The Information Contained in Money Market Interactions: Unsecured vs. Collateralized Lending

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Abstract

We study the information contained in the interaction between unsecured and collateralized money markets. We present a model to capture probabilities of migration between lending segments, and probabilities of liquidity shocks (which move the trading-activity in both markets in the same direction). We apply our model to a novel dataset of European interbank-lending, and we show that useful information is obtained from money market interactions. We report that information captured by our model describes historical macroeconomic and liquidity events in the European banking system, and explains interest rate spreads after controlling for different measures commonly used to characterize money markets.

JEL classification: E42, E58, G21, G28.

Keywords: Money markets, collateralized lending, unsecured lending, equilibrium model, structural model, systemic risk, liquidity.

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1 Introduction

Financial institutions rely globally on money markets to manage liquidity allocations. Money markets allow investors to efficiently exploit their liquidity surpluses though lending, which simultaneously represents an important channel of funding to their counterparts (who develop investment opportunities and projects), in the so-called wholesale banking system. Money markets are composed of diverse segments. Two relevant segments that have been commonly investigated, given their importance, are the unsecured money market –uncollateralized lending– and the collateralized money market –in which lending is protected through the use (and re-use) of collateral. However, unsecured and collateralized money markets are not independent of each other. In fact, interactions in lending segments can be especially relevant during periods of high uncertainty. For instance, recent empirical evidence suggests that in periods of crises, collateral lending can act as a shock absorber in money markets (see, e.g., Mancini *et al.*, 2015). Nevertheless, the vast majority of the existing literature focuses its analysis independently either on the unsecured segment or on collateralized lending.[1] The objective of this study is to fill this gap by studying the information contained in interactions between unsecured and collateralized channels. We want to answer the following questions: Can trading activity migrate between segments and, in doing so, provide meaningful information about the state of health of money markets and the banking system? Is the migration process short-lived, in the sense that trading volumes that move in one direction will move in the reverse direction in the near future? How do liquidity shocks in secured and unsecured lending segments differ? Do positive liquidity shocks have the same magnitude as negative liquidity shocks in term of lending activity?

To address these questions, we present a structural model that captures the information revealed in money market interactions. The model characterizes the trading behaviour of financial institutions in unsecured and collateralized lending channels, which depends on diverse states of the economy. States are associated with the possibility of both migration events (between collateralized and unsecured lending) and liquidity shocks. Migration events are movements in opposite directions in trading

[1] See, e.g., Furfine (2002), Angelini *et al.* (2009) , Harris (2011), Afonso *et al.* (2011), Brunnetti, Di Filippo and Harris (2011) and Acharya and Merrouche (2013) for unsecure money markets; while for collateralized segments see, e.g., Fostel and Geanakoplos (2008), Dunne *et al.* (2011), Gorton and Metrick (2010a,b), Gorton and Metrick (2012a,b), Krishnamurthy *et al.* (2013) Copeland *et al.* (2013), Boissel *et al.* (2014) and Gorton and Ordonez (2014).

activity from one market segment to the other; while liquidity shocks also represent changes in trading activity in both markets, but in the same direction. The model describes agents' decisions in relation to lending in each segment in the form of an extensive game-tree, which allows us to empirically obtain state probabilities from market data. Thus, the information extracted through our approach is different from other measures used to describe money market risks and liquidity changes, since information is obtained implicitly from the agents' strategic trading behaviour when they face diverse economic events over time.

The model is implemented using a bank-to-bank dataset of collateralized and uncollateralized lending activity in the Euro zone between June 2, 2008 and July 30, 2013. For the unsecured money market, we use data derived from TARGET2, which is the real-time gross settlement payment system owned and operated by the Euro system. For the European collateralized market, we use data pertaining to repurchase agreement contracts from one of the major Central Counterparty Clearing Houses (CCP) in Europe, Eurex Repo.[2]

We present evidence that there is useful information contained in the dynamic interactions between unsecured and secured channels, and the structural approach implemented allows us to extract and interpret this information. We report that migration probabilities and probabilities of liquidity shocks evolve over time, signalling the reaction of money markets to major macroeconomic and liquidity events that characterized the European banking system during the recent financial crisis. The information obtained about migration dynamics can explain interest rate spreads, even after controlling for changes in volume between segments, and after including measures used to characterize systemic stress in financial markets, such as the Composite Indicator of Systemic Stress (CISS), and the probability of simultaneous defaults by two or more large European banks (both reported by the ECB). Moreover, our measures regarding liquidity shocks are also significantly related to interest rate spreads, even when measures of excess liquidity in Europe are used as a control.

Our analysis of the interplay between unsecured and collateralized segments is of relevance from policy and academic perspectives. Firstly, it is crucial for policy makers

[2] A repurchase agreement (repo) is a collateralized loan based on a simultaneous sale and forward agreement to repurchase securities at the maturity date.

to understand how money markets interact, i.e. whether and how collateralized interbank lending offsets falls of unsecured interbank lending in periods of stress and calm. In fact, money markets proved to be one of the most prominent vehicles of contagion during the recent financial crisis, allowing the dissemination of market tensions or “freezes” among different, seemingly unrelated segments of financial markets. Secondly, collateralized money markets represent banks' main source of funding in Europe (see European Central Bank, 2014), hence the knowledge of the trading behaviour of collateralized lending and its connection with other funding channels are crucial for investors and the complete financial system. Thirdly, the level to which unsecured and secured interbank markets are well-functioning is a key factor in terms of the smooth transmission and implementation of Central Banks monetary policies.

The intuition behind our approach is illustrated by using a simple three-period equilibrium model. In this set-up, migration in trading activity between the unsecured money market and collateralized lending is mainly driven by differences in funding costs between both segments. For instance, there is a migration from the unsecured money market to collateralized lending either: i) when funding costs paid in the unsecured market increase, and/or ii) when funding costs paid in the collateralized money market decrease. Therefore, a migration from unsecured to collateralized money markets can be associated with potential bad news affecting the unsecured segment (e.g. a growth information costs to identify potential reliable borrowers) and/or good news for collateralized lending (e.g. when there is a reduction in the cost used in providing information to the counterparty with the objective of showing that the collateral used has a minimum standard to be a 'good quality asset')[3]

As mentioned previously, both unsecured and collateralized money markets have been widely analyzed in recent years; nevertheless research has tended to focus on them independently. On the one hand, there is a growing body of empirical literature on collateralized market activity, in which the repo market is analyzed in Europe (e.g. Dunne, 2011; Mancini *et al*. 2015; and Boissel *et al*. 2014), and in the United States (Gorton and Metrick, 2010a, b; Gorton and Metrick, 2012a, b; Krishnamurthy, Nagel, and Orlov, 2013; Copeland, Martin, and Walker, 2013). Collateralized lending is also studied

[3] Similar market dynamics, but of opposite sign, can be described in the case of a migration from the collateralized money market to unsecured lending.

from a theoretical point of view. For instance, among a number of studies, Fostel and Geanakoplos (2008) argue that during periods of stress, assets which can be used as collateral should fall less in value than other assets; they call this phenomenon 'flight-to-collateral'; while Gorton and Ordonez (2014) explain financial crises through endogenous dynamics of information in collateralized money market which may induce fragility as a rational credit boom develops.

On the other hand, in relation to unsecured funding, Afonso *et al*. (2011) claim that the decrease in volume and increase in interest rates in the unsecured money market for bank reserves in the U.S. (commonly referred to as Fed Funds) are due to an increase in counterparty risk, rather than liquidity hoarding by the banks. Similar results to Afonso *et al*. (2011) are presented by Wetherilt *et al*. (2009) in unsecured overnight funding in the UK, and by Angelini *et al*. (2009) for the Italian unsecured interbank market. By contrast, Acharya and Merrouche (2010) draw opposite conclusions for the unsecured market segment in the UK during the 2007/2008 financial crisis; while Furfine (2002) finds no evidence of either counterparty risk or liquidity hoarding in the unsecured interbank market in the U.S. at the time of the Russian debt crisis and the collapse of Long Term Capital Management in 1998.

The reduction of lending volume in the European unsecured money market is also documented in Brunnetti, Di Filippo, and Harris (2011) during the early phase of the recent financial crisis, and in Arciero *et al*. (2013) during the later phase of the European sovereign debt crisis. However, these studies do not provide a conclusive explanation of whether the decrease of unsecured interbank lending is due to (i) contraction in the entire money market and/or (ii) a substitution effect between unsecured and secured lending. In addition, theoretical literature shows that counterparty risk discourages unsecured lending, which has been variously related to informational friction (e.g. Stiglitz and Weiss, 1981), Knightian uncertainty (e.g. Caballero and Krishnamurthy, 2008), funding risk (e.g. Acharya and Skeie, 2011), liquidity hoarding in order to profit from potential fire sales (e.g. Diamond and Rajan, 2011) and inventory risk (e.g. Poole, 1968).[4]

[4] Our study also is related to the analysis of conventional and unconventional policy measures undertaken by Central Banks in recent years. For example, Krishnamurthy and Vissing-Jorgensen (2011) finds the quantitative easing (QE) can have a persistent effect on asset prices in the United States and Freixas, Martin and Skeie (2011) introduce a model to show that central bank liquidity provision in times of crisis

The paper is organized as follows: Section 2 presents the model. Section 3 introduces the data used in our study to understand the interaction between unsecured lending and the collateralized market segment. Section 4 presents the model estimation, analyzes the model specification and describes posterior probabilities. Section 5 documents the connection between money market interactions and interest rate spreads. Section 6 concludes.

2 The model

2.1 The intuition behind money market interactions

We provide a simple three-period model to describe dynamics in unsecured and collateralized lending segments. Consider an economy with three dates denoted by {0, 1, 2}, and a single consumption good that will be referred to as a dollar. The economy has a continuum consisting of two types of firms: Lenders, L, and borrowers, B. Firms, which will be also called banks, are risk neutral and derive utility from consuming at $t = 2$.

Banks differ in their initial endowments and investment opportunities. On the one hand, a bank type B does not have dollars as an initial endowment, but it has an investment opportunity at $t = 0$, only if an amount of dollars Q is invested. The investment opportunity delivers a dividend d at $t = 1$ and a return R at $t = 2$. On the other hand, a bank type L is born at $t = 0$ with an endowment of dollars M, high enough to maintain optimal production in the economy, where $M \geq Q$. Hence, resources are in the wrong hands and financial intermediation emerges: a bank L can transfer part of its endowment from $t = 0$ to consume at $t = 2$ by lending dollars to bank B (and bank L can charge for this service), and thus bank B can consume at $t = 2$ by exploiting the investment opportunity.

Financial intermediation is performed through two lending channels: an unsecured money market, UM, and a collateralized money market, CM. In the money market UM, a bank B can borrow at $t = 0$ an amount of dollars ξ_{UM} from bank L by paying an interest rate r_{UM} with the use of just a 'promise', and without committing any

is necessary. Among ECB's interventions, Main Refinancing Operations (MROs) have been analyzed in repo markets (e.g. Bindseil, Nyborg, and Strebulaev, 2009; and Dunne, Fleming and Zholos, 2011 and 2013) and during stress periods such as following the Lehman collapse (e.g. Cassola, Hortaçsu, and Kastl, 2013), while Krishnamurthy, Nagel, and Vissing-Jorgensen (2013) find that ECB's bond purchases significantly reduced the default risk of Italian, Spanish, and Portuguese government debt.

part of the investment opportunity as collateral. This 'promise' is accomplished through legal enforcements, potential guarantors, penalties, or simply the honesty of the borrower. The interest rate r_{UM} is expressed on a two-period basis, thus the amount paid by the loan in this market at $t = 2$ is $r_{UM}\xi_{UM}$. A bank L is willing to lend the amount ξ_{UM} to bank B, and thus to consume at $t = 2$ (and to receive the interest on the loan), but there is a quadratic cost, $k_{UM}(\xi_{UM})^2/2$ with $k_{UM} > 0$, that has to be paid by the lender when a loan is issued in this market segment. This cost emerges from potential exogenous expenses such as lawyers, and/or an investment research office with the aim of assessing the reliability of potential borrowers; this cost, once paid out, avoids potential defaults in the market UM.

