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## Temi di Discussione

(Working Papers)

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unsecured market for euro funds

by Edoardo Rainone

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# TESTING INFORMATION DIFFUSION IN THE DECENTRALIZED UNSECURED MARKET FOR EURO FUNDS

by Edoardo Rainone\*

## Abstract

Average rates in the decentralized unsecured market for euro funds, like the EONIA for the overnight maturity, are fundamental indicators of the smooth transmission of the signal rate by the central bank. Public information plays an important role in this context, as key interest rates are set by the central bank and average market rates are published daily, constituting common knowledge. Nevertheless, according to the theoretical literature on over-the-counter markets, private information may have an important role in a decentralized market. The diffusion of private information can generate prices that depend on the decentralized market structure. This is the first paper to use an ad hoc (network) version of the spatial autoregressive model to assess the presence of this mechanism. I propose a simple methodology to test whether the joint distribution of rates depends on the interbank network structure and to estimate information diffusion strength. The method is applied to a unique dataset collecting unsecured interbank loans and characteristics of banks operating in European central bank money. A wide time span including sovereign debt crises in the euro area is considered. I find that information diffusion played a greater role during periods dominated by strong uncertainty.

**JEL Classification:** E52, E40, C21, G21, D40.

**Keywords:** interbank markets, money, trading networks, payment systems, information aggregation, spatial autoregressive models, bilateral trading.

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# 1 Introduction<sup>1</sup>

Average rates in the unsecured money market and their volatility are key indicators for a large set of phenomena: financial tensions, market expectations and the cost of mortgages and loans to the real economy (the pass-through mechanism from market to banking rates). Some of the main market rates, such as EONIA and EURIBOR in the euro area, have a direct impact on lending and deposit rates, as shown in Gambacorta (2008) and other papers, determining the amount of households and firms' debts. Furthermore, following the model by Ho and Saunders (1981), banking rates are influenced by interest rate volatility. The mechanism investigated in this paper has sizeable implications for both average market rates and rates volatility, with indirect effects on the micro and macro-financial conditions of households and firms. Rates in money markets are an important issue for central banks, because uncontrolled market rates prevent smooth rate transmission. The financial stability of the system may also be threatened. In order to achieve these two fundamental goals, central banks closely monitor all the factors impacting interbank market rates.

Rates are supposed to be driven mainly by *public information* in money markets. Central banks determine the upper and lower bound for the cost of money and, by collecting information from banks and publishing it, provide operators with market average rates in order to avoid information asymmetry and to transmit their signal rate smoothly.<sup>2</sup> Nevertheless, given the *decentralized* nature of this market, *private information* may play an important role as argued by a growing theoretical literature on OTC markets. The process of trade can transmit some considerable information in a decentralized market featuring asymmetric information (Wolinsky; 1990). The idea that prices contain information appears in Hayek (1945) and was thoroughly investigated by the literature on information transmission in rational expectation equilibrium (Grossman; 1981; Grossman and Stiglitz; 1980). Recently, Babus and Kondor (2013) proposed a model with information diffusion in OTC markets. In their model, dealers have private information and each bilateral price partially aggregates the private information of other dealers, depending on the market network structure. They show in theory how it is

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<sup>1</sup>I wish to thank Giovanni di Iasio, Marco Rocco and Francesco Vacirca for sharing data and thoughts with me, Salvatore Alonzo and Fabrizio Palmisani for giving me the time and the opportunity to investigate this topic, for their comments, Vincent Ang, Paolo Angelini, Giuseppe Ferrero, Jacques Fournier, Simone Giansante, Lincoln H. Groves, Luigi Infante, Péter Kondor, Fabrizio Mattesini, Yves Zenou, two anonymous referees of Temi di discussione, as well as participants in the workshop The interbank market and the crisis held the Bank of Italy in Rome, participants at the 7th Irving Fisher Committee Conference at the BIS in Basel, colleagues of the Bank of Italy at the Financial Stability Directorate and, finally, participants at the Macro-prudential Research Network (MaRS) workshop at the ECB in Frankfurt. Special thanks go to Francesco Vacirca for his precious guidance through the unsecured money market dataset. I also thank colleagues at the Bank of Italy's Wholesale Payment Systems Division of the Payment System Directorate for their useful contribution to the discussions. All errors are my own responsibility. The author of this paper is member/alternate of one of the user groups with access to TARGET2 data in accordance with Article 1(2) of Decision ECB/2010/9 of 29 July 2010 on access to and use of certain TARGET2 data. The Bank of Italy and the PSSC have checked the paper against the rules for guaranteeing the confidentiality of transaction-level data imposed by the PSSC pursuant to Article 1(4) of the above mentioned issue. The views expressed in the paper are solely those of the author and do not necessarily represent the views of the Eurosystem.

<sup>2</sup>Here we simplify this process. Market rates are not always published by the central bank. They may be published by international non-profit making associations. In Europe, for instance, Euribor-EBF is entrusted with this task, see <http://www.euribor-ebf.eu/euribor-ebf-eu/about-us.html>. A corridor is often used to place lower and upper bounds on market rates. Bounds are determined by marginal lending and overnight deposit rates, which are set by the central bank. Other instruments can also be used in order to control market rates.

implied by decentralization and heterogeneity in dealers' valuations on the exchanged asset.<sup>3</sup> The authors also mention the fed funds market as an example. When translated in money markets, this mechanism of diffusion implies that if a lender increases (decreases) their assessment of the future value of central bank money because of a random idiosyncratic shock, this will have an impact on the loan rates they agree and, because of the diffusion process, on the rates of loans in which they are not directly involved.<sup>4</sup> Note that it also generates a higher (lower) variation in the average price.<sup>5</sup> Coming back to the pass-through mechanism, if a shock on one single rate has a stronger impact on average rates and variance because of the diffusion mechanism, it will also have a stronger impact on households' and firms' debts (other things being equal).

The present paper proposes a methodology to test the diffusion of private information, modelling rates. It requires additional complexity, which translates into an econometric model embedding the market network structure. To the best of my knowledge this is the first attempt to assess empirically the presence and diffusion of private information in a decentralized unsecured market by means of network econometrics. The econometric model can be used to test for one of the empirical predictions of the model of Babus and Kondor (2013), which can accordingly be taken as one of the possible micro-foundations for our empirical specification. To be more precise, their model generates a joint distribution of prices that depends on the market microstructure, i.e. the interbank network in this case.

Moving to the empirical argument, the market rate and its variance are respectively the first and second moment of the rate distribution, which is composed of single rates. The rate of a loan has usually been modeled as a function of lender and borrower characteristics and aggregate conditions, i.e.  $r_{ij,t} = f(i, j, t)$ ; see Afonso et al. (2011) and Angelini et al. (2011).<sup>6</sup>

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<sup>3</sup>They propose an OTC game in which dealers trade bilaterally with different prices for each transaction, the equilibrium price in a given transaction is a weighted sum of posterior beliefs of the counterparties. In their model the final value of the asset is uncertain and interdependent across dealers.

<sup>4</sup>We can also interpret valuation changes as strategic moves. Ewerhart et al. (2007) proposed a model in which commercial banks may manipulate market rates, and in which interest rate derivatives have a key role since they induce traders to leverage their positions. They analyse this strategic behavior in a theoretical framework with a corridor and find that manipulators gain control of market rates by using standing facilities. They also list episodes in which this scenario took place in the Eurosystem. The corridor is the interval delimited by the overnight deposit and marginal lending rates. The authors argue that widening the corridor is not an effective tool, while regular fine tuning as well as narrowing the corridor at the end of maintenance period can prove effective.

<sup>5</sup>Here, the behavioral mechanism can be synthesized as follows: when a bank has to evaluate the expected price of a loan, it can be influenced by the rates of other loans (in addition to its own characteristics, the counterpart's characteristics and liquidity conditions). The rates observed represent the private signals from other banks and reflect a mixture of their expectations. Note that here we use the term 'expectation'. Banks' production function in the money market features a 'lag', and indeed the final outcome is revealed at the end of a maintenance period. It naturally implies the presence of expectations about the future value of central bank money. Note also that the process of forming expectations about prices is typically conceived as based on *time-lags*, i.e.  $p_t^e = E(p_t | L_t^1 p_t, L_t^2 p_t, \dots)$ , where  $L_t$  is the time-lag operator (Muth; 1961; Nerlove; 1958). What we are hypothesizing here, is that it may be based on *network-lags*, i.e.  $p_t^e = E(p_t | L_n^1 p_t, L_n^2 p_t, \dots)$  where  $L_n$  is the network-lag operator.

<sup>6</sup> Afonso et al. (2011) tested the counterparty risk and liquidity hoarding hypothesis in the US federal fund market. They found that borrower characteristics were more important in explaining changes in market conditions after Lehman Brothers, while liquidity hoarding could not be listed as a main source of market contraction. Borrower characteristics were also found to be important after August 2007 by Angelini et al. (2011); however, the effects of bank-specific characteristics were modest and the authors found a more significant role of aggregate and market-wide factors using e-MID data. The evidence is supported by a low incentive in peer

This approach is justified because the unsecured money market is known to be a *decentralized* one, formed by bilateral relationships (between lenders and borrowers). Nevertheless, this set of interbank relationships generates a network, which has a specific topology that may matter in explaining bilateral rates. In other words, the position of a loan in the interbank network can be important in explaining its rate, i.e.  $r_{ij,t} = f(i, j, t, G)$ .<sup>7</sup> If microdata are available, this information can be used to model the rate of a loan with higher explanatory power and to test for cross-sectional (network-based) dependence among rates. The spatial econometrics literature has developed a large set of models to formalize this dependence and it recently focused on networks (Lee; 2007; Lee et al.; 2010; Liu and Lee; 2010). Conceptually, this cross-sectional dependence can be seen as a consequence of the process of private information diffusion in the interbank network, according to Babus and Kondor (2013).<sup>8</sup> Suppose, for instance, that bank  $i$  trades with bank  $j$  and bank  $j$  trades with bank  $k$ , then these two loans are *connected*. The diffusion of private information is measured by network-based spillover effects among rates of *connected* loans. I test this hypothesis rigorously, estimating the magnitude of the effect. Network theory and a rearranged spatial econometric toolkit are used respectively to formalize the local diffusion in rates and to identify and estimate the strength of information diffusion.

