regression: $Diff\_Y_i = \alpha + \beta * Diff\_X_i + \varepsilon_i$, where both differences are always defined as the difference post-fixed rate mechanism - pre-fixed rate in the relevant variable.
[b] Standard errors in parentheses.
[c] *, ** , *** significant at 10%, 5% and 1%, respectively.

distinguish banks that exhibit a significant increase in their willingness-to-pay for liquidity. The number of banks in each group is kept constant, and hence the figure shows that the banks whose willingness-to-pay substantially increased during 2008 were also allocated a larger share in the primary market.

4.2 Cost of funding and EURIBOR quotes

In light of the recent lawsuits and settlements regarding the alleged manipulation of the LIBOR quotes, let us briefly glance at the relationship between the EURIBOR quotes and the estimated funding costs. Recall our model of the banks' willingness to pay described in section 3.1. If a bank's willingness-to-pay (or even the bid) exceeds EURIBOR, it means that that bank did not believe it could get an unsecured loan at that rate during that week. The quotes by bank A depicted in figure 4.2 are fairly consistent with this. The quotes are most of the time above the estimated cost of funding. They also are virtually always above the submitted bids. On the other hand, bank B's quotes depicted in figure 4.2 tell a different story. This bank's quotes are very often significantly below the estimated cost of funding and they are also often below its bids. It would seem at the very least possible that bank B was enganging in some kind of a non-sincere behavior.

Next, we use our estimates of willingness-to-pay to find a share of banks that are likely unable to obtain an unsecured loan at EURIBOR. Figure 10 plots this share (with the y-axis on the left)

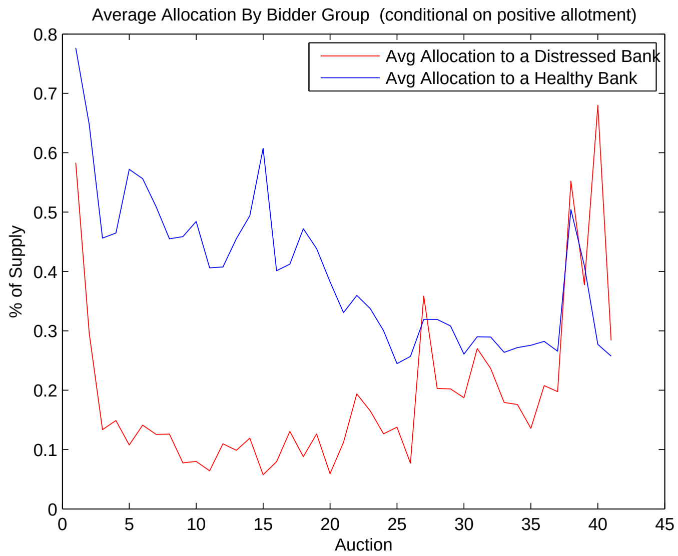


Figure 6: Average allocation

and also the unsecured rate (y-axis on the right). It clearly shows that there are large movements in this share, which suggests presence of systemic risk factors: not surprisingly, banks' financial situation tends to be correlated.

4.3 Banks' Balance Sheets and Changes in the Willingness-to-Pay

Before we go to our systemic risk measure, we re-examine whether our estimates (at a weekly frequency) are at all correlated with the balanace sheet variables one would expect it to be related to. We were able to match 390 bidders in our auction data set to the Bankscope database, which includes detailed data on banks' balance sheets. We used 30 variables, which we ex-ante deemed likely to be correlated with banks' willingness-to-pay.

Of the 30 balance sheet variables from Bankscope, 8 indeed exhibit a significant (at 10% level) correlation with our estimates of willingness-to-pay and also with bids. Since correlation among the chosen balance sheet variables might be an issue, we also conducted a joint hypothesis test of there being a significant correlation with at least one balance sheet variable. While it is clear from Table 5 that a simple Bonferroni correction would lead to a failure to reject that there is no correlation, we opted for a boostrapping procedure to conduct the joint hypothesis test. At every