In the collateralized money market, a bank B can also borrow at $t = 0$ an amount of dollars ξ_{CM} from bank L by paying an interest rate r_{CM} (which is also expressed on a two-period basis). However, in addition to the payment of interest rates, bank B gives to bank L ownership rights of a fraction, $\xi_{CM}\ /Q$, of the investment opportunity, with the objective of increasing the reliability of repayment. This ownership loss produces at time $t = 1$ that a bank type B receives only a fraction of the dividend from the investment opportunity, $(\xi_{UM}/Q)d$; while a bank type L receives the rest the dividends, $(\xi_{CM}/Q)d$. Moreover, there is a quadratic cost, $k_{CM}(\xi_{CM})^2/2$, with $k_{CM} > 0$, that must be paid by bank B when it borrows in this segment. This cost is associated with damage to reputation among potential future business partners (since collateralized lending gives a signal that the borrower is potentially unreliable), or it can simply reflect expenses associated with promoting and showing that the investment opportunity has an classification of 'good quality' and can be used as collateral.

Firms in this economy care only about outputs at $t = 2$. We assume that there is no uncertainty of any kind and the discount rate is equal to zero. Bank type B has a preference for the unsecured money market where costs are paid by the lender, and where there is no reduction in the amount of dividends received. Conversely, a bank type L prefers to lend dollars to a bank type B through the collateral money market, since potential costs are borne by the borrower (in addition to the benefits received by L in terms of project's ownership regarding dividends). Equilibrium in this economy is defined by dollar-volumes in each money market, ξ_{UM} and ξ_{CM}, where interest rates, r_{UM}

and r_{CM}, clear both market segments. This equilibrium is obtained by the banks' optimization problem:

i- A bank type L makes decisions at $t = 0$ by maximizing its utility, U^L, at $t = 2$:

$$\max_{\xi_{UM},\xi_{CM}} U^L = r_{UM}\xi_{UM} + r_{CM}\xi_{CM} + d\frac{\xi_{CM}}{Q} - \frac{1}{2}k_{UM}(\xi_{UM})^2$$

$$\begin{aligned} st.\quad & \xi_{UM} + \xi_{CM} = Q \\ & \tfrac{1}{2}k_{UM}(\xi_{UM})^2 \le r_{UM}\xi_{UM} + r_{CM}\xi_{CM} + d\tfrac{\xi_{CM}}{Q} \\ & 0 \le r_{UM} \text{ and } 0 \le r_{CM} \\ & 0 \le \xi_{UM} \text{ and } 0 \le \xi_{CM} \end{aligned} \tag{1}$$

ii- A bank type B also decides at $t = 0$ by maximizing its utility, U^B, at $t = 2$:

$$\max_{\xi_{UM},\xi_{CM}} U^B = RQ + d\frac{\xi_{UM}}{Q} - r_{UM}\xi_{UM} - r_{CM}\xi_{CM} - \frac{1}{2}k_{CM}(\xi_{CM})^2$$

$$\begin{aligned} st.\quad & \xi_{UM} + \xi_{CM} = Q \\ & r_{UM}\xi_{UM} + r_{CM}\xi_{CM} + \tfrac{1}{2}k_{CM}(\xi_{CM})^2 \le RQ + d\tfrac{\xi_{UM}}{Q} \\ & 0 \le r_{UM} \text{ and } 0 \le r_{CM} \\ & 0 \le \xi_{UM} \text{ and } 0 \le \xi_{CM} \end{aligned} \tag{2}$$

We can get expressions for the dollar-volumes in each market from the first order conditions of the maximization problem for the lender and the borrower, and by imposing that $\xi_{UM} + \xi_{CM} = Q$. Thus, dollar-volumes in the money market are given by:

$$\xi^*_{UM} = (1-h)Q; \quad \xi^*_{CM} = hQ \tag{3}$$

where $h = k_{UM}/(k_{CM} + k_{UM})$ is the relative cost parameter of the unsecured segment in relation to other cost parameters of the complete money market. The interest rate spread between unsecured and collateralized markets is obtained by market clearing and given by:

$$r^*_{UM} - r^*_{CM} = k_{CM}hQ + \frac{d}{Q}, \tag{4}$$

and $\pi = k_{CM}hQ$ is the risk premium before dividends of the unsecured lending rate over the collateralized market rate.[5] In this simple framework, migrations between collateralized and uncollateralized channels are driven by changes in the relative costs of funding as reflected by the level of h. In fact, the effect on ξ_{UM}^* and ξ_{CM}^* of a change in h is straightforward:

$$\frac{d\xi_{UM}^*}{dh} = -Q \leq 0; \quad \frac{d\xi_{CM}^*}{dh} = Q \geq 0 \tag{5}$$

Equation (3) and equation (5) show that a migration from the unsecured to the collateralized money market can be caused by an increase in the level of k_{UM}, since:

$$\frac{d\xi_{UM}^*}{dk_{UM}} = -\frac{k_{CM}}{(k_{CM}+k_{UM})^2} \leq 0 \quad and \quad \frac{d\xi_{CM}^*}{dk_{UM}} = \frac{k_{CM}}{(k_{CM}+k_{UM})^2} \geq 0,$$

and/or by a reduction in the value of k_{CM}, because:

$$\frac{d\xi_{UM}^*}{dk_{CM}} = \frac{k_{UM}}{(k_{CM}+k_{UM})^2} \geq 0 \quad and \quad \frac{d\xi_{CM}^*}{dk_{CM}} = -\frac{k_{UM}}{(k_{CM}+k_{UM})^2} \leq 0.$$

Hence, migrations between unsecured and collateralized money markets are associated with changes in the market condition in relation to funding costs in each (or in both) segment(s). On the one hand, the costs paid by the lender in the unsecured market (k_{UM}) go up when, for example, there is an increase in the high information costs associated with identifying potential reliable borrowers (which can be the case when the majority of financial institutions are not performing well, or because there is less credible information with which to identify potential reliable partners). On the other hand, there is a reduction in the costs paid by the borrower in the collateralized market (k_{CM}) in a scenario in which, for instance, there is a drop in the costs related to reputational issues, or a decrease in the costs used in providing information to the counterparty with the objective of showing that the collateral used in the loan is safe. Thus, changes in the relative funding costs can happen in just one of the lending channels, or in both simultaneously.

Equation (3) also illustrates the rationale for the introduction of liquidity shocks. Changes in liquidity levels generate an impact of same-sign in the amount of dollars traded in both segments. Thus, instead of having a migration between markets, as in the

[5] In addition, constraints of positive profits and rate restrictions $0 \leq r_{UM}$ and $0 \leq r_{CM}$ in the lender and borrower optimization problem generate intervals for the interest rates described by: $0 \leq r_{CM}^* \leq R - \pi + \pi h/2$ and $\pi + d/Q \leq r_{UM}^* \leq R + d/Q + \pi h/2$.

case of changes in k_{UM} and k_{CM}, changes in Q (i.e. a liquidity shock) move both money markets in the same direction in relation to the amount of dollars traded:

$$\frac{d\xi_{UM}^*}{dQ} = (1-h) \geq 0; \quad \frac{d\xi_{CM}^*}{dQ} = h \geq 0 \tag{6}$$

This is consistent with the empirical literature, where liquidity shocks have been associated with modifications in particular market needs, changes in the demand for immediacy (see Grossman and Miller, 1988) or to changes in central bank policies (see Ellingsen and Söderström, 2001).[6] Thus, this simple three-period model intuitively describes why trading activity in both markets has a tendency to move at times in opposite directions, and at others in tandem.

2.2 The structural model to capture the information contained in money market interactions

The structural model is based on the intuitions explained in the previous subsection in relation to money market interactions. The objective of the structural model is to capture dynamics, which cannot be captured in our three-period model. Suppose that there are two types of lending segment: an unsecured money market and a collateralized money market. States of the economy are associated with the possibility of both migration events (between unsecured and collateralized money markets) and liquidity shocks. Funding requirements in the economy, reflected in transactions in each of the money markets, arrive stochastically according to two Poisson processes with rates ξ_{UM} and ξ_{CM} for the unsecured market and the collateralized segment, respectively.

Suppose that both markets have activity over $i = 1, \dots, I$ trading days, with time evolving continuously within each single day and represented by $t \in [0, T]$. On each day and with a probability $\alpha \in (0,1)$, a 'migration event' takes place which affects the amount of dollars required in both lending channels. A migration event may provide a migration to the collateralized money market with a probability δ, or a migration to the unsecured segment with probability $1-\delta$. On the one hand, in the case of a migration to

[6] For instance, changes in central bank policies that may affect European money markets would include: the ECB's switch from variable-rate auction (VRA) to fixed-rate full allotment (FRFA) for its main refinancing operations (MRO); the ECB's determination to increase the maturity of longer-term refinancing operations up to three years; and the ECB's decision to accept a wider, riskier pool of assets as collateral from banks for their refinancing operations. All these measures potentially impact interbank lending and money markets in general (see Giannone *et al.*, 2012).

the collateralized money market, the activity in the unsecured segment is reduced by μ_{-UM}, where $\xi_{UM} > \mu_{-UM} > 0$; while the arrival rate of transactions in the collateralized market increases by μ_{+CM}. On the other hand, in the case of a migration to the unsecured segment, the arrival rate of transactions to the unsecured market (collateralized market) increases (decreases) by μ_{+UM} (μ_{-CM}), where $\xi_{CM} > \mu_{-CM} > 0$.

Trading activity might be also sparked by liquidity changes; thus we take into account potential liquidity effects. On each day a liquidity event can happen with probability η; such events impact both markets in the same direction in terms of the money required in each channel. Such liquidity events are called *liquidity shocks*. In the case of a liquidity shock, there is a positive (a negative) impact on liquidity requirements with probability θ (probability 1- θ) for both unsecured and collateralized markets, where $\theta \in (0,1)$. In the case of a positive liquidity shock (a negative liquidity shock) there is an increase (a reduction) on the arrival rate for the unsecured market and collateralized market at $\lambda_{+UM} > 0$ and $\lambda_{+CM} > 0$ ($\lambda_{-UM} > 0$ and $\lambda_{-CM} > 0$), respectively.[7] Figure 1 shows a diagram of market dynamics according to the model described above.

[Insert Figure1 here]

On each day, the market follows the path associated with one of the branches in Figure 1. Thus, from the model described above, the likelihood function on any day is:

[7] In the event of a negative liquidity shock $\xi_{UM} + \mu_{+UM} \geq \lambda_{-UM}$ and $\xi_{CM} - \mu_{-CM} \geq \lambda_{-CM}$ (i.e. the case of a migration to unsecured funding), while $\xi_{UM} - \mu_{-UM} \geq \lambda_{-UM}$ and $\xi_{CM} + \mu_{+CM} \geq \lambda_{-CM}$ (i.e. the case of a migration to collateralized lending).