I take advantage of a unique dataset collecting unsecured interbank loans and banks characteristics for the banks operating in European central bank money.<sup>9</sup> This large set of information allows us to distinguish rate variations due to macro shocks or to changes in banks economic outlook from those generated by the impulses coming from other loans. I consider a wide time span, ranging from 2008 to 2012, as this also enables us to study time series of diffusion intensity.

The first contribution of this paper is to offer an econometric test for private information diffusion in an OTC market. The second contribution is to assess the presence of this mechanism in the unsecured market for euro funds. This suggests a novel perspective from which money market dynamics can be studied and provides a new tool for measuring market tensions.

The main empirical findings are the following: *(i)* private information diffusion is considerable only when there are strong market tensions and great uncertainty, and *(ii)* information flows in multiple directions through the interbank network.

The rest of the paper is organized as follows. Section 2 outlines the link between the conceptual framework and the econometric setup, Section 3 discusses the implications of the diffusion mechanism on market rates. Section 4 describes the data and information used in the paper. Section 5 provides preliminary evidence and the basic ingredients of the analytical

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monitoring driven by the belief that central banks will intervene in the event of a crisis, an idea that is also supported by a discount granted to larger borrowers considered too big to fail.

<sup>7</sup> $G = \{g_{ij}\}$  represents the network formed by the bilateral trading relationships.

<sup>8</sup>Rates reflect the expectations of market operators, thus a cross-sectional dependence of rates, after having controlled for counterparts characteristics and aggregate conditions, may indicate a diffusion of expectations. Single rates can be observed only by the respective counterparts, so that they represent a piece of *private information* about the cost of money, contrasting with the *public information* provided by market rates, i.e. the average of rates. Each bank can see its past prices and the market average, so they respectively play the role of private and public information. Other definitions of private information are possible. Given that price is the outcome of interest here, this specification seems to be the most appropriate.

<sup>9</sup>Loans are detected by Furfine algorithm (with maturities from one day up to one year) implemented on TARGET2 data (Arciero et al.; 2013). TARGET2 is the European RTGS Payment System, see Section 4. Loans are then matched with lender and borrower characteristics. Banks characteristics are taken from Bankscope.

framework. Section 6 describes the econometric model and discusses the issues related to consistent estimators. Section 7 presents the results of the application on the euro unsecured money market. Section 8 presents the robustness checks and Section 9 concludes.

## 2 Conceptual Framework and Econometric Setup

Suppose that the market is composed of  $n$  banks that trade an asset bilaterally (central bank money) and are uncertain about its market value.<sup>10</sup> Assume that each bank receives a private signal about the value, implying that the information on the price of a unit of money,  $I$ , can be split into two components for each bank  $i$ ,  $I_M$  and  $I_i$ , respectively *public* and *private* information.<sup>11</sup> We can set bank  $i$ 's valuation as  $\theta_i = \bar{\theta} + \eta_i$ , where  $\bar{\theta}$  is the common component, which represents *public* information, while  $\eta_i$  is the individual one, which reflects *private* information. It implies that there is heterogeneity in banks' valuation. For example, we can posit that  $\bar{\theta} = n(\bar{p}_{k \in K}; \psi)$ , where  $K$  is a set of lags,  $\psi$  is a set of parameters and  $\bar{p}_k$  is the market rate at time  $k$ , implying that the public component is a function of market rates observed in the past. Alternatively, we can suppose that the contemporaneous term structure of interest rates is used:  $\bar{\theta} = b(\bar{p}^m, m \in M; \iota)$ , where  $M$  is a set of maturities,  $\iota$  is a set of parameters and  $\bar{p}^m$  is the market rate for maturity  $m$  (Alonzo et al.; 1994; Shiller and McCulloch; 1987). Observe that we can assume both are considered in  $\bar{\theta}$ .<sup>12</sup>

Bilateral trading and heterogeneity in valuations may imply price dispersion and the transmission of information. According to Babus and Kondor (2013), each price partially incorporates private signals of market participants. It also implies that if agent  $j$  trades with agent  $k$  then  $p_{jk}$  may affect  $p_{ij}$ . Indeed, the residual inverse demand function of dealer  $i$  in a transaction with dealer  $j$  in their model is a function of other prices.<sup>13</sup> In other words, being  $P$  a  $n \times 1$  vector of prices, we have  $P = F(P)$ , where  $F(\cdot)$  is a  $n \times 1$  vector of functions  $F(P) = (f_1(P), \dots, f_n(P))$ . Each price is thus determined as a function of other prices in a simultaneous equations framework:

$$\begin{aligned} p_1 &= f_1(p_1, \dots, p_n) \\ &\vdots \\ p_n &= f_n(p_1, \dots, p_n). \end{aligned} \tag{1}$$

The expression in (1) is very general, there are no assumptions about which variable influences which and there are no assumptions about sign, intensity, monotonicity or linearity of cross derivatives.<sup>14</sup> Observe that in this framework prices thus have a joint distribution that

<sup>10</sup>Note that, given that banks' production function in the money market has a 'lag' (the final outcome is realized at the end of a maintenance period), it naturally implies the presence of assessments of the value of central bank money.

<sup>11</sup>Note that this setting is the same as that of Babus and Kondor (2013)

<sup>12</sup>Note that we are assuming separability and therefore each bank processes the common information available in the same way. This assumption can be relaxed, but here it is useful for the sake of simplicity.

<sup>13</sup>They also show that  $p_{ij}$  can be represented as a function of posterior beliefs of  $i$  and  $j$ , which in turn are shaped by prices privately observed by  $i$  and  $j$ .

<sup>14</sup>This environment is interesting when the exact connections between variables are unknown. We could estimate bounds for the distribution of  $P$  in a partial identification framework, see Manski (2013) and Lazzati (2010). In this application we know the relationships between banks and thus we can trace which price is connected with which. The additional assumption we make is that the relationships between prices are linear.

is different from the product of marginal ones. If we assume the knowledge of market microstructure -i.e. the relationships between elements of  $P$ - and that the price of a loan that has  $b$  as a borrower and  $l$  as a lender is also a function of lender and borrower characteristics, we can write the single price equation as

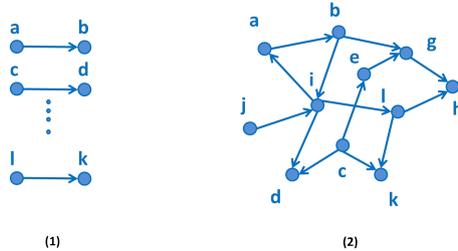
$$p_{bl} = f(c_{bl}(P), x_b, x_l, \epsilon_{bl}, \chi),$$

where  $\chi$  is a set of parameters.  $\epsilon_{bl}$  is a random component,  $c_{bl}(\cdot)$  is a loan-specific linear function which includes prices that are *connected* with  $p_{bl}$ ,<sup>15</sup>  $x_b$  and  $x_l$  are borrower and lender characteristics respectively. If we assume linearity, we have that  $p_{bl} = \alpha + \phi c_{bl}(P) + \gamma x_b + \mu x_l + \epsilon_{bl}$ , with  $\chi = (\alpha, \phi, \gamma, \mu)$ .

In other words, each price starts from a 'baseline' price,  $\alpha$ , determined by market-wide expectations (which captures  $\bar{\theta}$ , the common component representing public information), then spreads depending on counterparts' characteristics ( $x_b, x_l$ , for instance a risky borrower should be priced according to their probability of default) and finally a set of other prices ( $c_{bl}(P)$ ) play a role in determining the agreed (observed) price, capturing the diffusion of private information via prices.

Note that, according to this specification, if only public information matters, i.e.  $\theta_i = \bar{\theta}$ , the price equation is reduced to  $p_{bl} = \alpha + \gamma x_b + \mu x_l + \epsilon_{bl}$ . Thus a formal test for the presence and diffusion of private information consists in estimating the full model and checking whether we would reject the null  $\phi = 0$ . If private information matters, i.e.  $\eta_i \neq 0$ ,  $\phi$  will be significantly different from zero. In other words, this test tells us whether the joint distribution of prices is not the product of marginal ones, i.e. prices are interdependent, and, more specifically, whether it depends on the microstructure of the market (Figure 1).

Figure 1: From separate loans to the interbank network



(1) represents the set of single loans ignoring the network structure, (2) represents the interbank network structure considering the connectedness of loans.