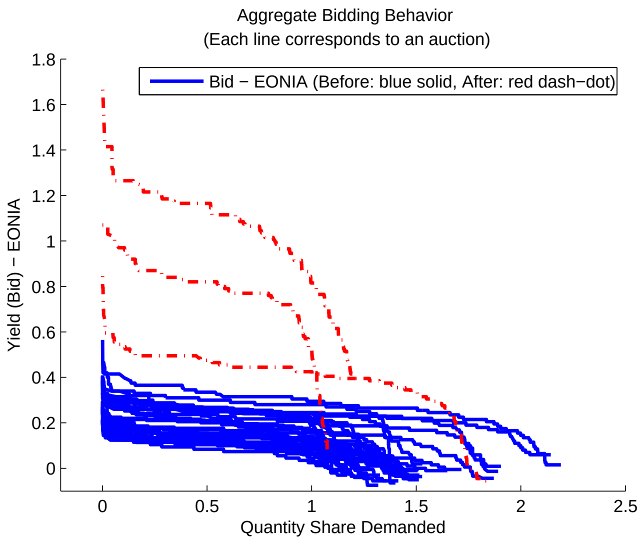


Figure 7: Aggregate Bids in 2008

bootstrap iteration, we took the first order statistic of the t-statistic of the coefficient of interest, β, from every regression and we tested whether the "most significant" one on the sample is different from zero based on the bootstrapped distribution. We easily rejected the null of no correlation at 5% level.

Table 5: Regressions of Differences in Balance Sheet Variables on Differences in Marginal Values

$Diff\_X_i$	β	S.E.	R^2	N
Deposits & Short Term Funding	-13,731.8	7,370.4*	0.01	363
Total Customer Deposits	-10,338.5	4,768.8**	0.01	362
Equity	-1,738.4	737.6**	0.02	363
Loan Loss Provisions	-289.3	148.4*	0.01	357
Due from Central Banks	-1,620.5	738.8**	0.02	316
Interest Income	-1,233.4	670.8*	0.01	363
Net Interest Margin	-0.42	0.17**	0.02	363
Write-Offs	13.12	7.01*	0.02	170

[a] Each line corresponds to a separate regression: $Diff\_X_i = \alpha + \beta * Diff\_MV_i + \varepsilon_i$, where $Diff\_X_i$ is always defined as the difference post-2007 - pre-2007 in the relevant variable

[b] *, ** significant at 10% and 5%, respectively

The significant correlates are: Deposits & Short Term Funding, Total Customer Deposits, Equity, Loan Loss Provisions, Due from Central Banks, Interest Income, Net Interest Margin, and

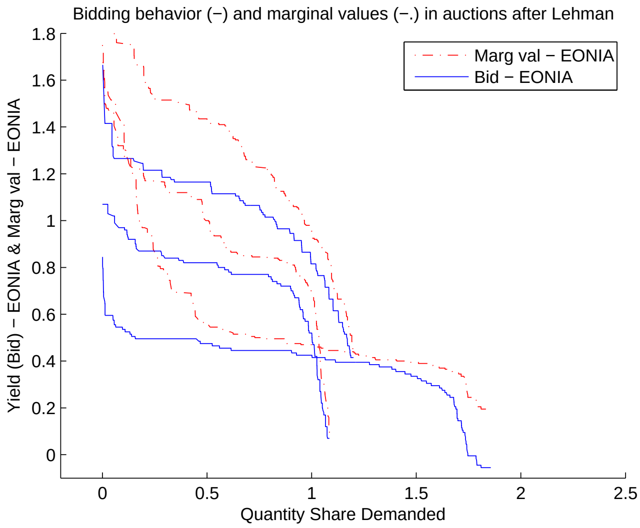


Figure 8: Aggregate Bids and Values Around Lehman Collapse

Write Offs. All these variables, except for write offs, are also significantly correlated with the changes in bids. In addition, Issued Loans and Demand Deposits are also significantly correlated with changes in bids, but not with the changes in marginal values. Table 5 summarizes least square regressions for those variables that are significantly correlated with the changes in marginal values. All coefficients have the expected signs: banks that experience the highest increase in the willingness-to-pay during 2008 at the same time experience the highest decrease in deposits, equity, reserves with central banks, interest income and highest increase in write-offs. Their net interest margin also decreases the most, suggesting that their funding costs likely increased the most.