$$
\begin{aligned}
&L(\varphi|(UM,CM)) \\
&= \alpha(1-\delta)\eta\theta\left\{e^{-(\xi_{UM}+\mu_{+UM}+\lambda_{+UM})}\frac{(\xi_{UM}+\mu_{+UM}+\lambda_{+UM})^{UM}}{UM!}e^{-(\xi_{CM}-\mu_{-CM}+\lambda_{+CM})}\frac{(\xi_{CM}-\mu_{-CM}+\lambda_{+CM})^{CM}}{CM!}\right\} \\
&+ \alpha(1-\delta)\eta(1-\theta)\left\{e^{-(\xi_{UM}+\mu_{+UM}-\lambda_{-UM})}\frac{(\xi_{UM}+\mu_{+UM}-\lambda_{-UM})^{UM}}{UM!}e^{-(\xi_{CM}-\mu_{-CM}-\lambda_{-CM})}\frac{(\xi_{CM}-\mu_{-CM}-\lambda_{-CM})^{CM}}{CM!}\right\} \\
&+ \alpha(1-\delta)(1-\eta)\left\{e^{-(\xi_{UM}+\mu_{+UM})}\frac{(\xi_{UM}+\mu_{+UM})^{UM}}{UM!}e^{-(\xi_{CM}-\mu_{-CM})}\frac{(\xi_{CM}-\mu_{-CM}}{CM!}\right\} \\
&+ \alpha\delta\eta\theta\left\{e^{-(\xi_{UM}-\mu_{-UM}+\lambda_{+UM})}\frac{(\xi_{UM}-\mu_{-UM}+\lambda_{+UM})^{UM}}{UM!}e^{-(\xi_{CM}+\mu_{+CM}+\lambda_{+CM})}\frac{(\xi_{CM}+\mu_{+CM}+\lambda_{+CM})^{CM}}{CM!}\right\} \\
&+ \alpha\delta\eta(1-\theta)\left\{e^{-(\xi_{UM}-\mu_{-UM}-\lambda_{-UM})}\frac{(\xi_{UM}-\mu_{-UM}-\lambda_{-UM})^{UM}}{UM!}e^{-(\xi_{CM}+\mu_{+CM}-\lambda_{-CM})}\frac{(\xi_{CM}+\mu_{+CM}-\lambda_{-CM})^{CM}}{CM!}\right\} \\
&+ \alpha\delta(1-\eta)\left\{e^{-(\xi_{UM}-\mu_{-UM})}\frac{(\xi_{UM}-\mu_{-UM})^{UM}}{UM!}e^{-(\xi_{CM}+\mu_{+CM})}\frac{(\xi_{CM}+\mu_{+CM})^{CM}}{CM!}\right\} \\
&+ (1-\alpha)\eta\theta\left\{e^{-(\xi_{UM}+\lambda_{+UM})}\frac{(\xi_{UM}+\lambda_{+UM})^{UM}}{UM!}e^{-(\xi_{CM}+\lambda_{+CM})}\frac{(\xi_{CM}+\lambda_{+CM})^{CM}}{CM!}\right\} \\
&+ (1-\alpha)\eta(1-\theta)\left\{e^{-(\xi_{UM}-\lambda_{-UM})}\frac{(\xi_{UM}-\lambda_{-UM})^{UM}}{UM!}e^{-(\xi_{CM}-\lambda_{-CM})}\frac{(\xi_{CM}-\lambda_{-CM})^{CM}}{CM!}\right\} \\
&+ (1-\alpha)(1-\eta)\left\{e^{-(\xi_{UM})}\frac{(\xi_{UM})^{UM}}{UM!}e^{-(\xi_{CM})}\frac{(\xi_{CM})^{CM}}{CM!}\right\}
\end{aligned} \tag{7}
$$

where $\varphi \equiv (\alpha,\delta,\eta,\theta,\xi_{UM},\xi_{CM},\mu_{-UM},\mu_{+CM},\mu_{+UM},\mu_{-CM},\lambda_{-UM},\lambda_{-CM},\lambda_{+UM},\lambda_{+CM})$ is the vector of parameters, while UM and CM are the (integer) numbers of transactions in the unsecured segment and the collateralized money market, respectively. In equation (7), each element represents the likelihood function of each of the branches in the diagram in Figure 1, which are weighted by their probabilities. Furthermore, on the dynamics across the I days the total likelihood function is:

$$
L(\varphi|M) = \prod_{i=1}^{I} L(\varphi|UM_i, CM_i), \tag{8}
$$

where UM_i and CM_i are the (integer) numbers of transactions in each market segment on day i, respectively, with $M = ((UM_1, CM_1), \dots, (UM_I, CM_I))$.

Equation (8) is maximized over φ given the data sample to obtain maximum-likelihood estimates of the parameters. Thus, this model allows us to use observable data on trading activity (from both the unsecured segment and the collateralized market channel) to make inferences about unobservable information contained in money market interactions. In effect, the trading game depicted in Figure 1 is actually composed of two sub-trees: one related to the migration effect, and one related to liquidity shocks. In particular, in the first tree α captures the probability that a migration event takes place, and δ is the conditional probability that this event is a migration from the unsecured towards the collateralized market. In the second tree η and θ represent respectively the probability of a liquidity shock and the conditional probability that such a shock is positive. Hence, the model captures the dynamic interaction between the unsecured and secured markets, allowing for relative trends that include both divergent (migration effect) and same-sign (liquidity shock effect) components.

Despite its simplicity, this structural model also provides a rich structure of money market interactions in terms of arrival intensities. For example, the parameters ξ_{CM} and ξ_{UM} describe the underlying intensities of the unsecured and secured markets; μ_{+CM} and μ_{-UM} measure the intensity of *divergent* market reactions associated with an increase in activity in the collateralized market, and a corresponding decrease in activity in the unsecured market. The values μ_{-CM} and μ_{+UM} also measure the intensity of *divergent* market reactions, which are associated with a decrease in activity in the collateralized market and a corresponding increase in activity in the unsecured market. Moreover, the parameters λ_{+UM} and λ_{+UM} (λ_{-UM} and λ_{-UM}) measure the intensity of *same-sign* market reactions to positive (negative) liquidity shocks.

3 The data

We use daily data of collateralized and uncollateralized lending activity in Europe between June 2, 2008 and July 30, 2013, which represents 1,325 trading days. For the unsecured lending market, we rely on data derived from TARGET2, the real-time gross settlement (RTGS) payment system owned and managed by the Euro system. Unsecured interbank loans are extracted from TARGET2 for maturities ranging from one day (overnight) up to one year, relying on the methodology developed by the Euro system to identify unsecured money market transactions (see Arciero *et al.*, 2013).[8] The algorithm identifies interbank loans by matching cash flows between banks during different periods. For instance, the algorithm matches a payment from bank *i* to bank *j* at time *t*, with its re-payment from bank *j* to bank *i* at time $t + \Delta t$ amounting to the initial value increased by a plausible amount, corresponding to prevalent interest rates applied to the period Δt.

[8] This methodology improves upon the original algorithm developed by Furfine (1999).

For the collateralized market we use repurchase agreement (repo) loans data. The repo market in Europe is mainly performed as bilateral inter-bank lending.[9] Our database includes all General Collateral Pooling (GCP) repos traded on the Eurex platform, which is the leading Central Counterparty Clearing House (CCP) for repos in Europe. We use GCP repos with maturities that range from overnight to one year. GCP repos represent more than 85% of all repos traded in Eurex.

The European repo market has several useful characteristics that allow us to isolate interactions and dynamics between unsecured and secured lending channels. In particular, the use of Eurex GCP repos allow us to use one of the largest collateralized funding channels in Europe, and simultaneously to reduce the impact of: deciding haircut levels; the selection of securities to be used as collateral, and additional funding objectives related to the use of the collateralized security *per se*. Firstly, haircuts in Eurex are not defined by the participants and cannot be negotiated. Instead, Eurex establish rules for haircuts independently of the agent and the security used as collateral –i.e. all securities in the GCP basket have the same haircut as the one that the ECB applies to its refinancing operations. Secondly, Eurex accepts a standardized and homogeneous pool of potential securities for collateralization; thus the type of collateral is not part of the agents' decision process. The pool of potential securities used as collateral in Eurex is a sub-group of those admitted for collateralization in open market operations by the ECB, since these securities also need to have at least an upper medium rating grade (i.e. A- or A3 in Moody's or in S&P, respectively).[10] Thirdly, differently to other repo transactions, such as *special* repos which are security driven, in GCP repos the agents' objective is mainly related to funding purposes rather than security itself.[11]

By using data on both segments, we are able to depict time-varying dynamics between unsecured and secured interbank lending channels in both normal and stressed times. Table 1 reports summary statistics of the dataset. Table 1 shows that both markets are characterized by a prevalence of contracts with very short-term

[9] About 67% of interbank repo transactions in the Euro area are conducted via central counterparty (CCP) platforms using anonymous electronic trading (see, European Central Bank, 2014).

[10] Thus, the eligibility requirements of the Eurex repo market are stricter than those posed by the ECB, reducing the maximum number of eligible securities from almost 45,000 to less than 25,000. However, Eurex still use as collateral a large basket of safe securities.

[11] There are two other important CCPs in Europe for repos: BrokerTec and MTS. Unlike Eurex, these markets appear to be security-driven, since the majority of their trading is performed via specific collateral assets (about 80% of the total).

maturities (overnight contracts). Overnight loans have an average market share (in terms of total traded amount) representing about 88% of the unsecured segment, and 84% of the secured segment.

[Insert Table 1 here]

Figure 2 presents the evolution of the daily trading activity in the unsecured and collateralized money markets. It is evident from Figure 2 that the reliance on unsecured borrowing has decreased dramatically overall since 2008. Looking more closely at the unsecured market, we note several trends: i) a sudden decrease in the second half of 2008, following the collapse of Lehman Brothers and the subsequent collapse of the market for commercial papers in the U.S.; ii) a partial recovery that started in the first quarter of 2009 and lasted until the second quarter of 2011; iii) a further decrease in activity which reached its lowest point in march 2013, surrounding the breakout of the European sovereign debt crisis; and iv) a tepid increase in activity in the second quarter of 2013.

[Insert Figure 2 here]

Figure 2 shows that, unlike the unsecured segment, activity in the repo market appears to be more stable, characterized by constant growth, which halted temporarily in the second half of 2012 and resumed in the first half of 2013. These trends show that secured and unsecured borrowing does not always move in the same direction. In fact, to further illustrate this relationship, Figure 3 shows the correlation, calculated for each year, between daily trading volumes in the unsecured and collateralized channels. Clearly, changes in correlation can be observed. During the years 2008 and 2011, the correlation between both segments is negative, in correspondence with the breakout of the subprime mortgage crisis in 2008 and the European sovereign debt crisis in 2011. For instance, the correlations in 2008 and 2011, for overnight lending are -0.25 and -0.32, respectively. The correlations are positive (and increasing over time) in the 2 years following the two crises, respectively 2009-2010 and 2012-13. The correlation changes showed in Figure 3 (and the trends observed in Figure 2) seem to suggest the presence of a partial migration effect between secured and unsecured funding in times of financial stress, while the two funding markets seem to move in the same way in more 'normal times'.

[Insert Figure 3 here]

4 Model estimation and results

4.1 Model estimation

The estimation of our model consists of recovering the parameters that describe the market characterization illustrated in Subsection 2.2. Estimating the parameter vector $\varphi \equiv (\alpha, \delta, \eta, \theta, \xi_{UM}, \xi_{CM}, \mu_{-UM}, \mu_{+CM}, \mu_{+UM}, \mu_{-CM}, \lambda_{-UM}, \lambda_{-CM}, \lambda_{+UM}, \lambda_{+CM})$ is much more complex than just estimating arrival rates from independent Poisson processes. The difficulty arises because, on any given day, we cannot directly identify migration events and liquidity shocks governed by these parameters. Thus, we do not know which Poisson process is operating on a particular date; however the model provides the structure necessary to extract information on such parameters from the observable trading data. For instance, we know that when we have a migration event, a certain amount of trading volume has to be reduced in one market; meanwhile the trading activity in the other segment has to increase (see Figure 1). In addition, we know that in the case of a liquidity shock both markets will jointly increase (or decrease) their lending activity.

The model is estimated by maximizing the sample likelihood function in equation (8) with daily aggregated trading volume (€ billion) for the unsecured and collateralized markets. We report the estimated parameters in Table 2. The parameters are obtained for each year and for the full sample. In addition, the parameters are reported for the aggregate set of maturities (long-term and short-term loans with maturities ranging from one day –overnight– up to one year) and for short-term loans (overnight maturities only).[12]

[Insert Table 2 here]

From Table 2, it is evident that parameters substantially change over time. For instance, the estimated probabilities of migration are larger in 2008 and 2011, reflecting economic turbulences that affected money markets on those years. This result is consistent with the correlation pattern observed in trading activity as reported in Figure 3. Moreover, the standard errors reveal that the parameters are estimated with reasonable precision, as in general all are statistically significant.

[12] MatLab codes for model estimations are available from the authors upon request.

Table 2 also shows that the parameters estimated with long-term and short-term loans –in the upper panel– are very similar to the parameters obtained using only overnight loans –in the bottom panel. For instance, the probability of a migration event given by α (of a liquidity shock given by η), obtained with the full sample for long-term and short-term loans is 56% (77%) while the same probability is 57% (76%) for the parameters calculated with only overnight loans. It is clear from the standard errors that we cannot reject the hypothesis that these parameters are the same. This is consistent with the results obtained in Mancini *et al*. (2015) who show that the main activity in the European interbank market is concentrated on short-term lending.