### 3 Mechanism of Diffusion and Market Rate

In this section I provide some insights into the impact of diffusion on market rates. The presence of diffusion in the unsecured money market has an impact on the market rate and its volatility, which in turn has an effect on banking rates (to the real economy). It seems worthwhile to provide an example of the implications that this mechanism has for the market

<sup>15</sup>This information comes from the knowledge of market microstructure.

rate. Suppose that there are four banks and three loans in the market and they do not change over time (Figure 2). Let  $\Delta p > 0$  be an idiosyncratic exogenous shock, and  $p_{ji} = p_{kj} = p_{gk} = p^* = \text{EONIA}$  are the prices before the shock.<sup>16</sup> Suppose  $\Delta p$  hits  $p_{ji}$ , without diffusion the new EONIA will be

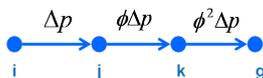
$$p^{**} = \frac{3p^* + \Delta p}{3},$$

with diffusion the new EONIA will be

$$p^{***} = \frac{3p^* + (1 + \phi + \phi^2)\Delta p}{3} > p^{**}, \text{ if } \phi > 0.$$

The difference between  $p^{***}$  and  $p^{**}$  ( $\frac{(\phi + \phi^2)\Delta p}{3}$ ) is generated by the diffusion mechanism, which brings the EONIA to a higher level after a positive shock received by a single loan. The propagation of this shock ( $\Delta p$ ) depends on the structure of the interbank network and on a *multiplier*  $\phi$ . This parameter captures the diffusion strength, according to our econometric setup. If it is constrained to be less than one in absolute value, it implies that the initial shock has a decaying effect on other loans when the distance in the network increases ( $\phi > \phi^2 > \phi^3 > \dots$ ).<sup>17</sup> A similar argument can be made for the effect on rate volatility. Note also that, given that the final effect of a shock depends on where it hits the interbank network, if a shock hits a *central* loan, it will have a higher impact on market rates than a *peripheral* loan. This example highlights the effect that the presence of this mechanism of diffusion has on market rates and the prominent role it may play when shocks occur.

Figure 2: Chain of loans



## 4 Money Market Microstructure and the Payment System

Money market microstructure has become an important research topic in recent years and is one of the main areas of interest for central banks and regulators.<sup>18</sup> The availability of

<sup>16</sup>Let us assume that all the banks are in the EONIA panel. Observe that a change in the signal rate by the central bank would not imply this mechanism of diffusion because it has an impact on all the rates, the following holds only for the propagation of a shock hitting a single loan.

<sup>17</sup>We will see in Section 6 that this is exactly the case for an 'average' SAR model.

<sup>18</sup>On the theoretical side, Afonso and Lagos (2012) recently proposed an insightful model for the market for US federal funds in which banks search for counterparties and negotiate the size and price of a loan. Tapping (2006) provided an interesting model in which banks negotiate on interest rate, which is not given as in general equilibrium models. This conceptual framework is particularly interesting and closer to reality, since transactions are likely to be negotiated on the phone, e.g. bilaterally. The constraint imposed by the reserve requirement allows a multiplicity of rates on the first day of the maintenance period and, given that banks can adjust both volumes and prices, it makes the public information on the average rate not useful for predicting future liquidity conditions.

transaction level data makes the study of microeconomic behavior possible by supporting the aggregate evidence at the macro level.<sup>19</sup>

The information about loans used in this paper is taken from TARGET2 (T2), the European RTGS (Real Time Gross Settlement) Payment System.<sup>20</sup> T2 allows banks to settle large value payments on their accounts in ECB money. The reserve requirement is managed on these accounts, so participating banks have to exchange money in T2 to meet the reserve requirement and make other payments.<sup>21</sup> The market for ECB money is thus generated by reserve requirements and liquidity needs (on the demand side) and has T2 as an institutionally designed support, as standard in modern economic systems.<sup>22</sup> Almost every type of market finally settles in T2, according to their nature. The main sources of liquidity for a bank are basically three: central bank, secured money market, and the unsecured money market (UMM).<sup>23</sup> The focus of this paper is on the third source.<sup>24</sup> Maturities are from overnight up

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<sup>19</sup>Several papers use micro-level information to describe the interbank market, Furfine (2001) explored federal funds transactions in the US market, focusing on bank size and participation. Hartmann et al. (2001) focused on several key aspects on which microdata can effectively help shed light: they studied the intraday patterns of rates and examined the effect of central bank actions, such as European Central Bank (ECB) announcements as well as Eurosystem main refinancing auctions, on market characteristics. Micro-level data have been used in several studies regarding price formation and dynamics. Indeed, price discovery in stocks and bond markets has gained increasing attention in recent years, with Furfine (2007) studying the role of fast arriving trades in NYSE market price movements, and Girardi and Impenna (2013) focusing on bonds and distinguishing between business-to-business and business-to-customer markets, by looking at the role played by order flow.

<sup>20</sup>For more information about TARGET2 see <http://www.ecb.europa.eu/paym/t2/html/index.en.html>.

<sup>21</sup>Many types of payments are settled in T2. A short list includes customer payments, securities systems payments, open market operations, treasury bond issues. This should give an idea of the importance of the system and its centrality to banks from a liquidity management perspective. Reserve requirements oblige banks to hold a certain amount of central bank money in their accounts on average during a maintenance period. A maintenance period is a time interval (roughly four weeks long) during which the amount of central bank money is averaged.

<sup>22</sup>The connection between Payment Systems and the interbank microstructure has been widely recognized (see Haldane et al. (2008) for a discussion). Recent studies highlight the impact of Payment System features on the money market, as Baglioni and Monticini (2008) do, noting how rates decline over the operating day (an intraday price of money) and explaining it by the switch to real-time settlement.

<sup>23</sup>Of course the list can be greatly expanded, intra-group transfers being just one example. However, I do not develop this argument as it is beyond the scope of this paper.

<sup>24</sup>UMM transactions can be settled basically in two ways. First, through ancillary systems, which are connected to and send payment instructions to the payment system, operating upon banks' accounts. Payments from an ancillary system can be labeled and isolated. The e-MID platform is an example of this type of ancillary system. This makes it easy to detect loans between banks. Second, the two legs (the loan and its pay-back) can be freely settled in the payment system avoiding passing through any specific trading platform (thus without labeling). In the second scenario UMM is confounded with other types of payments, making it more challenging to identify loans. Furfine (1999) proposed an algorithm that matches these two legs and identifies market microstructure. Arciero et al. (2013) applied this criterion to payments settled in T2, augmenting the maturity spectrum by up to one year. Furfine's algorithm is used to detect loans from a set of payments. By definition a loan consists of two payments, the first equal to  $l$  and the second equal to  $l(1+i)$ , where  $i$  is the interest rate. The algorithm matches those two legs, see Furfine (1999) for details. See Armantier and Copeland (2012) for an assessment of the quality of Furfine-based algorithms. Arciero et al. (2013) contains detailed information about the algorithm and its practical implementation in T2. I will not go into the details of the algorithm because it is beyond the scope of the paper. In Arciero et al. (2013) the database is based on settler banks, as information on final agents was not available at that time. The three central banks that provide T2 as a service (Banca d'Italia, Banque de France and Deutsche Bundesbank) recently made this data available and then let the same authors run the algorithm. I am grateful to both Arciero et al. (2013) and the three central banks for providing this essential information, and making this paper and a wider investigation possible.

to one year. The time span considered here is from June 2008 to the end of 2012.<sup>25</sup> The very basic time unit considered is the maintenance period (hereinafter MP).<sup>26</sup>

Interbank networks have been widely described in the economic literature and knowledge about financial networks has grown rapidly in the recent years, noteworthy examples are Iori et al. (2008) in their analysis of the Italian overnight money market on e-MID, and Boss et al. (2004) who did the same with the Austrian interbank market. Soramäki et al. (2007) analysed the connectivity of Fedwire, the American RTGS Payment System.<sup>27</sup> The European money market has been widely described in the literature, see Arciero et al. (2013) and other papers, it therefore seems redundant to do so again in this paper. What is new here is the combined use of information about loans (links) and banks (nodes) in the interbank network. I therefore give descriptions of the final sample resulting from the matching of loans and bank information. Balance sheet data is from Bankscope. *Total assets* expressed in millions of euros captures the dimension of each bank. Balance sheet items are included as percentages of total assets. On the asset side *Loans*, *Fixed Assets* and *Non-Earning Assets* are included.<sup>28</sup> On the liability side, *Deposits and Short-term Funding*, *Other Interest Bearing Liabilities*, *Other Reserves* and *Equity* are included.<sup>29</sup> Country dummies are included as well: Italy, France, Spain, Netherlands, Greece, Ireland, United Kingdom, Austria, Portugal, Luxembourg, Cyprus, Switzerland, Finland and Belgium have a specific dummy.<sup>30</sup> Other European countries are grouped in one dummy as well as the US, Japan and other non-European countries. Given the high dimensionality considered here, time series of sample average and standard deviation for each variable considered in the final sample are reported in Figure 11. Banks operating in the system are not constrained to be European, even though the majority of operators are from countries belonging to the Eurosystem. The mean of country dummies represents the incidence of banks from the respective country in each time period. Sharp changes in different directions are observed after the 2011 LTRO, most notably for Total Assets. Balance sheet composition shows a rather large time variance, with the exception of Loan Assets. A continuous decrease in equity is observed after the sovereign debt crisis in 2011 in unsecured money market participants. Country participation is quite stable until the 2011 LTRO. Large decreases are seen in Italian and Spanish banks, which are the ones that drew most heavily on the LTRO facilities. The reverse trend is observed for banks in the UK, France and the Netherlands. Finally, Figure 12 reports the time series of the number of banks in our sample operating in the market: we witness a large drop after the 2011 LTRO.

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<sup>25</sup>T2 starting date was 19 November 2008. The analysis only goes to the end of 2012. The database is up to date so the analysis can be updated regularly.