Now we will examine the relative changes in banks' various balance sheet measures for two groups of banks. We classify banks by our preferred measure: the changes in the estimated willingness-to-pay. For each bank, we first compute the quantity-weighted willingness-to-pay in a given auction. This is necessary since banks may submit multiple steps in their bids and thus their estimated willingness-to-pay is a function of the size of the loan requested. For each bank, we then look whether the mean of its willingness-to-pay was increasing during 2008. We implement this procedure by regressing the time series of our estimates of a bank's willigness-to-pay on a dummy indicating the latter half of the sample. We flag those banks, for whom the difference in

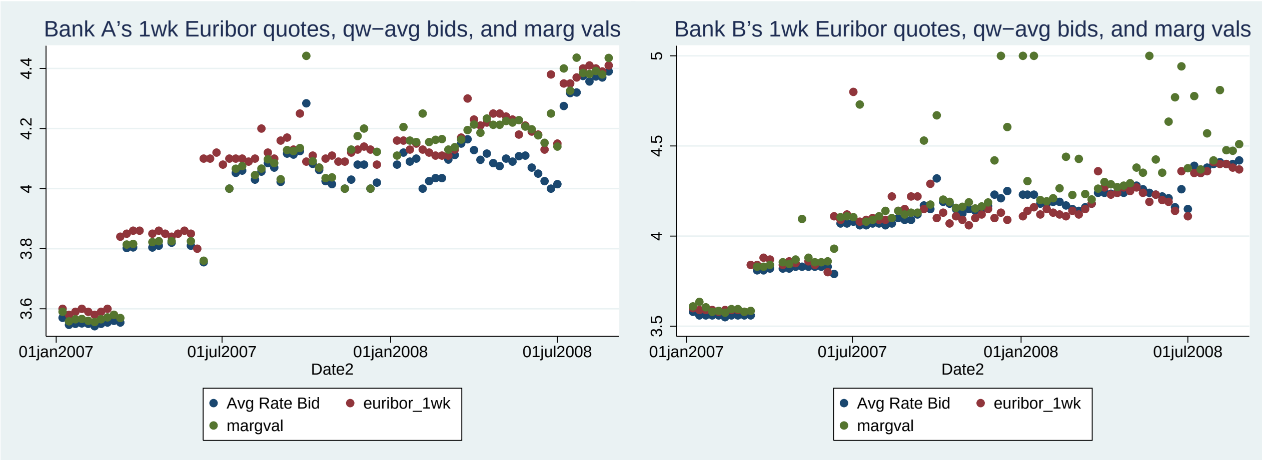


Figure 9: Bank A and B's EURIBOR quotes, Bids and Estimated Funding Costs

means is significant on 5% level. This procedure results in 82 out of the total of 588 banks that we observe bidding both in the first and in the second half of the sample (i.e., before and after May 2008) being flagged. For each bank in our sample we also construct the change in various balance sheet measures between 2009 and 2007. Finally, we run a t-test to compare means of these changes across the two groups of banks: the ones that were flagged by our procedure and the other ones that were not. It is reassuring that for those variables, for which there is a significant difference between the means across the two groups, this difference is of the expected sign.

First, let us consider the Tier 1 ratio, which is a ratio of a bank's equity capital to its total risk-weighted assets (i.e., the higher this ratio the more financially sound a bank should be). While the Tier 1 ratio improves virtually for all banks in our sample (the mean Tier 1 in 2007 is 8.84 and in 2009 it is 10.52), it improves significantly less on average for the flagged banks (1.11 versus 1.78). The same story holds for Total Capital Ratio (1.09 versus 1.64). Similarly, while the Cost-to-Income ratio improves slightly on average between 2007 and 2009 (from 57.09 to 56.84), it actually worsens for the flagged banks (increases by 3.90 while the banks that are not flagged improve by -3.03). Among other variables that exhibit significant differences across the two groups are Long-Term Funding (deteriorates much more for the flagged group between 2007 and 2009), Loan-Loss-Reserves, which worsen for the flagged group, but improve for the others, Off-Balance-Sheet Items, which increase by $1,793$ million for the flagged group while they decrease by 2213 for the others, Net