4.2 Model specification

The objective of our study is firstly to evaluate whether money market interactions provide useful information regarding the status of the economy and, in particular, information related to market conditions faced by the banking sector. However, beforehand, we have to analyze whether our market characterization provides a useful interpretation and description of how unsecured and collateralized segments interact. Thus, in this subsection we analyze whether our model is correctly specified.

One way to address specification issues is to compare our structural model with alternative specifications, which may also describe money market interactions. If our structural approach is 'better' in the sense of explaining the data more completely, then we would expect the log-likelihood value to be larger for our model than for other market descriptions. This is a natural mechanism for testing and comparing the efficacy of alternative setups.

Table 3 reports the results of these specification tests. For each alternative specification, we show the log-likelihood value, which is compared to our structural model described in Figure 1. The first alternative model in Table 3 reflects the case in which there are no migration events ($\alpha = 0$), the second model represents the case in which there are no liquidity shocks ($\eta = 0$), and the third model reflects the case in which there are neither migration events nor liquidity shocks ($\alpha = 0$ and $\eta = 0$). The tests are performed for each year and for the full sample and over both sets of maturities (loans with maturities ranging from one day –overnight– up to one year, and for only overnight loans).

[Insert Table 3 here]

Table 3 confirms the worth of our structural model. The log-likelihood values of other money market specifications are significantly smaller than the market characterization described in Figure 1. For example, the log-likelihood values for all other specifications obtained for the full sample are significantly lower (at 1% significance level) than the log-likelihood value of the original specification, with values of -10873.35 and -10627.05 respectively for the complete set of maturities and for overnight contracts.

Table 4 presents six additional specification tests performed by imposing restrictions on the set of arrival intensities, which describes money market migrations and liquidity shocks. The three starting models account for restrictions on the size of migration events. The first alternative model in Table 4 reflects the case in which the complete substitution effect between markets, i.e. a variation in trading in one market is fully compensated for by a variation of opposite sign in the other market; thus we impose that: $\mu_{-UM} = \mu_{+CM}$ and $\mu_{+UM} = \mu_{-CM}$. The second model reflects the case in which the migration intensity is symmetric in both migration events: $\mu_{-UM} = \mu_{+UM}$ and $\mu_{-CM} = \mu_{+CM}$ (i.e. increases when there is a migration in the unsecured market are equivalent to reductions in the same market when there is a migration in the opposite direction, which also applies to the collateralized market). Combining the effects of the two specifications illustrated in the first and second model, the third model reflects the scenario in which migration intensities are equal both *within* and *across* markets, which we obtain by imposing: $\mu_{-UM} = \mu_{+UM} = \mu_{-CM} = \mu_{+CM}$.

We also perform in Table 4 an analogous set of alternative specification tests over changes in the intensity specifications that describe liquidity shocks. The next three models account for restrictions on how liquidity shocks impact both markets. The fourth model reflects the case in which intensities of liquidity shocks are assumed to be symmetric between markets, i.e. $\lambda_{+UM} = \lambda_{+CM}$ and $\lambda_{-UM} = \lambda_{-CM}$ (i.e. the growth in the unsecured market is equivalent to the augment in the collateralized market when they face a liquidity shock, and *vice versa*). The fifth model illustrates the case in which, for a given market, the magnitude of a positive liquidity shock is equal to the magnitude of a negative liquidity shock, i.e. $\lambda_{-UM} = \lambda_{+UM}$ and $\lambda_{-CM} = \lambda_{+CM}$. The sixth model reflects the scenario in which liquidity shocks' intensities are equal both *within* and *across* markets, i.e. $\lambda_{-UM} = \lambda_{+UM} = \lambda_{-CM} = \lambda_{+CM}$.

[Insert Table 4 here]

Similarly to Table 3, Table 4 shows that log-likelihood values of alternative money market specifications are significantly lower than the likelihood values for the unrestricted model. In general the log-likelihood values for all other specifications obtained are significantly smaller, at 1% of significance, than the likelihood value for the unrestricted model for the full sample. The only one exception is model 5, however this specification underperforms compared to the unrestricted models in the years 2011 and 2012 for the complete set of maturities, and in the years 2008 and 2011 for the set including overnight loans only, which were turbulent years, due to the collapse of Lehman Brothers and the debt crisis in Europe. Thus, Table 3 shows that the unrestricted model is in general better suited overall to capture money market trends, and especially during periods of stress.

Table 3 and Table 4 suggest that our money market description may provide some economic insight into the nature of interactions between lending channels, since these tables show that alternative setups do not characterize data as well as our specification. Moreover, these results suggest that models incorporating migration effects in money markets (movements in opposite directions in the trading activity of lending in money markets with and without collateral), liquidity shocks (changes in the same direction in both segments), and incorporating flexibility in the intensity of these effects, are necessary ingredients in capturing economic dynamics affecting money market interactions.

4.3 Posterior probabilities

We calculate daily *posterior* probabilities through our structural model by using the Bayes rule. We use *posterior* probabilities to analyze whether there is useful information contained in the dynamic interaction between unsecured and secured channels on a daily basis. Posterior probabilities are obtained on each date using daily data of trading volume from both segments, and by using the parameters estimated in each year, $\hat{\varphi} \equiv (\hat{\alpha}, \hat{\delta}, \hat{\eta}, \hat{\theta}, \hat{\xi}_{UM}, \hat{\xi}_{CM}, \hat{\mu}_{-UM}, \hat{\mu}_{+CM}, \hat{\mu}_{+UM}, \hat{\mu}_{-CM}, \hat{\lambda}_{-UM}, \hat{\lambda}_{-CM}, \hat{\lambda}_{+UM}, \hat{\lambda}_{+CM})$. The use of *posterior* probabilities allows us to have daily measures of money market interactions in terms of money market migrations and liquidity shocks.

The intuition behind *posterior* probabilities is straightforward. For example, the first three branches in the money market trading game, described in Figure 1, represent the complete migration effect from the collateralized market to the unsecured segment. The *posterior* probability of a migration from the collateralized to the unsecured segments on day i, $P_{Mig,CM\to UM}(\hat{\varphi}; UM_i, CM_i)$ is the probability that day i belongs to either branch 1, 2 or 3. Thus, $P_{Mig,CM\to UM}(\hat{\varphi}; UM_i, CM_i)$ is obtained by dividing the daily likelihood function of being in the first three branches –i.e. the first three elements in equation (7)– by the total likelihood function for this particular day –i.e. the complete expression in equation (7). Consequently, $P_{Mig,CM\to UM}(\hat{\varphi}; UM_i, CM_i)$ can be obtained by using daily volume data in each market (UM_i and CM_i, on day i) along with the parameters estimates $\hat{\varphi}$. Thus:

$$\begin{aligned} P_{Mig,CM\to UM}(\hat{\varphi}; UM_i, CM_i) &= \frac{P(\hat{\varphi}|\text{Mig. Event } CM \to UM; UM_i, CM_i)P(\text{Mig. Event } CM \to UM; UM_i, CM_i)}{P(\hat{\varphi}|UM_i, CM_i)} \\ &= \Bigg[\hat{\alpha}(1-\hat{\delta})\hat{\eta}\hat{\theta}\left\{e^{-(\hat{\xi}_{UM}+\hat{\mu}_{+UM}+\hat{\lambda}_{+UM})}\frac{(\hat{\xi}_{UM}+\hat{\mu}_{+UM}+\hat{\lambda}_{+UM})^{UM}}{UM!}e^{-(\hat{\xi}_{CM}-\hat{\mu}_{-CM}+\hat{\lambda}_{+CM})}\frac{(\hat{\xi}_{CM}-\hat{\mu}_{-CM}+\hat{\lambda}_{+CM})^{CM}}{CM!}\right\} \\ &+ \hat{\alpha}(1-\hat{\delta})\hat{\eta}(1-\hat{\theta})\left\{e^{-(\hat{\xi}_{UM}+\hat{\mu}_{+UM}-\hat{\lambda}_{-UM})}\frac{(\hat{\xi}_{UM}+\hat{\mu}_{+UM}-\hat{\lambda}_{-UM})^{UM}}{UM!}e^{-(\hat{\xi}_{CM}-\hat{\mu}_{-CM}-\hat{\lambda}_{-CM})}\frac{(\hat{\xi}_{CM}-\hat{\mu}_{-CM}-\hat{\lambda}_{-CM})^{CM}}{CM!}\right\} \\ &+ \hat{\alpha}(1-\hat{\delta})(1-\hat{\eta})\left\{e^{-(\hat{\xi}_{UM}+\hat{\mu}_{+UM})}\frac{(\hat{\xi}_{UM}+\hat{\mu}_{+UM})^{UM}}{UM!}e^{-(\hat{\xi}_{CM}-\hat{\mu}_{-CM})}\frac{(\hat{\xi}_{CM}-\hat{\mu}_{-CM}}{CM!}\right\}\Bigg]/L(\hat{\varphi}|(UM_i, CM_i)). \end{aligned} \tag{9}$$

Analogously, the posterior probability of a migration event from the unsecured segment to the collateralized market, $P_{Mig,UM\to CM}(\hat{\varphi}; UM_i, CM_i)$, can be calculated on a daily basis by using the fourth to sixth branches in Figure 1 (which illustrate the total migration effect from the unsecured funding to the collateralized money market):

$$\begin{aligned} P_{Mig,UM\to CM}(\hat{\varphi}; UM_i, CM_i) &= \frac{P(\hat{\varphi}|\text{Mig. Event } UM \to CM; UM_i, CM_i)P(\text{Mig. Event } UM \to CM; UM_i, CM_i)}{Pr(\hat{\varphi}|UM_i, CM_i)} \\ &= \Bigg[\hat{\alpha}\hat{\delta}\hat{\eta}\hat{\theta}\left\{e^{-(\hat{\xi}_{UM}-\hat{\mu}_{-UM}+\hat{\lambda}_{+UM})}\frac{(\hat{\xi}_{UM}-\hat{\mu}_{-UM}+\hat{\lambda}_{+UM})^{UM}}{UM!}e^{-(\hat{\xi}_{CM}+\hat{\mu}_{+CM}+\hat{\lambda}_{+CM})}\frac{(\hat{\xi}_{CM}+\hat{\mu}_{+CM}+\hat{\lambda}_{+CM})^{CM}}{CM!}\right\} \\ &+ \hat{\alpha}\hat{\delta}\hat{\eta}(1-\hat{\theta})\left\{e^{-(\hat{\xi}_{UM}-\hat{\mu}_{-UM}-\hat{\lambda}_{-UM})}\frac{(\hat{\xi}_{UM}-\hat{\mu}_{-UM}-\hat{\lambda}_{-UM})^{UM}}{UM!}e^{-(\hat{\xi}_{CM}+\hat{\mu}_{+CM}-\hat{\lambda}_{-CM})}\frac{(\hat{\xi}_{CM}+\hat{\mu}_{+CM}-\hat{\lambda}_{-CM})^{CM}}{CM!}\right\} \\ &+ \hat{\alpha}\hat{\delta}(1-\hat{\eta})\left\{e^{-(\hat{\xi}_{UM}-\hat{\mu}_{-UM})}\frac{(\hat{\xi}_{UM}-\hat{\mu}_{-UM})^{UM}}{UM!}e^{-(\hat{\xi}_{CM}+\hat{\mu}_{+CM})}\frac{(\hat{\xi}_{CM}+\hat{\mu}_{+CM})^{CM}}{CM!}\right\}\Bigg]/L(\hat{\varphi}|(UM_i, CM_i)). \end{aligned} \tag{10}$$

Similar expressions can be obtained for the posterior probabilities of positive liquidity shocks, $P_{l+}(\hat{\varphi}; UM_i, CM_i)$, and the posterior probabilities of negative liquidity shocks $P_{l-}(\hat{\varphi}; UM_i, CM_i)$.