<sup>26</sup>See <http://www.ecb.europa.eu/home/glossary/html/act4m.en.html#226> for details. This has at least two big advantages compared with other choices. First, for economic reasons, banks are constrained to hold an average amount of ECB money in their T2 account during the MP, making it a natural candidate for money market analysis. Second, for statistical reasons, this makes it possible to compare different MPs. Hamilton (1996) and Prati et al. (2003) showed that days in the MP are not comparable as market conditions may be completely different. Furthermore, it makes data tractable when we consider a large time interval.

<sup>27</sup>Besides the description of financial networks several papers used this information to address questions concerning economic mechanisms and agents behavior. One example is Becher et al. (2008), using data from CHAPS, the English RTGS Payment System.

<sup>28</sup>*Other Earning Assets* are dropped because of collinearity.

<sup>29</sup>*Loan Loss Reserves* and *Other (Non-Interest Bearing)* are dropped.

<sup>30</sup>Germany is the reference category.

## 5 Preliminary Evidence

Rate volatility in the euro UMM shows significant time-variation. Panel (a) of Figure 13 depicts the variance of rates across loans with maturities from overnight to three days agreed in each maintenance period. We can see that it increased markedly after Lehman, and the first and second sovereign crises, and decreased considerably after ECB intervention with the 2011 LTRO.<sup>31</sup> During these crises the credit default swap of the hardest hit countries increased sharply, and the default risk of banks belonging to those countries also increased. This led to great uncertainty in the interbank money market.<sup>32</sup> If we take two maintenance periods, the first from 2010-01-20 to 2010-02-09 (before the first sovereign crisis) and the second from 2011-07-13 to 2011-08-09 (after the second sovereign crisis), we can see from panel (b) of Figure 13 that the density changes dramatically. The price dispersion has increased considerably in the second period.

The main reason behind this change is the generalized increase in perceived risk by treasurers. An additional source of variation might be the propagation of changes in agents' expectations. Agents may show updated expectations by changing their reference rates, thus sending signals to other agents. If this mechanism is at work, we should see a higher variance for *connected* prices during *hot periods*, because they involve agents who receive more signals.<sup>33</sup> Panel (a) of Figure 14 shows the variance computed for *connected* and *unconnected* prices, the variance between connected prices is usually higher than the one computed for unconnected ones (this happens in roughly 80 percent of total observations), apparently confirming the intuition.<sup>34</sup> Connectedness can also act as a valid support for searching (and even finding) lower prices. Panel (b) of Figure 14 depicts the average price for the two subsamples defined previously. It emphasizes that connected prices are on average lower than unconnected ones; the spread starts to be significant after the first sovereign crisis and approaches zero after the 2011 LTRO.<sup>35</sup> The rest of the paper is based on the subsample of connected prices.

The question is: does rate volatility have a network nature? In other words: are connected rates likely to be more similar? In order to answer these questions we need a coherent analytical framework, which is introduced in the next section.

### 5.1 Decentralized Market and Network of Prices

The basic unit is the price of a loan in this analysis. Modeling outcomes of arcs instead of outcomes of nodes is not common in the network and spatial econometric literature. Here the

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<sup>31</sup>The first sovereign debt crisis was in April 2010 and hit Ireland, Greece and Portugal, while the second sovereign debt crisis was in August 2011 and hit Italy and Spain.

<sup>32</sup>In addition expectations about the reaction of the central bank may create additional dispersion, see Hartmann et al. (2001).

<sup>33</sup>A price of a loan is connected whether or not it shares borrower or lender with other loans. Normal times are not properly identifiable in this time span, so we should call them hotter periods.

<sup>34</sup>Here we are looking at intra MP volatility, so that intraday volatility is flattened. Gaspar et al. (2008), starting from empirical evidence, proposed a model that fits the intraday price volatility and gives a micro-foundation of observed higher rate dispersion at the end of the maintenance period. Hamilton (1996) and Prati et al. (2003) provide empirical analysis of a large variation of intraday volatility depending on the day's position in the maintenance period, respectively for the US federal funds market and for G-7 and Euro zone interbank markets. Hamilton (1996) tested for a martingale hypothesis, finding evidence against it. Prati et al. (2003) argue that central banks' operating procedures in particular are decisive in shaping rate volatility.

<sup>35</sup>From Figure 14 we can also observe a sharp decrease in interbank rates after the 2011 LTRO. Bech and Klee (2011) develop a model to explain this phenomenon.

switch is mandatory because we are not interested in a node specific outcome, prices are bilateral by definition, so that they are *couple-specific*.<sup>36</sup> Furthermore, a structural interpretation of price correlation in a decentralized market is provided by Babus and Kondor (2013), whose micro-founded model delivers such a relation.

Supposing that bank  $i$  trades with bank  $j$  and bank  $j$  trades with bank  $k$ , we want to address the following question: to what extent does the price of the loan of bank  $i$  to bank  $j$  affect the price of the loan of bank  $j$  to bank  $k$  (Figure 3)?

Figure 3: Connection between two prices



In order to answer this question, it is useful to consider the *loans' network* instead of the *banks' network*. In network analysis the units are usually nodes connected via links and diffusion is measured considering their adjacency matrix,<sup>37</sup> but here we are constrained to invert the role of these two sets of elements. The nodes are the loans (previous adjacency matrix entries) and the links are the banks. Spillovers can thus be measured through a *loans' adjacency matrix* where banks have the role of connectors between loans. More formally let  $C$  be the set of active banks in the UMM, for the sake of simplicity suppose it refers to a specific maturity  $m$  and time  $t$ , two banks are connected if a loan of maturity  $m$  is agreed at time  $t$ . Let  $P$  be the matrix that keeps track of these connections, where the element  $p_{ij}$  is equal to the price of the loan if bank  $j$  lends to bank  $i$ , where  $i, j \in C$ , zero otherwise.<sup>38</sup> Note that it is a directed weighted adjacency matrix among banks. Following the criterion specified above, two prices,  $p_o = p_{ij}$  and  $p_q = p_{lk}$ , are connected if  $i = k$ , in other words if the borrower of  $o$  coincides with the lender of  $q$ . In this way the connections between prices can be traced with a *loans' adjacency matrix*  $A$ , where the element  $a_{qo}$  is equal to one if price  $o$  influences price  $q$ , zero otherwise. See Appendix A for technical details. Observe that this criterion of connectivity is set by the econometrician and is a subjective choice; in Section 8 I discuss this point and check for different diffusion mechanisms.

## 5.2 Assessing the Role of Interbank Network

For a preliminary answer to our main questions, Moran's I, a popular index in Economic Geography, can be helpful. This statistic is commonly used to assess whether adjacent units are more likely to be similar (Moran; 1950). In spatial analysis this test is used to find preliminary evidence of spillovers among units for a certain economic outcome and to check spatial-correlation of residuals after a regression analysis. Let  $m$  be the maturity of a loan agreed at time  $t$  and  $d$  the distance between two prices in the price network, as defined above:

<sup>36</sup>In Appendix B I show in detail why taking a node-specific outcome may create problems in the estimation of diffusion strength.

<sup>37</sup>The adjacency matrix keeps track of connections among nodes and produces a graph in a matrix form.

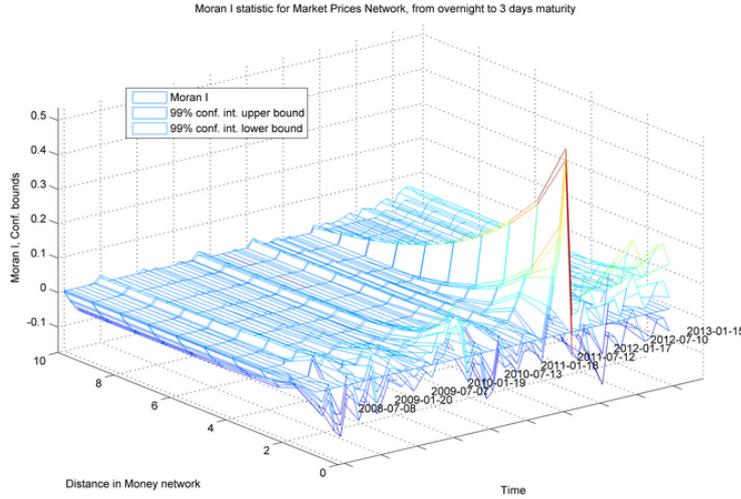
<sup>38</sup>Given that MP is considered a time interval, the average price of loans from  $i$  to  $j$  is considered in this analysis.

the Moran's I is computed as

$$I_{m,t,d} = \frac{\bar{P}'_{m,t} A_{m,t}^d \bar{P}_{m,t}}{\bar{P}'_{m,t} \bar{P}_{m,t}} = \frac{N_{m,t} \sum_{o=1}^{N_{m,t}} \sum_{q=1}^{N_{m,t}} a_{oq,m,t,d} (p_{o,m,t} - \bar{p}_{m,t})(p_{q,m,t} - \bar{p}_{m,t})}{(\sum_{o=1}^{N_{m,t}} \sum_{q=1}^{N_{m,t}} a_{oq,m,t,d}) \sum_{o=1}^{N_{m,t}} (p_{o,m,t} - \bar{p}_{m,t})^2} \quad (2)$$

where  $\bar{P}_{m,t} = \text{vec}(P_{m,t}) \times I(\text{vec}(P_{m,t}) \notin \emptyset)$  is the vector of prices,  $P_{m,t}$  is the matrix of prices related to loans agreed at time  $t$  with maturity  $m$ , as defined above,  $N_{m,t}$  is the number of loans observed at time  $t$  for the maturity  $m$  and  $A_{m,t}^d$  is the row-normalized loans' adjacency matrix for distance  $d$ .<sup>39</sup> Here we consider a maximum distance of ten in order to assess the length of the radius for a possible spillover.<sup>40</sup> I computed the statistic for five ranges of maturities: (i) from one to three days, (ii) from four to ten days, (iii) from eleven days to one month, (iv) from one month to three months, and (v) from three months to one year. For the maturities from one to three days (Figure 4), the network correlation among rates does not seem to be constant over time, and Moran's I is particularly high in two hot periods, the second quarter of 2010 and the third quarter of 2011. One can note that these two periods coincide with the peaks of market tensions deriving from the spike in sovereign spreads. In 2011 the index reaches its maximum. Moran's I decreases with the distance between prices; it is typical in a process of diffusion, but for some periods it does not converge towards zero when the distance increases.<sup>41</sup>