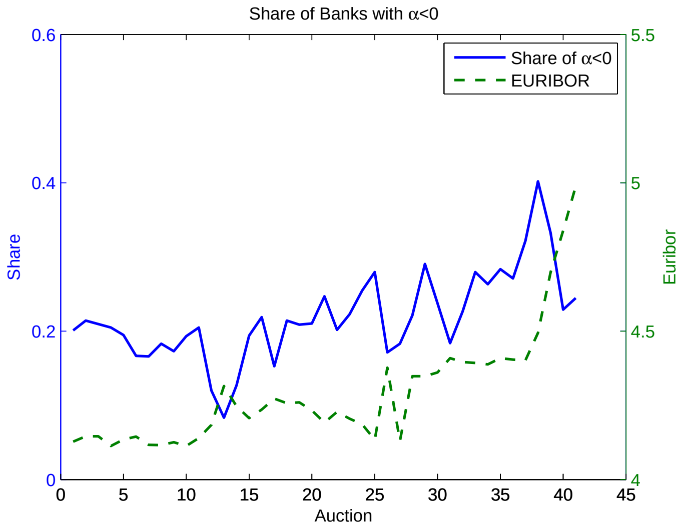


Figure 10: Share of Banks unable to borrow at EURIBOR

Gains on Trading and Derivatives decline for everybody, but much more so for the flagged group (-123 versus -8 million). The flagged banks also decreased their issuance of mortgages (-785) while the other group increased the mortgage loans by 1370 on average. The amount due from central banks (i.e., the reserves and deposits parked with the central banks) increased substantially for the flagged banks (by 276.8) compared to the decrease among the other banks of -24 on average. On a more comforting note, the flagged banks increased their positions in government securities significantly more than the other banks (1635 versus 417). Net Interest Margin worsened for the flagged banks (-0.006) while it improved for the others (0.13). The difference in the change in Profit-Before-Tax is significant only at 12% level, but the difference amounts to 100% (-443 versus -212). Overall, out of the 30 variables considered, there is a significant difference in 8 of those across the two groups and the sign of this difference is as expected. We view this as evidence in favor of our cost of funding estimates (and the changes thereof) containing information about the financial situation of individual banks.

Table 6: Bailout Logit Regression (1^{st} Wave)

	Bailout Aug 07-Sep 08		
Δ Willingness-to-Pay post-pre Aug 2007	6.72**		7.37*
	(3.33)		(3.92)
Δ Bids post-pre Aug 2007	-19.39		-26.43
	(14.96)		(16.74)
Δ Willingness-to-Pay post-pre May 2008		-3.24	-4.41
		(4.85)	(5.85)
Δ Bids post-pre May 2008		2.33	2.53
		(8.70)	(9.99)
Constant	-4.00***	-4.44***	-3.12**
	(1.16)	(0.54)	(1.22)
Mean of Dependent variable	0.01	0.01	0.01
pseudo-R^2	0.08	0.01	0.10
N	384	369	297

[a] Standard errors in parentheses.
[b] *, ** , *** significant at 10%, 5% and 1%, respectively.

4.4 Predicting Bailouts

Finally, to provide further evidence on informational content of our estimates of willingness-to-pay for liquidity we estimated a logit model of probability of a bank receiving bailout in various waves as a function of the changes in the willingness-to-pay. These bailouts can be split roughly into three waves. The first wave includes 6 bailouts that occured before Lehman Brothers declared bankruptcy. Therefore, we would expect that these banks suffered an adverse shock earlier than 2008 already. We use the estimates of willingness-to-pay from 2007 from Cassola et al. (forthcoming) to try to capture this. The second wave includes bailouts that occured before May of 2009, i.e., through the trough of the equity markets in March 2009. And the third wave includes the bailouts until the end of 2011.