We compute every day *posterior* probabilities by using daily trading volumes from both markets and the parameters estimated in each year for only the complete set of maturities (i.e. with the parameters reported in Table 2 upper panel in years 2008, 2009 and so on until 2013). We do not use the sub-set of overnight loans since, as reported in Table 2, the behaviour of money market interactions for the complete set of maturities (i.e. short-term and long-term maturities) is very similar to the behaviour of the interactions of lending channels with only overnight loans.[13]

In Figure 4 we present posterior probabilities of migration (upper panel) from June 2008 to July 2013 together with the probability of simultaneous defaults by two or more large banks (bottom panel), which is a measure of systemic risk in the European Banking System reported by the ECB. Figure 4 shows that the posterior probability of migration from unsecured to collateralized money markets grows in relation to events that negatively affect money markets and increase counterparty risks and uncertainty; while the posterior probability of migration from collateralized to unsecured channels moves in the opposite direction. For instance, the posterior probabilities of migration from the unsecured to the collateralized market increased: i) in the fourth quarter of 2008, when money markets froze following the default of Lehmann Brothers; ii) in the fourth quarter of 2010, during the first phase of the European sovereign debt crisis; iii) and in the second half of 2011, during the second phase of the breakout of the European sovereign debt crisis.

[Insert Figure 4 here]

Similarly to Figure 4, Figure 5 shows posterior probabilities of liquidity shocks (upper panel) in conjunction with a measure of excess liquidity in the Euro system (bottom panel). Excess liquidity is measured as the sum of the Euro system credit institutions' current accounts, and the net amount of ECB's standing facilities (Mancini *et al.*, 2015 use a similar measure for their analysis of the European repo market).

[13] The use of lending data with the complete set of maturities to calculate *posterior* probabilities has an additional benefit, in relation to the analysis of the worth of the information contained in money market interactions. Besides money market interactions between unsecured and collateralized lending, money markets can also exhibit internal interactions in term of changes in the maturity of the loans in each segment. For instance, banks may decide to reduce the maturity of the loans in periods of stress. Despite the fact that maturity interactions are not very important in the European money market as reported in Table 1 (since loans that are not overnight represent a minority part of lending), the use of data and parameters estimated with the complete trading activity (long-term and short-term loans) reduces the impact of not capturing changes in the maturities over time in each lending channel.

[Insert Figure 5 here]

Similarly to Figure 4, Figure 5 shows that our characterization of money market interactions is able to capture aggregate changes in the Euro system's overall liquidity conditions, which often occurred at times when the ECB implemented measures in response to the worsened funding situation of the European banking system. For example, the probability of negative liquidity shocks is reduced after the start of the Covered Bond Purchase Programme (CBPP1) and the Securities Market Programme (SMP). The probability of positive liquidity shocks increases after the second Covered Bond Purchase Programme (CBPP2), and after the two Long-Term Refinancing Operations (LTROs, versions I and II). Nevertheless, the probability of negative liquidity shocks increases considerably after the implementation of the program of Outright Monetary Transactions (OMT).

5 Money market interactions and interest rates spreads

We have seen that our structural characterization of money market interactions makes sense as an explanation for dynamics between unsecured and secured lending channels. As described in Section 4, the structural model is estimated using only the information extracted from aggregate trading volumes from each money market segment; thus we do not use any information pertaining to interest rate spreads. However, our estimated parameters have implications for interest rate spreads, as explained in equation (4) in the three-period equilibrium model used to motivate our structural approach; hence this linkage provides a natural procedure to examine the reasonableness of our setup.[14]

We calculate on each day weighted average rates, r_t^{UM} and r_t^{CM}, for the unsecured segment and for the collateralized money market, respectively. To eliminate the effect of changes in the ECB target rates, we adjust money market rates to incorporate modifications in the ECB corridor, $r_t^{ECB,lending} - r_t^{ECB,deposit}$, as:

[14] The use of only trading volume in our structural approach is consistent with the three-period model, where the equilibrium is defined by the volumes in each market after the firms' optimizations (see equation 1 and equation 2). Nevertheless, agents' decision about trading activity in each segment should still affect interest rates through market clearing.

$$R_{UM,t} = \frac{r_t^{UM} - r_t^{ECB,deposit}}{r_t^{ECB,lending} - r_t^{ECB,deposit}} \tag{11}$$

and

$$R_{CM,t} = \frac{r_t^{CM} - r_t^{ECB,deposit}}{r_t^{ECB,lending} - r_t^{ECB,deposit}}. \tag{12}$$

We regress the interest rate spread, $R_{UM,t}$ - $R_{CM,t}$, on posterior probabilities of migration and liquidity shocks (together with several control variables). The objective of this regression analysis is to detect whether the information contained in money market interaction, which is obtained by our structural approach, can appropriately explain interest rate spreads between lending channels. The results of these regressions are reported in Table 5.

[Insert Table 5 here]

As illustrated in Table 5, we employ the 1-period lagged posterior probabilities of migration and the 1-period lagged posterior probabilities of liquidity shocks as independent variables. In addition, we use as control variables the 1-period lagged interest rate spread, the 1-period lagged volume ratio traded between the collateralized and unsecured channels, the 1-period lagged probability of simultaneous defaults of two or more large banks, the 1-period lagged Composite Indicator of Systemic Stress ($CISS$), and a 1-period lagged proxy for excess liquidity in Europe (which was explained in the previous section).

The use of lagged variables should eliminate endogeneity problems, since state variables at any point in time are not affected by market signals that agents are not yet aware of. In addition, lagged variables should have a smaller effect than their contemporaneous versions on the current interest rate spread; hence we can consider the results of this regression analysis as conservative. Therefore, in the case that we find significant parameters for the measures obtained with our structural model, even under this conservative regression analysis (and after using several controls), it is an important indication that supports our hypothesis in relation to the fact that useful information is contained in money market interactions.

We run least-squares regressions with heteroskedasticity and autocorrelation-consistent (HAC) standard errors. Since the value of $CISS$ is provided once per week by the ECB, we also run weekly regressions in which daily variables are weekly-averaged.

Table 5 shows that the posterior probability of migration from the unsecured to collateralized money markets, $P_{Mig,UM\rightarrow CM,t\text{-}1}$, is strongly significant and positively affects the interest rate spread when using daily data. This result is consistent with the three-period model illustrated in Section 2. On the one hand, equation (3) states that a migration effect from unsecured to collateralized segments is accompanied by an increase in the parameter h, which is the relative cost parameter of the unsecured segment in relation to other cost parameters of the complete money market. Thus, an increase in h is associated with a growth in $P_{Mig,UM\rightarrow CM,t\text{-}1}$. On the other hand, equation (4) shows that increases in the spread between unsecured and secured market rates is related to rises in h; hence $R_{UM,t}$ - $R_{CM,t}$ should be positively related to $P_{Mig,UM\rightarrow CM,t\text{-}1}$. This result is robust when we use the probability of migration from collateralized to unsecured money markets, $P_{Mig,CM\rightarrow UM,t\text{-}1}$ (but, as expected, with negative values reflecting the opposite direction). We view the analysis reported in Table 5 as important evidence for the validity of our model to capture relevant information from money market interactions, which can be used to characterize economic conditions in the financial system.

The parameter associated with $CISS_{t-1}$ has the same positive sign as the one of $P_{Mig,UM\rightarrow CM,t-1}$, which is consistent with our expectations, since in turbulent periods we expect to observe a migration from unsecured to collateralized funding. However, the probability of simultaneous defaults by two or more large banks, $ProbSimult_{t-1}$, has a negative impact on the spread between the unsecured and collateralized market rates. We interpret these results in the sense that our migrations probabilities ($P_{Mig,UM\rightarrow CM,t\text{-}1}$ and $P_{Mig,CM\rightarrow UM,t\text{-}1}$) simultaneously describe both money markets; instead $CISS_{t-1}$ and $ProbSimult_{t-1}$ predominantly reflect the conditions of one lending segment. On the one hand, as explained in the three-period model in Section 2, a migration effect is associated with: a change in the level of costs of the unsecured market segment (k_{UM}), and/or a change in the costs of the collateralized money market (k_{CM}). For instance, equations (3) to (5) show that a migration from the unsecured to collateralized money markets is related to bad news in the unsecured segment (i.e. an increase in k_{UM}) and/or good news for collateralized lending (i.e. a reduction in k_{CM}). On the other hand, the positive sign of $CISS$'s parameter is associated with more potential dangers –the implicit costs of lending– of one segment: the unsecured money market (i.e. an increase in the level of $CISS_{t-1}$ is related to an increase in k_{UM}). In fact, the value of $CISS$ captures money market dynamics through 3-month Euribor rates (realized volatility and spreads with the 3-month French T-bills) which are averaged interest rates at which Euro zone banks offer to lend 'unsecured' funds (see Hollo *et al.*, 2012). For that reason, the regression parameters of $CISS_{t-1}$ and $P_{Mig,UM\rightarrow CM,t-1}$ are positive. Conversely, the negative sign of the parameter associated to $ProbSimult_{t-1}$ can be explained because its value is more connected to the lending costs in the other market segment: the collateralized money market and the behaviour of assets used as collateral (i.e. an increase in the value of $ProbSimult_{t-1}$ is associated to an increase in k_{CM}). Hence, a migration from unsecured to collateralized lending (reflected in $P_{Mig,UM\rightarrow CM,t-1}$) is positively related to $CISS_{t-1}$, but negatively related to $ProbSimult_{t-1}$. This is consistent with the way how $ProbSimult$ is calculated by the ECB, where there is an important component of the collateralized money market. The value of $ProbSimult$ is obtained from CDS, in which the writer of the CDS insurance has to put up enough collateral to cover their positions (see ECB Financial Stability Review, June 2012, Box 8, pp. 99-100).[15]

Table 5 also shows that the posterior probability of positive (negative) liquidity shocks is negatively (positively) related to the interest rate spread. A higher probability of positive (negative) liquidity shock means higher probability of joint increase (decrease) in trading activity for both unsecured and secured markets. We attribute the sign of the coefficient on the posterior probability of liquidity shocks to the different effect that liquidity shocks have on the demand for unsecured and secured funding. For example, liquidity injections by the ECB may satisfy market demand for unsecured reserves more than they satisfy market demand for collateralized loans, resulting in a relatively larger decrease in unsecured interbank rates in relation to the collateralized segment. A similar rationale can be applied to the case of liquidity absorptions.

[15] Regarding the CDS collateralization, the International Swaps and Derivatives Association Margin Survey (ISDA Margin Survey 2014) shows that credit derivatives transactions are almost fully collateralized compared to other derivatives.

The results of Table 5 regarding the connection between $R_{UM,t}$ - $R_{CM,t}$ and liquidity shocks are also consistent with equation (4) of the three-period model in Section 2, since: $\partial(r^*_{UM} - r^*_{CM})/\partial Q = k_{CM}h \ - dQ^2$; hence this result can be obtained when the partial derivative of the interest rate spread in relation to the volume traded is negative (i.e. when $k_{CM}h < dQ^2$). However, when controlling for Excess Liquidity in the Euro system $EL_{t\text{-}1}$, posterior probabilities $P_{l+,t\text{-}1}$ and $P_{l\text{-},t\text{-}1}$ are significant only when using weekly data. We interpret this result as caused by the presence of end-of-week noise, end-of-refinancing-period distortions, and fine-tuning effects. Nevertheless, the parameters for liquidity shocks in the regression analysis have a consistent direction in relation to weekly regressions –i.e. the interest rate spread is negatively (positively) associated to $P_{l+,t\text{-}1}$ ($P_{l\text{-},t\text{-}1}$).

6 Conclusion

We introduce in this paper a structural model to capture the information revealed in the interaction between unsecured and collateralized money markets. We obtain measures of migration probabilities between market segments and probabilities of liquidity shocks. The measures obtained by the model are different from other variables used to describe periods of stress in money markets and liquidity changes, due to the fact that in our model the information revealed by 'how' lending channels interact is obtained implicitly from the agents' strategic trading behaviour, in each market and as economic conditions evolve.

The intuition behind our approach is illustrated by a simple three-period equilibrium model. In this model, differences in costs across lending channels induce a migration effect in trading activity between unsecured and collateralized money markets, while liquidity shocks induce same-sign movements in market activity across the two market segments. By employing such a framework, we are able to explain the time-varying degree of correlation between unsecured and collateralized markets in terms of market volumes.