Figure 4: Moran's I statistic for maturities from one to three days, computed for distances from 1 to 10



Anselin (1996) interpreted Moran's I as a regression coefficient in a regression of  $A_{m,t}^d \bar{P}_{m,t}$  on  $\bar{P}_{m,t}$ , but it must be noted that Moran's I is not a consistent estimator of spillover effects,

<sup>39</sup>A distance equal to one means that the two loans share the lender or the borrower (they are directly connected); a distance equal to two means that the two loans are connected through another one (they are indirectly connected), and so on. Row normalization consists in dividing each element of the adjacency matrix by its row sum; more formally the generic element of a row normalized adjacency matrix  $A$  is  $a_{ij} = a_{ij}^* / \sum_j a_{ij}^*$  where  $a_{ij}^*$  is the generic element of the adjacency matrix  $A^*$ .

<sup>40</sup>Operationally, it means that we set to ten the maximum length of a path in the network. Increasing the maximum distance does not provide additional information.

<sup>41</sup>This may indicate the presence of cycles in chains of loans.

and therefore it cannot be stated that the spillovers among rates in the third quarter of 2011 was higher than in the second quarter of 2010; it simply tests the existence of spillover effects. In order to estimate consistently the magnitude of the latter we need to employ a different approach. Note also that a rate depends on lender and borrower characteristics: if an assortative (dissortative) matching takes place in UMM the statistical significance of Moran's I may be driven by banks covariates.<sup>42</sup>

The focus so far has been on maturities from overnight to three days so far. Moran's I is less likely to be significantly different from zero as the maturity increases (Figure 15). As we can see, the index signals a high network correlation for maturities up to one month.<sup>43</sup> From this preliminary evidence it appears that rates on short maturities are more sensitive to the decentralized (network) nature of the market while for long ones the bargained rates do not depend strongly on their neighbors.<sup>44</sup> This is why I will focus mainly on short maturities (up to three days).

## 6 Econometric Model

Moran's I offers some evidence of a diffusion mechanism, although this index cannot account for the matching process and the problem of omitted variables. Furthermore, it is not a consistent estimator of spillover effects, and, for this reason, we have to deal with these issues using different tools. In this section I introduce an ad hoc version of a spatial auto regressive model (SAR) model to assess effectively the role of private information and estimate consistently the size of its diffusion strength. If bank characteristics are meant to be the main driver of loan price deviations from the public signal (EONIA), as shown in [Angelini et al. \(2011\)](#) and [Afonso et al. \(2011\)](#), then it is important to include them when explaining the price variations between different loans. Furthermore, if the matching process between lender and borrower is driven by those characteristics, their interaction may create an *apparent* diffusion among loans driven by omitted variables. Controlling for bank covariates is fundamental in assessing the presence and magnitude of spillovers in prices. For instance, we can find a high network correlation among prices, looking at Moran's I statistic, simply because similar banks lend to each other. If we want to test robustly whether a change in a specific rate is truly determined by deviations of other rates from the average market rate, we need to clear up this endogenous source of variation.

Suppose we want to estimate the effect of adjacent prices on a price, in matrix form we have

$$\bar{P}_{m,t} = \alpha_{m,t} + \phi_{m,t} A_{m,t} \bar{P}_{m,t} + \epsilon_{m,t}^* \quad (3)$$

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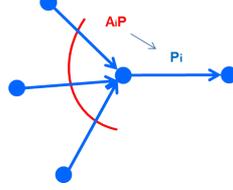
<sup>42</sup>If assortative matching is at work, banks that are similar to each other tend to connect; dissortative means exactly the contrary. If banks connected with an assortative matching during the first and second sovereign crisis and the price was a function of the same characteristics that drive the link formation process, the higher Moran's I would just reflect this change in the matching process.

<sup>43</sup>The period between the first and second sovereign crisis seems to be the one most affected by spillovers among rates for maturities from four days to one month. Maturities of over one month seem to be less impacted, even though maturities from one to three months seem to be affected during the second sovereign crisis and maturities over three months during the first sovereign crisis.

<sup>44</sup>Standard errors are larger for maturities longer than three days, because the relative networks are much sparser, highlighting a thin market. The low market density, and consequently low network density, precludes a robust estimation of spillovers. Paths longer than length two (two connected loans) are few and, as we will see in the next section, sound instrumental variables are difficult to find.

the vector  $A_{m,t}\bar{P}_{m,t}$  contains the average price of connected loans for each price, capturing the informational spillover (Figure 5). The  $i_{th}$  element of  $A_{m,t}\bar{P}_{m,t}$  is thus equal to  $\sum_{j=1}^{N_{m,t}} a_{ij,m,t}p_{j,m,t}$ , which is the mean price of loans connected to loan  $i$ , given that  $a_{ij,m,t} = a_{ij,m,t}^*/\sum_j a_{ij,m,t}^*$  and  $a_{ij,m,t}^*$  is equal to one if the loans are connected, zero otherwise.  $\epsilon_{m,t}^*$  is the error component,  $\alpha_{m,t}$  is a constant and  $\iota$  is a  $N_{m,t} \times 1$  vector of ones, all evaluated for maturity  $m$  at time  $t$ .<sup>45</sup> The term  $\alpha_{m,t}$  captures the general market conditions for maturity  $m$  at time  $t$ . The single price equation is thus

Figure 5: Informational spillover



$$p_{bl,m,t} = p_{o,m,t} = \alpha_{m,t} + \phi_{m,t} \sum_{q=1}^{N_{m,t}} a_{oq,m,t} p_{q,m,t} + \epsilon_{o,m,t}^* \quad (4)$$

If lender and borrower characteristics matter in price determination, suppose linearly, the OLS estimate of  $\phi_{m,t}$  may be not consistent because of the problem of omitted variables, given the elements included in the error term

$$\epsilon_{o,m,t}^* = x_{b,m,t}\beta_{B,m,t} + x_{l,m,t}\beta_{L,m,t} + \epsilon_{bl,m,t}, \quad (5)$$

where  $x_{l,m,t}$  and  $x_{b,m,t}$  are  $1 \times K$  vectors collecting respectively the borrower and lender characteristics, while  $\beta_L$  and  $\beta_B$  are the respective coefficients. If  $[x_{b,m,t}, x_{l,m,t}]$  is correlated with  $\sum_{q=1}^{N_{m,t}} a_{oq,m,t} p_{q,m,t}$  inconsistency occurs. Note that in this framework it is may be true as two prices are neighbors if the borrower of one coincides with the lender of the other. More formally, the bias is

$$b_{m,t} = \beta_{B,m,t}\bar{P}'_{m,t}A'_{m,t}X_{B,m,t} + \beta_{L,m,t}\bar{P}'_{m,t}A'_{m,t}X_{L,m,t}, \quad (6)$$

it is evidently different from zero if  $\text{corr}(a_{oq,m,t}p_{q,m,t}, x_{b,m,t}) \neq 0$  or  $\text{corr}(a_{oq,m,t}p_{q,m,t}, x_{l,m,t}) \neq 0$ , and it occurs if  $a_{oq,m,t}p_{q,m,t} = f(x_{b,m,t}, x_{l,m,t})$  and  $f(\cdot)$  allows for such a correlation.<sup>46</sup> I include this information with data available from Bankscope; balance sheet variables and country dummies are also considered here. The econometric model expressed in matrix form is thus the following

$$\bar{P}_{m,t} = \alpha_{m,t}\iota + \phi_{m,t}A_{m,t}\bar{P}_{m,t} + \beta_{B,m,t}X_{B,m,t} + \beta_{L,m,t}X_{L,m,t} + \epsilon_{m,t}, \quad (7)$$

<sup>45</sup>Row normalizing  $A_{m,t}$  means that we are looking at the effect of the average neighbor prices. It evidently makes more sense than considering the non row-normalized adjacency matrix in this context, because the latter produces a sum (instead of an average) of neighbor prices and it is not a meaningful statistic for price setting.