Table 6 reports the results of logit regressions for the first wave of bailouts. The results clearly show that the dynamics of willingness-to-pay for liquidity during 2007 captured by the difference in the mean WTP before and after August 2007 is significantly correlated with the likelihood of a bank needing a bail out, but the straightforwardly obtained dynamics of the bids is not. Perhaps more importantly, bailouts that came later, i.e., in the second half of 2008 or later, are no longer significantly related to the changes in the willingness-to-pay during 2007. Unfortunately, we did not obtain a similar significant relationship between changes in the willingness-to-pay for liquidity during 2008 and later bailouts. This could potentially be simply due to the data from 2008 not including any such clear break as the outbreak of the subprime market crisis in August 2007 and therefore the difference in mean willingness-to-pay or bids has to be constructed more or less arbitrarily.[6] Changes in bids in the first and second half of 2008 are significantly correlated with the likelihood of a bank being bailed out in the second wave, but when we also include the dynamics of the willingness-to-pay during 2008, the relationship becomes insignificant.

4.5 Aggregate and Systemic Risk

In a parallel project (Bonaldi, Hortaçsu & Kastl 2013) we develop a model of the European financial market, which is aimed to provide foundations for the dynamics of the cost of funding measures that are crucial for the weekly liquidity auctions. The model is an extension of Acemoglu, Ozdaglar & Tahbaz-Salehi (2013) with added bank heterogeneity. It provides the foundations for the genesis of the financial network and it thus motivates our estimation approach. Here, we will only briefly describe the estimation method that is used to recover the network structure and how this structure is further used to recover our measure of systemic risk and we refer the reader to the other paper for details on the underlying theory and more on the estimation.

To fix ideas, consider the following simple model of the dynamics of the cost of funding:

$$v_{i,t} = \sum_{j} \sum_{l=1}^{L} \beta_{j,l}^{L} v_{j,t-l} + \gamma X_{it} + \varepsilon_{i,t} \tag{4}$$

where L denotes the number of lags, X_{it} includes state variables such as interest rates balance sheet variables and EURIBOR quotes. Model given by (4) is a variant of a dynamic panel data model, which has been studied in Holtz-Eakin, Newey & Rosen (1988) or Arellano & Bond (1991), among others. The cross-effects, $\beta_{j \neq i}$ capture the indirect impact of a shock to i's willingness-to-pay, such as a negative shock to part of its portfolio, on other banks' willingness-to-pay. A possible channel through which this indirect impact might operate is the exposure of other banks to i's bonds, which are likely to lose value following the shock due to i's increased probability of default.

[6] This could also be interpreted as a significant course of a measurement error in the explanatory variable.

Our measure of systemic risk of bank i is defined as the sum of all off-diagonal elements of the above described system divided by the number of rivals, which summarizes the total externality as an average impact on a rival:

$$SR_i^L = \frac{\sum_{j \neq i,l} \beta_{j,l}^L}{N-1} \tag{5}$$

Given this definition, we obtain a different measure SR^L for each different choice of lags, L. Perhaps the most natural one to choose, therefore, is the $MA(\infty)$ representation of the above system and the associated SR_i^∞.

In order to estimate this object, we have to deal with several issues: the number N is very large (much larger than the number of observations for each bank, T). We therefore proceed in several steps. First, we recover the implied network structure by employing an adaptive version of the least absolute shrinkage and selection operator (LASSO) (Tibshirani 1996). This estimator is similar to a ridge regression, since it solves:

$$\min \left[\sum_{i=i}^{N} \left(v_{i,t} - \sum_{j} \beta_{i,j} v_{j,t-1} - \gamma X_{it} \right)^2 \right] \; s.t. \; \sum_{j} |\beta_{i,j}| \leq \rho$$

where ρ is a parameter. In practice, we set this parameter by leave-one-out cross-validation. The resulting matrix A, which is just a stack of vectors β, is sparser than that corresponding to a regular OLS, since the contraint in LASSO forces many (weaker) links to zero and only keeps the strong ones.

Using this estimated matrix of links and their strengths, we estimate the importance of each bank in the network by evaluating their respective Katz centrality measure (Katz 1953):

$$C_{Katz}(i) = \sum_{k=1}^{\infty} \sum_{j=1}^{N} \phi^k \left(A^k \right)_{ji}$$

where ϕ is the decay parameter, which ensures that nodes "further" away are penalized when evaluating the importance of a node. Note that for $\phi = 1$, there is a nice link between the Katz centrality measure and the MA^∞ representation of the system.