We perform an empirical analysis for money markets in the Euro zone using our structural model. We present evidence that interactions between lending segments provide useful information, which can be extracted and analyzed under our approach. We show that posterior probabilities of migration are related to economic events, while liquidity shock probabilities are related to changes in liquidity conditions. We present evidence that the information contained in money market interactions can explain the behaviour of interest rate spreads, even after controlling for differences in volume between lending segments and other variables related to systemic risk and excess of liquidity. This result gives a natural mechanism to test whether the information revealed by money market interactions has a role in determining variables relevant to the economy. Moreover, we test the robustness of our market design against a variety of alternative specifications and show that the proposed structure is better suited to explain the complex dynamics in trading activity *within* and *across* unsecured and collateralized money markets.

We believe that this study represents a first attempt at linking theoretical and structural models to analyze money market interactions. Clearly much more empirical and theoretical work needs to be done to better understand the rich information that can be extracted from connections between unsecured and collateralized segments. However, our model seems to be a satisfactory starting point as a model highlighting the role of information revealed in in the dynamic relationship of lending channels.

Finally, the analysis presented in our study is simple and intuitive, and it can easily be implemented to other economies. Nevertheless, other interesting issues remain to be addressed. For instance, the study of money market interactions under the various possible specific features of banks (size, network centrality, or based on ratings), or different money market designs have been left for future research.

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Table 1
Summary statistics

The table contains summary statistics of daily volumes in the European money market (€ billion), by year and for the full sample. Daily volume is reported for the total market (long-term and short-term loans with maturities ranging from one day –overnight– up to one year) on the upper panel, and for the short-term loans (only overnight loans) on the bottom panel. The sample includes total daily aggregated amounts between June 2, 2008 and July 30, 2013. Unsecured Interbank loans are obtained from TARGET2. Collateralized Interbank loans are provided by Eurex.

Year	Obs.	Mean	Median	Std. Dev.	Skew	Kurt	Min	Max	Mean	Median	Std. Dev.	Skew	Kurt	Min	Max
		Unsecured market							Collateralized market						
		Total: Short-term and long-term loans													
2008	151	98.40	101.44	19.79	0.02	2.50	42.72	150.00	14.77	14.28	5.28	0.80	3.18	5.30	31.36
2009	256	67.59	68.47	12.45	0.02	2.35	40.21	100.26	18.36	17.45	5.93	0.57	4.39	1.99	41.31
2010	258	68.98	68.49	12.28	0.20	2.13	36.95	98.28	19.93	18.67	7.63	0.74	3.37	3.10	43.87
2011	257	63.89	63.72	12.10	0.04	2.31	31.66	91.44	33.60	34.19	9.21	0.05	2.70	8.04	57.96
2012	256	24.60	24.69	8.80	0.38	2.15	7.83	46.00	27.54	26.52	7.46	0.46	4.49	4.32	58.63
2013	147	18.59	18.25	3.98	0.40	2.74	8.97	29.84	33.13	33.56	8.62	0.07	2.35	13.01	54.99
Full Sample	1,325	56.91	59.50	27.74	0.12	2.52	7.83	150.00	24.62	23.43	10.24	0.51	2.75	1.99	58.63
		Short-term loans													
2008	151	86.71	86.19	18.23	0.03	2.80	29.89	131.28	12.42	11.12	4.87	0.84	2.97	4.20	26.44
2009	256	59.08	58.44	11.92	0.07	2.38	32.69	90.89	14.85	14.52	5.43	0.54	4.92	0.00	38.34
2010	258	60.97	60.30	12.26	0.18	2.10	25.72	89.39	16.02	14.50	6.58	0.94	3.82	3.10	37.21
2011	257	56.63	56.64	11.54	-0.11	2.63	17.84	83.26	28.48	28.49	8.09	0.06	2.92	2.74	50.86
2012	256	20.48	19.52	7.62	0.34	2.17	6.20	38.06	23.09	22.33	6.55	0.31	3.46	3.97	43.19
2013	147	16.19	15.72	3.93	0.49	2.55	7.91	26.28	29.08	29.22	8.39	0.10	2.35	10.84	51.43
Full Sample	1,325	49.91	51.91	25.10	0.15	2.49	6.20	131.28	20.61	19.49	9.21	0.55	2.77	0.00	51.43

Table 2

Estimated parameters of the structural model used to analyze money market interactions

The table presents parameter estimates for the structural model (described in Figure 1) used to analyze money market interactions. The parameters are obtained in each year and for the full sample between June 2, 2008 and July 30, 2013. The parameters are reported for the total market (i.e. long-term and short-term loans with maturities ranging from one day –overnight– up to one year) on the upper panel, and for the short-term loans (only overnight loans) on the bottom panel. Standard errors are calculated through bootstrapping and reported in parentheses.

Year	α	δ	η	θ	ξ_{UM}	ξ_{CM}	μ_{-UM}	μ_{+CM}	μ_{+UM}	μ_{-CM}	λ_{-UM}	λ_{-CM}	λ_{+UM}	λ_{+CM}
					Total: Short-term and long-term loans									
2008	0.74	0.30	0.25	0.87	77.82	12.99	0.00	8.93	31.84	1.33	24.36	4.25	21.97	3.10
	(0.08)	(0.10)	(0.16)	(0.26)	(7.70)	(1.60)	(6.63)	(1.62)	(4.40)	(1.22)	(14.82)	(1.34)	(7.29)	(2.26)
2009	0.34	0.66	0.59	0.51	69.42	16.87	4.69	8.16	0.12	8.25	15.60	2.19	12.58	4.20
	(0.07)	(0.17)	(0.07)	(0.15)	(3.95)	(1.24)	(4.60)	(2.06)	(5.32)	(2.68)	(2.74)	(2.49)	(3.09)	(2.75)
2010	0.40	0.39	0.70	0.41	71.26	21.41	0.00	11.69	0.00	7.44	14.14	5.53	12.61	2.74
	(0.08)	(0.12)	(0.08)	(0.21)	(5.30)	(2.59)	(0.92)	(1.38)	(4.44)	(1.94)	(3.05)	(1.58)	(3.61)	(2.80)
2011	0.66	0.51	0.56	0.92	63.80	27.36	12.56	7.59	12.36	6.70	16.58	6.38	1.97	11.95
	(0.05)	(0.10)	(0.06)	(0.15)	(3.69)	(2.91)	(2.36)	(1.92)	(3.19)	(2.73)	(6.47)	(2.91)	(3.26)	(2.47)
2012	0.36	0.56	0.63	0.27	28.37	26.15	0.04	9.62	0.13	10.09	11.95	1.42	10.03	10.08
	(0.14)	(0.21)	(0.14)	(0.22)	(4.43)	(2.22)	(3.66)	(3.54)	(4.92)	(5.13)	(3.81)	(5.91)	(2.76)	(3.15)
2013	0.47	0.38	0.58	0.34	19.33	36.67	2.26	7.46	0.00	5.40	3.58	11.97	5.21	6.43
	(0.12)	(0.23)	(0.06)	(0.11)	(0.86)	(2.42)	(1.69)	(3.06)	(1.27)	(2.30)	(0.72)	(2.40)	(0.75)	(1.77)
Full Sample	0.56	0.47	0.77	0.46	47.51	23.67	0.00	14.57	37.54	9.76	27.18	0.00	26.87	0.00
	(0.02)	(0.06)	(0.03)	(0.03)	(4.75)	(1.09)	(3.64)	(0.62)	(1.62)	(0.62)	(3.41)	(0.47)	(3.45)	(0.00)
					Short-term loans									
2008	0.81	0.32	0.20	0.90	70.23	9.59	0.60	9.07	24.14	0.00	43.46	2.41	22.89	2.83
	(0.09)	(0.09)	(0.16)	(0.22)	(6.40)	(1.11)	(6.84)	(1.28)	(3.87)	(0.91)	(12.61)	(1.32)	(25.73)	(68.46)
2009	0.42	0.87	0.56	0.53	59.14	13.80	3.58	7.61	0.00	8.15	12.51	4.73	15.20	0.00
	(0.09)	(0.25)	(0.09)	(0.19)	(5.14)	(1.76)	(4.74)	(3.39)	(7.41)	(3.58)	(4.47)	(3.60)	(4.58)	(2.80)
2010	0.43	0.26	0.71	0.41	62.91	18.63	0.00	11.25	0.00	6.66	13.91	5.09	13.11	1.26
	(0.08)	(0.12)	(0.11)	(0.20)	(4.85)	(2.49)	(2.25)	(2.05)	(6.43)	(2.61)	(4.37)	(1.34)	(2.94)	(3.07)
2011	0.58	0.50	0.48	0.93	56.72	23.76	13.41	6.83	12.58	5.55	11.24	12.54	1.05	10.77
	(0.05)	(0.12)	(0.06)	(0.11)	(3.58)	(2.54)	(2.33)	(1.75)	(2.59)	(2.35)	(7.05)	(4.38)	(5.12)	(3.43)
2012	0.71	0.38	0.44	0.40	16.34	21.01	2.83	7.61	9.24	0.00	2.57	7.33	8.67	11.13
	(0.12)	(0.18)	(0.11)	(0.16)	(3.83)	(1.43)	(2.51)	(2.31)	(4.38)	(4.39)	(3.63)	(3.87)	(2.49)	(2.31)
2013	0.45	0.49	0.62	0.44	15.76	31.07	0.50	7.04	1.01	7.28	3.15	10.64	5.25	6.80
	(0.10)	(0.20)	(0.05)	(0.10)	(0.95)	(2.43)	(0.89)	(2.20)	(1.37)	(2.35)	(0.86)	(2.51)	(0.72)	(2.34)
Full Sample	0.57	0.45	0.76	0.43	41.70	20.00	0.00	13.23	33.79	8.71	24.33	0.00	24.44	0.00
	(0.03)	(0.04)	(0.02)	(0.03)	(3.67)	(0.56)	(1.83)	(0.51)	(1.40)	(0.45)	(2.71)	(0.41)	(2.35)	(0.06)

Table 3
Model specification tests in terms of migration and liquidity setups

This table reports statistics for differences in log-likelihood ratios of our structural model (unrestricted model in this table) in relation to three model specifications in which we modify the setup of probabilities regarding migration events and liquidity shocks. Tests are performed in each year and for the full sample. In addition, tests are applied to the total market (long-term and short-term loans with maturities ranging from one day –overnight– up to one year) on the upper panel, and for the short-term loans (only overnight loans) on the bottom panel. The χ^2 statistic is provided, where *, ** and *** indicate significance at 10%, 5%, and 1%, respectively.

Year	Unrestric. model	Restric. Model α=0		Restric. Model η=0		Restric. Model α=0; η=0	
	Likelih. ratio	Likelih. ratio	χ^2	Likelih. ratio	χ^2	Likelih. Ratio	χ^2
			Short-term and long-term loans				
2008	-1095.70	-1132.35	73.29***	-1103.76	16.1**	-1261.25	331.09***
2009	-1821.60	-1828.63	14.06**	-1847.30	51.39***	-1923.01	202.82***
2010	-1855.38	-1849.70	-11.35	-1932.20	153.65***	-2043.92	377.07***
2011	-1917.08	-1990.15	146.13***	-1924.24	14.31**	-2082.38	330.6***
2012	-1766.15	-1766.54	0.78	-1803.63	74.94***	-1955.05	377.79***
2013	-929.45	-918.96	-20.98	-934.50	10.11	-966.53	74.17***
Full Sample	-10873.35	-12462.04	3177.38***	-11909.93	2073.17***	-19632.85	17519***
			Short-term loans				
2008	-1066.98	-1109.55	85.14***	-1086.32	38.68***	-1230.49	327.01***
2009	-1794.20	-1820.79	53.18***	-1823.93	59.45***	-1906.72	225.04***
2010	-1816.32	-1805.66	-21.33	-1883.28	133.92***	-2002.06	371.49***
2011	-1879.68	-1951.92	144.47***	-1891.60	23.84***	-2029.59	299.82***
2012	-1708.69	-1690.84	-35.71	-1726.45	35.51***	-1854.34	291.3***
2013	-922.33	-909.00	-26.67	-928.20	11.73*	-968.43	92.2***
Full Sample	-10627.05	-12061.90	2869.69***	-11570.90	1887.7***	-18679.40	16104.71***

Table 4
Model specification test in terms of modification of setups regarding arrival intensities for migrations and liquidity shocks

This table reports statistics for differences in log-likelihood ratios of our structural model (unrestricted model in this table) in relation to three model specifications in which we modify setups regarding arrival intensities for migrations and liquidity shocks. Tests are performed in each year and for the full sample. In addition, tests are applied to the total market (long-term and short-term loans with maturities ranging from one day –overnight– up to one year) on the upper panel, and for the short-term loans (only overnight loans) on the bottom panel. The χ^2 statistic is provided, where *, ** and *** indicate significance at 10%, 5%, and 1%, respectively.