<sup>46</sup>In other words, if the link formation process and price determination are driven by bank characteristics, then the bias is non-zero, demonstrating the necessity of including covariates in this framework.

where  $X_{B,m,t}$  and  $X_{L,m,t}$  are two  $N_{m,t} \times K$  matrices collecting respectively the lender and borrower characteristics for each loan observed,<sup>47</sup>  $\epsilon_{m,t}$  is an error term i.i.d. normally distributed with zero mean and variance  $\sigma_{\epsilon_{m,t}}$ . Note that equation (7) is basically one of the possible empirical counterparts of the price equation outlined in Section 2.<sup>48</sup>

## 6.1 Accounting for Endogeneity

**Simultaneity** Another issue arises when we want to estimate equation (7), the simultaneity. If each price depends on the others, simultaneity characterizes the set of individual equations. We have to account for possible endogeneity of  $A_{m,t}\bar{P}_{m,t}$ , as usual in network models, see Lee et al. (2010), Kelejian and Prucha (2004) and Kelejian and Prucha (1998) for a detailed discussion. This step is fundamental, because we can be completely misled by OLS estimation if it is inconsistent. The simultaneity of equations in model (7) creates an intrinsic endogeneity likelihood if

$$E[(A_{m,t}\bar{P}_{m,t})'\epsilon_{m,t}] = E[(A_{m,t}(I - \phi_{m,t}A_{m,t})^{-1}(\alpha_{m,t}\iota + \beta_B X_{B,m,t} + \beta_L X_{L,m,t} + \epsilon_{m,t}))'\epsilon_{m,t}] \neq 0,$$

because from the reduced form of equation (7) we have  $\bar{P}_{m,t} = (I - \phi_{m,t}A_{m,t})^{-1}(\alpha_{m,t}\iota + \beta_B X_{B,m,t} + \beta_L X_{L,m,t} + \epsilon_{m,t})$ . The last inequality holds if

$$E[(A_{m,t}(I - \phi_{m,t}A_{m,t})^{-1}\epsilon_{m,t})'\epsilon_{m,t}] = \sigma_{\epsilon_{m,t}}^2 \text{tr}(A_{m,t}(I - \phi_{m,t}A_{m,t})^{-1}) \neq 0.$$

Note that endogeneity is basically determined by the structure of the observed network, represented by  $A_{m,t}$ . The literature of spatial and network econometrics investigated in depth several methods to treat the endogeneity created by these simultaneous equations, Kelejian and Prucha (1999) and Liu and Lee (2010) proposed a GMM approach, and Lee (2004) used a Quasi-Maximum Likelihood Estimator. In this paper we use an instrumental variable approach, following Lee et al. (2010), Lee (2007) and Kelejian and Prucha (1998). The IVs are substantially 'network embedded', in other words the network topology is used to create IVs that are correlated with the variables to be instrumented, being independent from the error term.<sup>49</sup> The expected value of the endogenous variable,  $E(A_{m,t}\bar{P}_{m,t})$ , meets these two conditions. Taking advantage of the reduced form, the theoretical best IV is thus derived as

$$TIV_{m,t} = E(A_{m,t}\bar{P}_{m,t}) = E[A_{m,t}(I - \phi_{m,t}A_{m,t})^{-1}(\alpha_{m,t}\iota + \beta_B X_{B,m,t} + \beta_L X_{L,m,t})], \quad (8)$$

since  $E((I - \phi_{m,t}A_{m,t})^{-1}\epsilon_{m,t}) = 0$ . Given that the parameters in equation (8) are unknown,  $TIV_{m,t}$  is unfeasible. Assuming  $|\phi_{m,t}| < 1$ ,<sup>50</sup> the term  $(I - \phi_{m,t}A_{m,t})^{-1}$  is an infinite sum of elements  $\sum_{k=0}^{\infty} \phi_{m,t}^k A_{m,t}^k$ . A linear approximation of vectors appearing in equation (8) can thus be used for the empirical IV. In practice we use a second order approximation

$$EIV_{m,t} = [A_{m,t}[X_{B,m,t}, X_{L,m,t}], A_{m,t}^2[X_{B,m,t}, X_{L,m,t}]]. \quad (9)$$

<sup>47</sup>Note that in this framework a bank can be represented many times in both of these matrices, depending on its activity in the UMM.

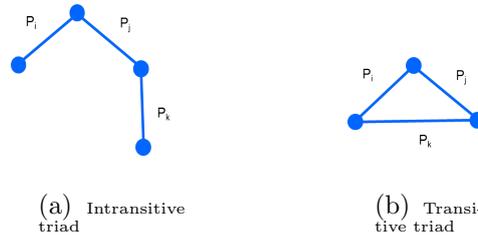
<sup>48</sup>Here we set  $c_i(p_{t-l, l \in L}) = A_o P$

<sup>49</sup>2SLS estimation is faster and, consequently, more convenient when multiple repeated cross-section data are analysed.

<sup>50</sup>This is a sufficient condition for the invertibility of  $(I - \phi_{m,t}A_{m,t})$ ; it also determines the parameter space for spillover effects.

Identification is guaranteed if  $(A_{m,t}, \bar{P}_{m,t}, \iota, X_{B,m,t}, X_{L,m,t})$  has full column rank, it can be shown that if  $(\iota, X_{B,m,t}, X_{L,m,t})$  has full column rank and  $I_{m,t}$ ,  $A_{m,t}$  and  $A_{m,t}^2$  are linear independent this condition is met (Bramoullé et al.; 2009). In other words, the network must not be composed of transitive triads. A transitive triad consists of three loans, say  $i$ ,  $j$  and  $k$ , that are fully connected. Each loan is connected with the other two. If a network is composed only of transitive triads (Figure 6, panel (b)), then  $I_{m,t}$ ,  $A_{m,t}$  and  $A_{m,t}^2$  are linear dependent. The intuition is as follows, if we use the exogenous characteristics of loan  $k$  as an instrument for the price of loan  $j$ , when the price of loan  $i$  is the dependent variable, we have no exclusion restriction if loan  $k$  is connected with loan  $i$ . We will see that the interbank unsecured money market network meets this condition in almost every maintenance period considered.

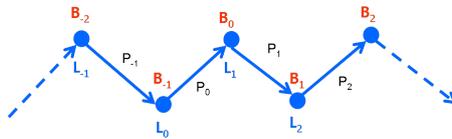
Figure 6: Network structure and identification



Panel (a): the network is formed by an intransitive triad, so that  $I_{m,t}$ ,  $A_{m,t}$  and  $A_{m,t}^2$  are linear independent. Panel (b): the network is formed by a transitive triad, so that  $I_{m,t}$ ,  $A_{m,t}$  and  $A_{m,t}^2$  are linear dependent since  $A_{m,t}^2 = I_{m,t} + A_{m,t}$ . For the sake of simplicity, loans and prices are supposed to be symmetric in this example.

Because arcs are units and nodes are connectors, we are obliged to use only a *one side* IV due to collinearity issues. Let us make a simple example, suppose we want to evaluate the effect of  $p_1$  on  $p_2$  in Figure 7. We cannot use  $[B_0, L_0]$ , where  $L_0$  are the characteristics of the lender and  $B_0$  are the characteristics of the borrower of a loan with price  $p_0$  as IV, because  $B_0 = L_1$  and it implies a not full rank matrix of instruments. Consequently only  $L_0, L_1, \dots$  can be used in the *IV chain*, which is thus extended only on the lender side, when the optimal IV is approximated.<sup>51</sup>

Figure 7: Instrumental variables' chain



Consequently the applied IV in this context is the following

$$AIV_{m,t} = [A_{m,t} X_{L,m,t}, A_{m,t}^2 X_{L,m,t}]. \quad (10)$$

<sup>51</sup>It does not change the asymptotics, both the optimal and approximated IV feature this 'duplication', it is sufficient to drop the duplicated vectors to go back to a standard framework.

Note that this approach must be used in every application in which flows or interactions between nodes are modeled including spillover effects and node characteristics. The estimation of parameters using this approach is consequently

$$\hat{\theta}_{m,t,2SLS} = (Z'P_QZ)^{-1}(Z'P_QY), \quad (11)$$

where  $Z = [I, A_{m,t}, \bar{P}_{m,t}, X_{B,m,t}, X_{L,m,t}]$ ,  $P_Q = Q(Q'Q)^{-1}Q'$ ,  $Q = [I, AIV_{m,t}, X_{B,m,t}, X_{L,m,t}]$  and  $\hat{\theta}_{m,t,2SLS} = [\hat{\alpha}_{m,t,2SLS}, \hat{\phi}_{m,t,2SLS}, \hat{\beta}_{B,m,t,2SLS}, \hat{\beta}_{L,m,t,2SLS}]$ .

**Endogenous interbank network** The network econometrics literature recently focuses on another important issue: the possible endogeneity of connections among agents. The presence of unobservables driving both the link formation and the outcome equation may lead to biased estimates. In this application it may be that banks are linked because they are in the same community or location, or more in general because of the presence of a social networks among treasurers. In a broader view this may be interpreted as a selection bias, following the concept illustrated in many papers by Heckman, Lee and other labour econometricians. Notable papers dealing with this issue are Goldsmith-Pinkham and Imbens (2013), Hsieh and Lee (2014), Patacchini and Rainone (2014), Qu and Lee (2015) and Arduini et al. (2015). The first three papers use Bayesian methods to control for the presence of unobservables, Qu and Lee (2015) uses a parametric frequentist approach, while Arduini et al. (2015) uses a semiparametric approach. Bayesian models may be unfeasible when the sample size is high. Both Bayesian and parametric frequentist approaches suffer from the possible misspecification of the unobservables functional form.