Causality versus Correlation: It is important to point out that the our analysis so far cannot distinguish between the causal impact of a shock to bank i's cost of funding (due to some advers shock to the balance sheet, for example) on bank j's subsequent cost of funding and common factors which would shift both. Similarly to Adrian & Brunnermeier (2011) we do not necessarily view this as a deficiency, since the goal of our measure is to understand the likelihood that if some bank i seemed to be getting into difficulties, what would be the chances that the whole financial system might get into difficulties. It is therefore not necessarily important if it was caused by a unilateral action of or shock to bank i or if it was some catastrophic event that may have impacted a whole host of banks. Nevertheless, we hope to do more on this issue. First of all, as Adrian & Brunnermeier (2011) we include other explanatory variables that should hopefully capture some of such common factors. It is comforting to see that the inclusion of these additional state variables does not alter our results in any important way. Furthermore, there are several moment conditions that we hope to utilize: for example, the bailouts are positive shocks, some of which are targeted on a single bank and other on multiple ones.

Figure 11 depicts the estimated network for the subset of banks that participate in Reuters' EURIBOR survey, which should (in theory) be the most important banks in the EURO zone. A dot corresponds to the coefficient from the LASSO regression of the x-axis bank's estimate of marginal value on the y-axis bank's lagged marginal value. The blue dots stand for a significant positive coefficient from the LASSO estimation, while the red dots correspon to negative coefficients.

Since we may not think that the financial network should be consistent with negative coefficients, we also estimated the model imposing non-negativity constraints on the coefficients. Not surprisignly, this affects the magnitude of the estimated coefficients, but the distibution of the significant positive links stays roughly the same. It might seem from this figure that banks 7 and 22 are very important, since their lagged values have affect the highest number of other banks. This would be misleading, however: while they have the highest degree (the most number of links in the network), this figure takes into account neither the strength of the link (i.e., the magnitude of the coefficients) nor the fact the shock can propagate further through the links of the affected banks.

Figure 12 depicts the network after we imposed the non-negative coefficients in the LASSO estimation. The numbers in the circles correspond to the Katz centrality measure, i.e., to our

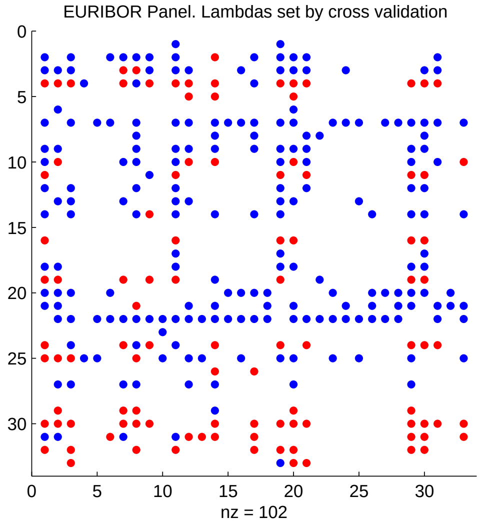


Figure 11: Significant Links in the Network

measure of systemic risk. The arrows are the links (i.e., significant estimated coefficients). The different colors represent the different banks. To ease the exposition, we placed the four banks with highest Katz centrality score on the circle first, so that they are far apart, and then placed the other banks at random locations. We can clearly see that the two banks with highest Katz centrality measure ranking have a lot of links. Since banks 3 and 4 do not have as many links, their high rank must be caused by their links being very strong.

Experimenting with different values of ρ parameter in the lasso regression and ϕ parameter in the Katz centrality measure, we found it comforting that the set of the most important banks that came out from our algorithm was constant: the top 7 banks with $C_{Katz} > 2$ was invariant. Out of these 7 most "central" banks, 1 was forced to merge and 3 obtained substantial government bailouts.

Perhaps a more interesting relationship is the one between the vulnerability ranking, which can be obtained analogously to our systemic ranking, and bailouts. The vulnerability ranking is constructed by using the significant coefficients affecting bank i, whereas the systemicness ranking by using significant coefficients caputring bank i's effect on other banks. When the estimation is restricted to the EURIBOR panel, the banks obtaining targeted bailout rank according to this vulnerability ranking as 1, 2, 5, 7, 10, 16, 19, 30. This may suggest that the bailouts targeted mostly the most fragile banks.

Estimated Network. Sample: EURIBOR Panel. Nonnegative LASSO coefs.