Year	Unrestric. model	Restric. Model $\mu_{-UM}=\mu_{+CM}$ $\mu_{+UM}=\mu_{-CM}$		Restric. Model $\mu_{-UM}=\mu_{+UM}$ $\mu_{+CM}=\mu_{-CM}$		Restric. Model $\mu_{-UM}=\mu_{+UM}=$ $\mu_{+CM}=\mu_{-CM}$		Restric. Model $\lambda_{+UM}=\lambda_{+CM}$ $\lambda_{-UM}=\lambda_{-CM}$		Restric. Model $\lambda_{-UM}=\lambda_{+UM}$ $\lambda_{-CM}=\lambda_{+CM}$		Restric. Model $\lambda_{-UM}=\lambda_{+UM}=$ $\lambda_{-CM}=\lambda_{+CM}$	
	Likelih. ratio	Likelih. Ratio	χ^2	Likelih. Ratio	χ^2	Likelih. Ratio	χ^2	Likelih. Ratio	χ^2	Likelih. Ratio	χ^2	Likelih. Ratio	χ^2
						Short-term and long-term loans							
2008	-1095.70	-1107.34	23.27***	-1106.54	21.67***	-1107.27	23.12***	-1109.02	26.64***	-1096.48	1.55	-1109.56	27.7***
2009	-1821.60	-1827.17	11.13***	-1820.07	-3.07	-1827.39	11.58***	-1823.05	2.9	-1822.18	1.15	-1823.26	3.31
2010	-1855.38	-1864.76	18.75***	-1859.88	9.00**	-1864.90	19.03***	-1862.11	13.45***	-1855.97	1.18	-1875.17	39.58***
2011	-1917.08	-1925.61	17.06***	-1917.21	0.26	-1925.62	17.08***	-1920.59	7.01**	-1927.19	20.23***	-1922.94	11.72***
2012	-1766.15	-1794.99	57.67***	-1766.36	0.41	-1794.89	57.47***	-1764.36	-3.59	-1785.98	39.64***	-1763.98	-4.35
2013	-929.45	-929.71	0.54	-929.35	-0.19	-929.57	0.24	-936.49	14.08***	-930.50	2.11	-936.62	14.34***
Full Sample	-10873.35	-11154.20	561.69***	-11035.51	324.32***	-11154.25	561.79***	-11103.66	460.63***	-10873.56	0.43	-11122.91	499.12***
						Short-term loans							
2008	-1066.98	-1085.98	38.00***	-1075.89	17.82***	-1085.67	37.37***	-1089.40	44.84***	-1069.60	5.24*	-1091.17	48.37***
2009	-1794.20	-1803.16	17.91***	-1788.91	-10.58	-1805.12	21.84***	-1788.49	-11.43	-1793.16	-2.09	-1797.40	6.39*
2010	-1816.32	-1820.49	8.34**	-1821.79	10.94***	-1820.57	8.51**	-1820.91	9.17**	-1815.79	-1.05	-1821.61	10.58**
2011	-1879.68	-1883.61	7.86**	-1879.90	0.44	-1886.04	12.72***	-1880.51	1.66	-1886.93	14.5***	-1886.69	14.02***
2012	-1708.69	-1720.06	22.74***	-1694.96	-27.46	-1718.47	19.56***	-1707.64	-2.1	-1710.88	4.37	-1710.82	4.25
2013	-922.33	-921.34	-1.99	-922.25	-0.16	-921.27	-2.12	-926.51	8.36**	-922.15	-0.36	-926.28	7.89**
Full Sample	-10627.05	-10886.25	518.39***	-10771.50	288.9***	-10884.50	514.9***	-10840.86	427.61***	-10627.00	-0.09	-10844.29	434.47***

Table 5

Money market interactions and interest rate spreads

This table shows the results of regressions on the interest rate spread, $R_{UM,t}$ - $R_{CM,t}$, in relation to probabilities of migration and liquidity shocks (jointly to several control variables). Explanatory variables in the regressions are shown in the first column which are lagged one period. Regressions are based on daily data (columns 2-7) and weekly data (columns 8-13) from June 2008 to July 2013. $R_{UM,t}$ and $R_{CM,t}$ are calculated as in equation (11) and equation (12), respectively. $P_{Mig,CM \rightarrow UM,t\text{-}1}$ and $P_{Mig,UM \rightarrow CM,t\text{-}1}$ are the posterior probabilities of migration (unsecured to collateralized market, and *vice versa*) obtained from equation (9) and equation (10). $P_{l+,t\text{-}1}$ and $P_{l\text{-},t\text{-}1}$ are the posterior probabilities of liquidity shocks (positive and negative liquidity shocks, respectively) obtained as described in Section 4. $Vol_{CM,t\text{-}1}/Vol_{UM,t\text{-}1}$ is the volume ratio traded between the collateralized and unsecured lending channel. $ProbSimult_{t\text{-}1}$ is the probability of simultaneous defaults of two or more large banks, which is provided by the ECB. $CISS_{t\text{-}1}$ is the Composite Indicator of Systemic Stress which is provided on a weekly basis by the ECB. $EL_{t\text{-}1}$ is a proxy for the excess liquidity in Europe, which is measured as a credit institution's current account plus the difference between the amounts borrowed and lent at the ECB's standing facilities. The heteroskedasticity and autocorrelation-consistent (HAC) standard errors are shown in parentheses. The stars *, ** and *** indicate significance at 10%, 5%, and 1%, respectively.

	$R_{UM,t}$ - $R_{CM,t}$											
	Daily						Weekly					
const.	-0.01*	0.00	-0.01	-0.01***	-0.01***	-0.01***	-0.02**	0.00	-0.01	-0.04***	-0.02***	-0.03***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)
$R_{UM,t\text{-}1}$ - $R_{CM,t\text{-}1}$	0.58***	0.61***	0.58***	0.57***	0.62***	0.58***	0.54***	0.61***	0.58***	0.55***	0.64***	0.57***
	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)	(0.07)	(0.07)	(0.07)	(0.08)	(0.07)	(0.08)
$P_{Mig,CM \rightarrow UM,t\text{-}1}$	-0.01***	-0.01***	-0.01***				-0.01	-0.02***	-0.02**			
	(0.00)	(0.00)	(0.00)				(0.01)	(0.01)	(0.01)			
$P_{Mig,UM \rightarrow CM,t\text{-}1}$				0.02***	0.01*	0.02***				0.02	0.03**	0.03**
				(0.01)	(0.00)	(0.00)				(0.01)	(0.01)	(0.01)
$P_{l+,t\text{-}1}$	0.00	-0.02***	0.00				-0.01**	-0.02**	-0.01*			
	(0.00)	(0.00)	(0.00)				(0.01)	(0.01)	(0.01)			
$P_{l\text{-},t\text{-}1}$				0.00	0.01***	0.00				0.01**	0.01**	0.01**
				(0.00)	(0.00)	(0.00)				(0.01)	(0.01)	(0.01)
$Vol_{CM,t\text{-}1}/Vol_{UM,t\text{-}1}$	0.00	0.01***		0.00	0.01***		0.01**	0.01**		0.01**	0.01**	
	(0.00)	(0.00)		(0.00)	(0.00)		(0.01)	(0.00)		(0.00)	(0.00)	
$ProbSimult_{t\text{-}1}$	-0.08**		-0.08**	-0.12***		-0.12***						
	(0.03)		(0.03)	(0.04)		(0.04)						
$CISS_{t\text{-}1}$							0.04*		0.02	0.03*		0.02
							(0.02)		(0.02)	(0.02)		(0.02)
$EL_{t\text{-}1}$	0.04***		0.05***	0.06***		0.06***	0.02		0.03***	0.03***		0.04***
	(0.01)		(0.01)	(0.01)		(0.01)	(0.01)		(0.01)	(0.01)		(0.01)
Adj. R^2	0.50	0.48	0.49	0.51	0.48	0.50	0.57	0.56	0.56	0.58	0.56	0.57

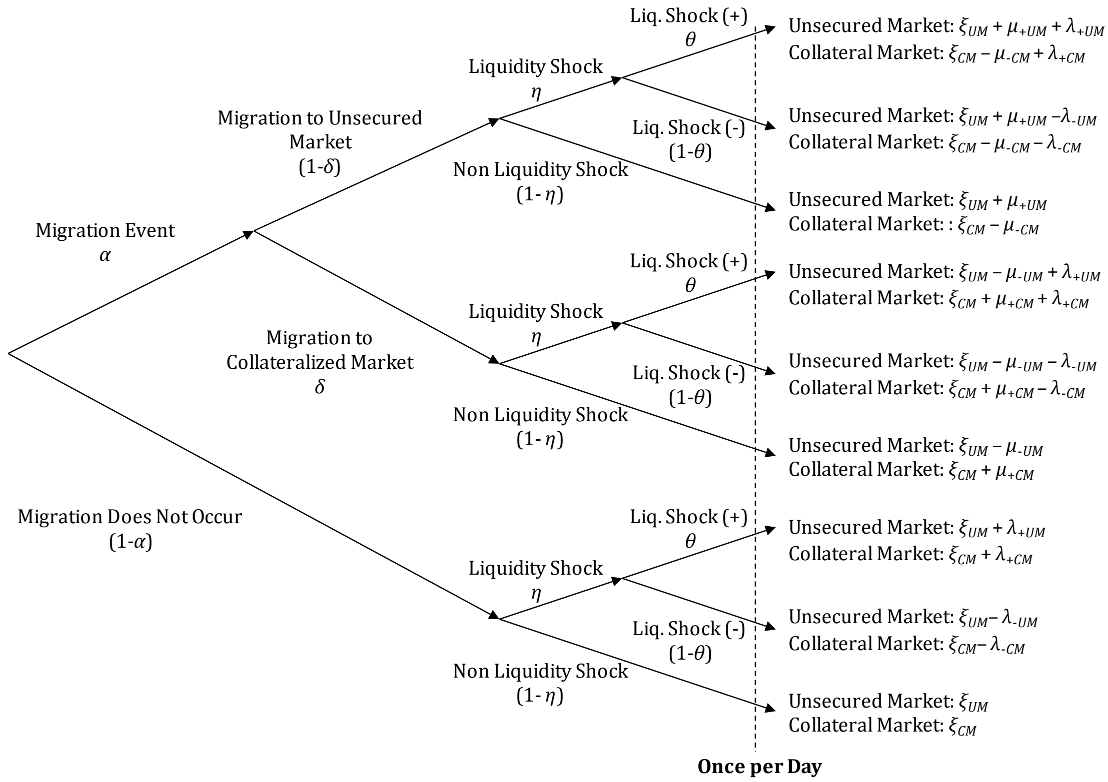

Figure 1. Dynamics in unsecured and collateralized money markets. This tree diagram reflects the trading process that is characterized in our money market model, in which α is the probability that a migration event occurs, δ is the probability of a migration to the collateralized market, η is the probability of a liquidity shock, θ is the probability that the liquidity shock is positive, and ξ_{UM} (ξ_{LQ}) is the transaction arrival rate in the unsecured segment (collateralized money market). In the case of a migration to the unsecured market, the arrival rate of transactions in the unsecured (collateralized) segment increases (decreases) by μ_{+UM} (μ_{-CM}); while in the case of a migration to the collateralized market, the arrival rate of transactions in the unsecured (collateralized) market decreases (increases) by μ_{-UM} (μ_{+CM}). In the event of a positive liquidity shock (a negative liquidity shock) there is an increase (a reduction) on the arrival rate for the unsecured market and collateralized market at λ_{+UM} and λ_{+UM} (λ_{-UM} and λ_{-UM}), respectively.