Given the high size of the sample and the lack of priors about unobservables distribution, the semiparametric approach proposed by Arduini et al. (2015) seems strictly preferable in this application. Let

$$g_{ij} = f(x_i, x_j) + v_{ij} = c_{ij} + v_{ij},$$

where  $g_{ij}$  represents the linking (lending) decision, it is equal to one if  $j$  lends money to  $i$  and 0 otherwise ( $g_{ii}$  is assumed to be zero).  $c_{ij} = f(x_i, x_j)$  is the deterministic component which is a function of the observable characteristics of bank  $i$  and bank  $j$ ,  $v_{ij}$  is the unobservable component. Recalling that our outcome equation for a certain maturity and time is

$$p_{ij} = \alpha + \phi \sum_{kl} a_{ij,kl} p_{kl} + \beta_i x_i + \beta_j x_j + \epsilon_{ij},$$

and given that  $a_{ij,kl} = g_{ij} g_{lk}$ , if  $v_{ij}$  is not independent from  $\epsilon_{ij}$  the estimate of  $\phi$  may be biased. Let us define

$$\psi(c_{ij}) = E(\epsilon_{ij} | g_{ij}, x_i, x_j) = E(\epsilon_{ij} | g_{ij}, c_{ij}),$$

as the correction term which controls for this possible dependence. Since  $\psi(c_{ij})$  is an unknown function, we can use a vector of functions  $\tau_k$  with the properties that for large  $K$  a linear combination can approximate the unknown function. Following Arduini et al. (2015) the approximating functions are power series. The empirical equation to be used is thus

$$p_{ij} = \alpha + \phi \sum_{kl} a_{ij,kl} p_{kl} + \beta_i x_i + \beta_j x_j + \sum_h \gamma_h \hat{\tau}_{ij}^h + u_{ij}, \quad (12)$$

where  $u_{ij}$  is an error term with zero mean. The estimation of such a model has two steps. In the first the dyadic link formation model is estimated, obtaining  $\hat{\tau}$ . The second step is a SC2SLS (selection corrected) IV estimation which includes the semiparametric correction term, see Arduini et al. (2015) for the details.

## 7 Empirical Analysis

Given the wide time span and the large volume of trades, we can estimate a regression for each time (maintenance period) and evaluate all the parameters for each time observation, keeping track of time patterns in spillover effects.<sup>52</sup> In this section we will focus on overnight to three day maturities.<sup>53</sup> In the empirical analysis both OLS and 2SLS are performed for each time observation (MP). The OLS estimates of  $\phi_{m,t}$  in model (7) are reported in the first row panels of Figure 16, while 2SLS estimates are plotted in the second row. The baseline model is estimated in the first column panels, model (7) is augmented with the lender network-lag (i.e.  $AX_{L,m,t}$ ) in the second column panels.<sup>54</sup> This is our benchmark model, and every statement is referred to these estimates unless it is not specified. The characteristics included in the model are the balance sheet variables and country dummies, description and relative descriptive statistics are provided in Section 4. The results of the empirical analysis are represented in Figures (16)-(19).

The first evidence to emerge is that the price transmission is not constant throughout the time span considered, and 2SLS estimates of  $\phi_{m,t}$  are not significantly different from zero for each MP considered (panel (c) and (d) of Figure 16).<sup>55</sup> Information diffusion becomes considerable after the major crises that characterize the time interval, i.e. the first and second sovereign crisis. The higher risk perceived by treasurers after these macro shocks seemed to focus more attention on market signals and private information diffusion as a consequence.<sup>56</sup> Note that, given that  $A_{m,t}$  is row-normalized,  $\phi_{m,t}$ s are perfectly comparable through  $t$  even if the standard deviation of rates changes dramatically across time (see Figure 13).<sup>57</sup> It follows that an increase in rate volatility per se does not have an effect on estimated spillovers. Variations in liquidity conditions of the system, including the occurrence of a crisis, do not hamper the results because they are captured by the term  $\alpha_{m,t}$ , being common to every loan.

The second interesting point is that the estimation results using a 2SLS estimation with  $AIV_{m,t}$  as instrument do not drastically change the qualitative conclusions derived from the

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<sup>52</sup>A repeated cross-section is more convenient to estimate with respect to a panel version, given the large sample size available at each time. We are also able to simply estimate a time varying spillover effect  $\phi_{m,t}$  and robustly trace its evolution over time.

<sup>53</sup>As mentioned before, we could potentially analyse several maturities. The reason is that the number of loans is very low for maturities higher than one week in the time interval under analysis. The small sample size may lead to bad inference.

<sup>54</sup>This term is the *contextual effect*, which controls for neighbors' observables. In this model the set of instruments is augmented as well  $AIV_{m,t} = [A_{m,t}X_{L,m,t}, A_{m,t}^2X_{L,m,t}, A_{m,t}^3X_{L,m,t}]$

<sup>55</sup>Note that, when significantly different from zero, the estimate is almost always positive. A couple of times its sign is negative, which is a less intuitive result. According to Babus and Kondor (2013), it may be observed when there are central dealers in the market. Observe also that the main hypothesis we want to test is whether prices are jointly distributed depending on the network structure; it includes the possibility of a negative estimated parameter.

<sup>56</sup>Observe that, according to the spatial econometrics literature,  $\phi_{m,t}$  is supposed to be independent of the network structure. The first measures the intensity of diffusion, the second represents the routes it passes through. This implies that  $\phi_{m,t}$  does not reflect changes in how a shock propagates owing to a different network structure. It is straightforward to consistently compare cross-sectional estimates of  $\phi_{m,t}$  across time.

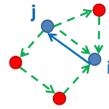
<sup>57</sup> $\phi_{m,t}$  represents the marginal effect of  $A_{m,t}\bar{P}_{m,t}$  on  $\bar{P}_{m,t}$ , so that an increase in the standard deviation of  $\bar{P}_{m,t}$  does not affect the estimated coefficient. It would increase the standard deviation of both terms ( $A_{m,t}\bar{P}_{m,t}$  and  $\bar{P}_{m,t}$ ) with the same pace. Observe that it is not true if  $A_{m,t}$  is not row-normalized, i.e we use an 'aggregate model' (not an 'average' one). Table 1 compares the estimates obtained in the baseline results (column 1) and estimates obtained using normalized rates (column 2), for the 2011-09-14 – 2011-10-11 MP. Estimates of  $\phi$  are exactly the same.

OLS estimation. In fact  $\hat{\phi}_{m,t,OLS}$  and  $\hat{\phi}_{m,t,2SLS}$  are quite similar as can be seen from panels (i)-(l) of Figure 16, even if point estimates are different and OLS shows a small bias. The time series of first stage F statistic is plotted in the last panel of Figure 16; there are no values below ten, which means that the instruments are not weak in all time observations. The closeness between OLS and 2SLS is due to the particular topology of the UMM network; as remarked earlier the endogeneity problem is generated by the observed network topology. It is generated by *circularity*, Figure 8 shows a simple example of this. More specifically, the higher the number of *cycles* in the network the higher the circularity, and the more important is the endogeneity issue.<sup>58</sup> As we can see in the third row-panels of Figure 16, where the time series of  $tr(A_{m,t}(I - \hat{\phi}_{m,t,2SLS}A_{m,t})^{-1})$  and  $\hat{\sigma}_{m,t,2SLS}^2 tr(A_{m,t}(I - \hat{\phi}_{m,t,2SLS}A_{m,t})^{-1})$  are plotted, the level of circularity is quite low (see Figure 8), and consequently the OLS bias is not huge in most of the cases.

Another interesting aspect is that the sparseness of the interbank network after the LTROs generates a very large increase in estimated standard errors for both OLS and 2SLS, and thus information diffusion assessment after April 2012 is not reliable.<sup>59</sup>

The last interesting fact is that including the lender characteristics of the influencing loan (i.e.  $AX_{L,m,t}$ ) is important in order to fit the data better. In fact the *generalized  $R^2$*  (plotted in the last row of Figure 16) is strictly preferable for the augmented model.<sup>60</sup> In the fourth panel of Figure 16 Moran's I is computed for the residuals of 2SLS estimators; excluding  $AX_{L,m,t}$  leads to a strong network-correlation in residuals, while including it leads to an extremely frequent rejection of residual network-correlation.<sup>61</sup> Note also that including  $AX_{L,m,t}$  leads to a higher estimated price transmission.

Figure 8: An example of network circularity



In this example the level of circularity between  $i$  and  $j$  is high.

If we look at the time series of other coefficients in model (7), we can see considerable time variations for the impact of lender and borrower characteristics on the price of a loan.

<sup>58</sup>Endogeneity is an issue if  $\sigma_\epsilon^2 tr(A(I - \phi A)^{-1}) \neq 0$ , the term  $tr(A(I - \phi A)^{-1})$  reflects network topology. More specifically, let  $T = A(I - \phi A)^{-1}$  and  $M = (I - \phi A)^{-1} = \sum_{k=0}^{\infty} (\phi A)^k$  then  $tr(A(I - \phi A)^{-1}) = \sum_{i=1}^n t_{ii} = \sum_{i=1}^n (\sum_{j=1}^n a_{ij} m_{ji})$ . The term  $a_{ij}$  is 1 if  $i$  influences  $j$  and zero otherwise, while  $m_{ji}$  is different from zero if at least one path starts from  $i$  and arrives at  $j$  and  $\phi \neq 0$ , in other words  $m_{ji}$  measures the direct and indirect (through other units) influence of  $i$  on  $j$  (scaled by  $\phi$ ). When  $t_{ii} = a_{ij} m_{ji} \neq 0$  it means that *circularity* is in place, loops involving  $i$  and  $j$  are present and, of course, endogeneity ensues.

<sup>59</sup>The sample size, which depends on  $n^2$ , dramatically decreases after this date, and it is not possible to make robust comparison.

<sup>60</sup>Since we are evaluating the fitting quality of 2SLS a *generalized  $R^2$*  is used; see Pesaran and Smith (1994) for details.

<sup>61</sup>Some MPs show network-correlation of residuals. This may be caused by the omission of some unobservable bank characteristic. The fact that the problem is small does not reduce the robustness of the results. The inclusion of unobservable factors is discussed below.