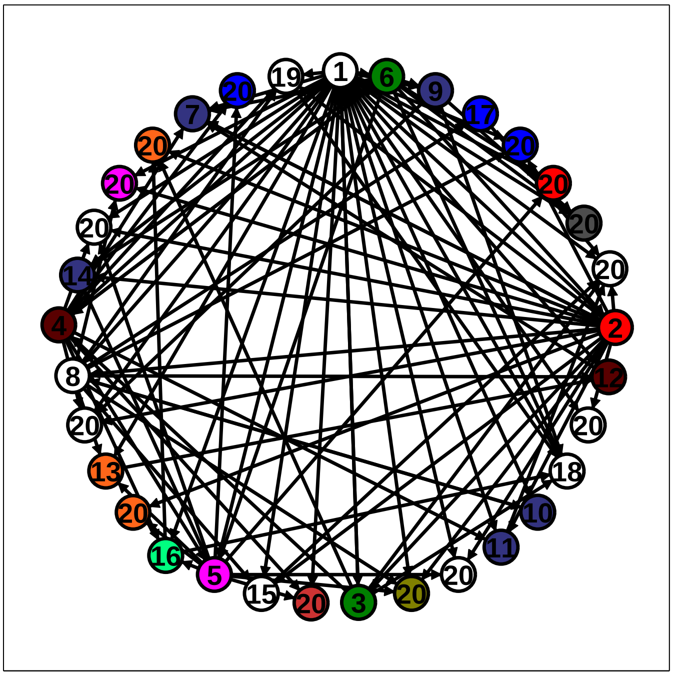


Figure 12: Financial Network

5 Conclusion

This paper provides a detailed analysis of the bidding behavior of banks in the Euro area during the heart of the recent financial crisis: from the beginning of 2008, through the fall of Lehman Brothers, all the way to the initial fixed rate tenders offered during the last three months of 2008. We demonstrate that the bidding data submitted with weekly frequency is informative about the financial state of individual banks. We show that the changes in the marginal willingness-to-pay are significantly correlated (in the expected direction) with several performance measures based on balance sheet data, which, however, are available only ex-post or very infrequently. Further, we also use this data to investigate the systemic risk. In future work, we will try to address the counterfactual of what would happen if the ECB were to switch back to awarding liquidity in weekly discriminatory auctions rather than through fixed rate tenders.

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6 Appendix

Table 7 summarizes all 30 balance sheet-based variables that we downloaded from Bankscope database.

Table 7: Variables from Bankscope Database (2008)

	N	Mean	Std Dev
Loans	542	11,642.1	32,909.2
Deposits and Short Term Funding	542	15,031.35	44,263.1
Total Customer Deposits	540	8,383.5	25,480.3
Derivatives	143	10,261.5	40,131.2
Long Term Funding	532	5,966.3	24,309.4
Equity	542	1,008.0	3,720.2
Off Balance Sheet Items	521	3,915.0	16,705.8
Reserve for Impaired Loans/NPLs	154	778.1	1,510.3
Liquid Assets	542	6,933.3	35,572.7
Net Gains on Trading and Derivatives	484	-14.9	220.0
Net Gains on Assets at FV	102	-170.2	895.8
Loan Loss Provisions	535	84.8	286.4
Profit before Tax	542	20.1	578.3
Net Income	542	15.2	529.6
Total Capital Ratio	357	13.6	4.6
Tier 1 Ratio	189	9.5	3.7
Mortgages	383	2,930.3	9,102.9
Total Problem Loans	130	1,290.3	2,230.3
Due from Central Banks	454	389.4	3,153.5
Govt Securities	458	1,451.1	5,540.2
Total Assets	542	25,645.2	85,647.2
Deposits - Demand	529	3,768.3	12,047.9
Interest Income	541	1,274.5	3,927.9
Loan Loss Res / Gross Loans	154	2.54	4.94
Net Interest Margin	530	1.96	0.81
ROAA	542	0.46	2.30
ROAE	542	4.45	19.23
Cost to Income Ratio	535	62.8	29.8
Liquid Assets/ (Dep & ST Funding)	492	34.5	186.0
Write Offs	97	2.24	10.85