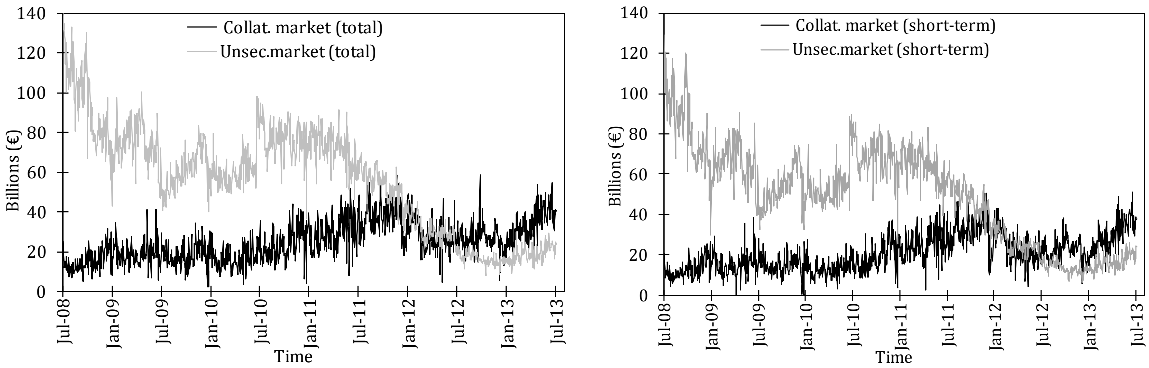

Figure 2. Evolution of the daily trading activity in the unsecured lending segment and in the collateralized money market. The figure presents the evolution of the daily aggregate volume of funding (€ billions) in the unsecured segment and in the collateralized money markets from June 2, 2008 to July 30, 2013 (1,325 business days). Trading activity is reported for the total market (i.e. long-term and short-term loans with maturities ranging from one day –overnight– up to one year) on the left hand side, and for short-term loans (i.e. only overnight loans) on the right hand side.

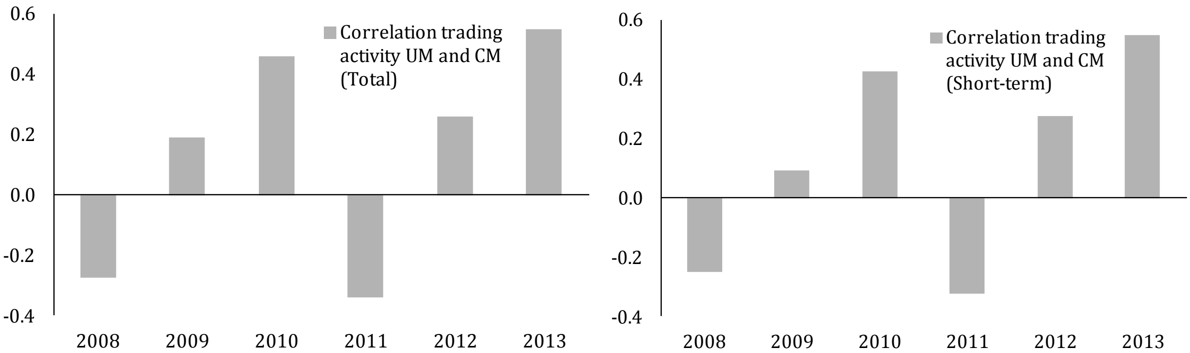

Figure 3. Correlation changes of the trading activity in money markets. The figure shows the correlation over time (in each year) between daily aggregate volume of funding (€ billions) in the unsecured segment and in the collateralized money market from 2008 to 2013. Correlations are reported for the total market (i.e. long-term and short-term loans with maturities ranging from one day –overnight– up to one year) on the left hand side, and for short-term loans (i.e. only overnight loans) on the right hand side.

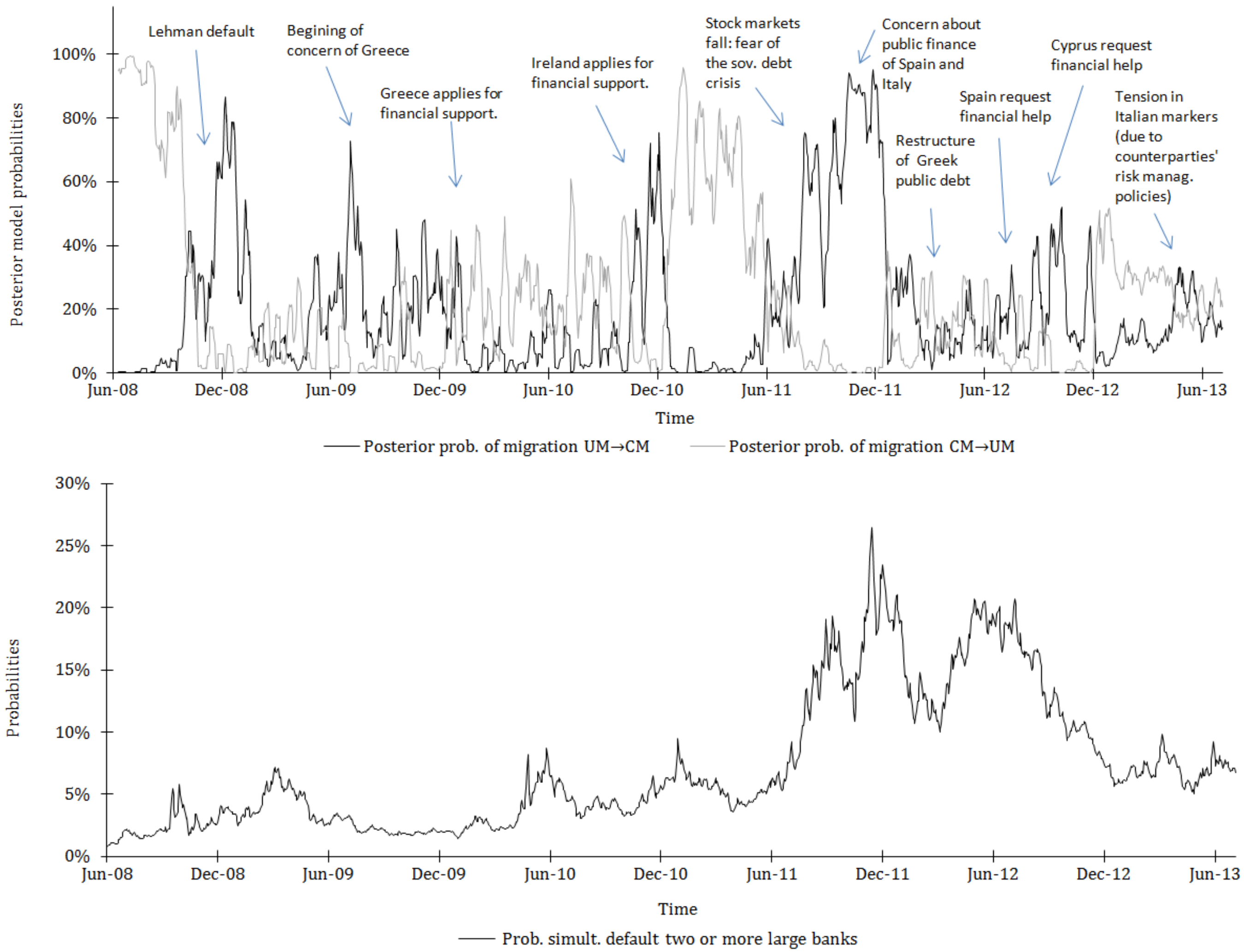

Figure 4. Evolution of the posterior probabilities of migration and a systemic risk measure. The figure shows the evolution between 2008 and 2013 of posterior probabilities of migration (unsecured to collateralized market, and *vice versa*) obtained on a daily basis from equation (9) and equation (10). These posterior probabilities are obtained on a daily basis by using the parameters estimated in each year for the total market with short-term and long-term loans (i.e. with the parameters reported in Table 2 upper panel in years 2008, 2009 and so on until 2013). We also report the evolution of the probability of simultaneous defaults by two or more large banks, which is a daily measure provided by the ECB.

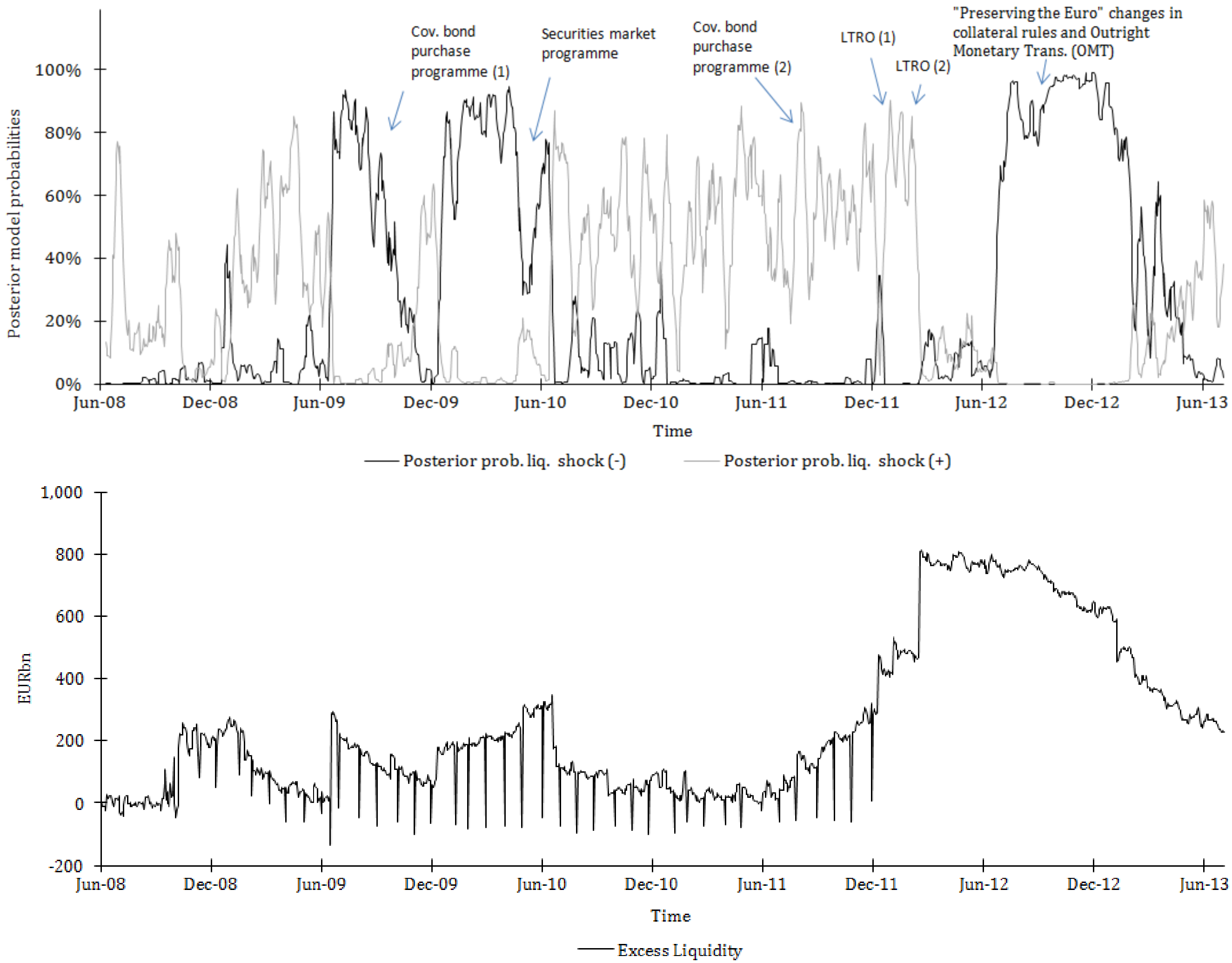

Figure 5. Evolution of the posterior probabilities of liquidity shocks and excess liquidity. The figure shows the evolution between 2008 and 2013 of posterior probabilities of liquidity shocks (positive and negative liquidity shocks), obtained on a daily basis as described in Section 4. These posterior probabilities are obtained on a daily basis by using the parameters estimated in each year for the total market with short-term and long-term loans (i.e. with the parameters reported in Table 2 upper panel in years 2008, 2009, and so on until 2013). We also report the evolution of a proxy for excess liquidity in Europe, which is measured as a credit institution's current account plus the difference between amounts borrowed and lent at the ECB's standing facilities.