In Figure 17 time series for coefficients of lender and borrower balance sheet characteristics are plotted. Figure 18 depicts the time evolution of lender’s country dummies, while Figure 19 depicts that of borrower country dummies. Coefficients of both country and balance sheet variables diverge from zero at the beginning of the time period considered, i.e. after Lehman Brothers, and after the first and second sovereign crisis. This might be interpreted as a higher elasticity of prices to bank characteristics during crises, and corroborates previous analysis made with unsecured money market data (Afonso et al.; 2011; Angelini et al.; 2011). It seems that balance sheet variables are more important at the beginning of the time series, namely after the Lehman crises in 2008, probably because more attention was paid to the banks’ financial resilience and the likelihood of toxic assets, so that certain types of banks were inclined to pay (or earn) a higher (or lower) price with respect to the market average. Note that in this period a significant transmission among prices is found. The price of money seems to be more sensitive to banks’ size (both as lender and/or borrower) before the first sovereign crisis as the coefficients of *Total Assets* show in Figure 17. Having a large percentage of loans within assets seemed to make lenders request a higher price after the first and second sovereign crisis. From Figure 19 one can see that Italian borrowers paid higher rates after the first and second sovereign crisis, roughly 12 basis points more than German ones, while Spanish borrowers paid roughly 10 basis points more than German ones. Greek borrowers paid more only after the first sovereign crisis, but the effect was limited and the quite large standard errors highlight a reduced participation of Greek borrowers from then on.<sup>62</sup> In general terms, the effects of balance sheet composition and country dummies seem to have some considerable time-variation in the period under analysis and to explain price variation especially during hot periods.<sup>63</sup> In Appendix C the empirical analysis is augmented including network measures in the econometric model. As a final step I estimated model (12) in order to check whether the possible presence of unobservables driving both the link formation and the outcome equation may lead to different qualitative conclusions. Figure 20 shows that it is not the case, the estimates of  $\phi$  are very close to the baseline ones and the same conclusions hold.

## 8 Robustness Checks

I test the robustness of my findings with respect of three important aspects. The first consists in checking whether the observed connections among banks really matter in determining the rate of a loan, the second is the direction of information flows, while the third is the relevance of final agent detection. While the first and second aspects are important to secure more confidence about the consistency of the estimated spillover effects and the mechanism generating spillovers among rates, the third may be seen as a falsification test and provides insights into the relevance of final agents information availability.

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<sup>62</sup>Here the reference category is Germany for both lenders and borrowers, and the country dummies are interpreted with respect to the average price paid (or earned) by German borrowers (lenders).

<sup>63</sup>As highlighted in Section 5 this analysis is based on the subsample of connected price, so that all the coefficients estimated on this subsample except the diffusion parameter ( $\phi_{m,t}$ ) might not have a full external validity -i.e. exogenous variables-. Observe that  $\phi_{m,t}$  cannot by definition have an external validity.

## 8.1 Network Randomization

In this section I want to test whether the observed connections among banks really matter in determining the rate of a loan. If there is some common unobservable factor determining the high correlation among connected prices, and we are not accounting for it, our result might be spurious. Note that it is highly unlikely in our empirical framework, as we are controlling for macro, micro and country-specific effects. Furthermore, our identification and estimation strategies depend on the correct specification of network links. Our identification strategy hinges upon non-linearities in group membership, i.e. on the presence of intransitive triads, as shown in Section 6.1.<sup>64</sup>

In addition, given that the observed interbank network is detected by the Furfine algorithm and it features type I and II errors, the network can include 'false loans', while not including 'true loans'.<sup>65</sup> The exercise proposed in this section goes in this direction, I sequentially include non observed loans and exclude observed loans, virtually increasing the size of type I and II errors of the Furfine algorithm. If these errors are big, loans are connected almost at random. In this case we should not find any diffusion of information, because it is estimated using a completely false structure of connections. In other words, I test the robustness of my results with respect to the misspecification of network topology. In order to cope with possible critiques I implement a numerical exercise by means of Monte Carlo simulations. I artificially modify part of the interbank network and estimate our model with a misspecified interbank market. I use simulated data to answer questions such as: Do our results change if some links are misspecified? To what extent? How many links need to be misspecified before explaining away our results?

**A numerical experiment.** I use a simulation approach to randomly change a certain percentage of links in the interbank network,  $p$ , one hundred times for each value of  $p$  ranging from 0 to 1 with a pace of .001. I thus draw one hundred network structures (samples) of size equal to the real one for each value of  $p$ , one hundred thousand network structures in total.

The first empirical issue that we face in our procedure has to do with the relationship between the strength of spillover effects and network density. Because spillover effects may vary with network density (Calvó-Armengol et al.; 2009), our numerical exercise needs to generate a constant number of links after replacement. Let  $L$ , with cardinality  $l$ , be the set of existent links in the network and  $O$ , with cardinality  $o$ , the set of non-existent links in the same network. The number of 'possible changes' consistent with our constraint is  $c = \min(n, o)$ . In other words, we can exchange only a fraction of existent links with non-existent links (and viceversa) if we want to maintain constant the total number of links in our network of a given size (network density). The percentage of randomly replaced links  $p$  is thus calculated over the possibly interchangeable links (excluding overlapping), rather than over the total number of network links. The actual percentage will be  $q = p \cdot c$ .

The second empirical issue here is that this theoretical portion of links that we want to change may not correspond to a discrete number of links. For example, a replacement rate

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<sup>64</sup>There may be, for example, some 'unobserved' network link which, if considered, would change the network topology and break some intransitivities in network links.

<sup>65</sup>The algorithm estimates the interbank network, matching pairs of payments and labeling them as a loan. It can match payments that do not belong to the same loan or do not match payments that belong to the same loan. As long as it concerns this paper's findings, it implies that two loans might be falsely connected by a false loan or, viceversa, might be falsely unconnected by a missing actual loan, thus biasing our estimates.

of 20 per cent in a network with 7 possibly interchangeable links would imply that 1.4 links need to be changed. Do we swap one link (i.e. one existent into non-existent and one non-existent into existent at random) or two links (i.e. two couples)? I implement this decision rule rigorously, as follows.

Let  $p \in (0, 1)$  be our desired replacement rate. In order to obtain a number of changes as close as possible to the desired one, the actual number of changes  $s$  is:

$$s = \begin{cases} [q] & \text{if } u > a \\ [q] + 1 & \text{if } u < a \end{cases}$$

where  $a = q - [q]$ , and  $u$  is a random extraction from a variable uniformly distributed on  $(0, 1)$ .

Let us consider a simple example. Suppose we have an undirected network composed of 4 nodes, {A, B, C, D}, and links {AB, AC, BC, CD}. In this situation  $l = 4$ ,  $o = 2$  ({AD, BD}) and therefore  $c = 2$ . We can make at the most two changes within the set of "possible changes" {(AB AD), (AB BD), (AC AD), (AC BD), (BC AD), (BC BD), (CD AD), (CD BD)}. This means that we can extract randomly just two couples out of eight. Now suppose that our desired replacement rate  $p$  is 0.3 (30%), yielding to an actual replacement rate  $q$  of 0.6 (30 of 2). At this point our algorithm draws  $u$ . If  $u < .6$  than  $s = 1$  and we will replace one link (i.e. we extract at random one couple), otherwise nothing will happen. Clearly, given that 0.6 is closer to 1 than to 0, the probability of extracting  $u < .6$  is higher than the probability of extracting  $u < .6$ , as desired.<sup>66</sup>

**Simulated evidence** Given the high dimensionality of our dataset, I focus on one MP, the one in which we found the highest price transmission during the second sovereign crisis. 2SLS estimation of  $\phi$  was roughly 0.2 at that time. Our link replacement procedure enables us to simulate different network structures ( $A_{m,t}$  matrix in model (7)) that differ from the real one by a given (increasing) number of misspecified links  $p$ . In practice we estimate for each replication the following model

$$\bar{P}_{m,t} = \alpha_{m,t} \iota + \phi_{m,t}^{p,l} A_{m,t}^{p,l} \bar{P}_{m,t} + \beta_{B,m,t} X_{B,m,t} + \beta_{L,m,t} X_{L,m,t} + \epsilon_{m,t}, \quad (13)$$

where  $A_{m,t}^{p,l}$  is the resulting adjacency after  $p$  per cent of links have been changed in the  $l_{th}$  replication and  $\phi_{m,t}^{p,l}$  is the relative estimated parameter. As mentioned before, for each percentage of randomly replaced links, we draw one hundred network structures (samples) of size and network density equal to the real one. We then estimate model (13) replacing the real  $A_{m,t}$  matrix with the simulated ones ( $A_{m,t}^{p,l}$ ) in turn, so that in total we estimate model (13) one hundred thousand times. The crucial question for our purposes is what is the percentage of network structure misspecification over which spillover effects are washed out.

Figure 21 plots the averages of the estimates of spillover effects for each replacement rate with 90 per cent confidence bands. Standard errors have been calculated assuming drawing independence and taking into account the variation between estimates for each replacement rate.<sup>67</sup> I find that spillover effects remain statistically significant up to a percentage of ran-

<sup>66</sup>This algorithm has been written in Matlab. The code is available upon request.

<sup>67</sup>Specifically, the standard error at each replacement rate, say  $i$ , is computed as follows:  $\sigma_i = \sqrt{W_i + B_i}$  where  $W_i = \frac{1}{n} \sum_{j=1}^n \sigma_{ij}^2$ ,  $B_i = \frac{1}{n} \sum_{j=1}^n (\phi_{ij} - \bar{\phi}_i)^2$ ,  $\sigma_{ij}^2$  is the estimated variance of the  $j_{th}$  estimator at the  $i_{th}$  replacement rate,  $\phi_{ij}$  is the  $j_{th}$  estimate at the  $i_{th}$  replacement rate and  $\bar{\phi}_i$  is the mean across the  $n$  estimates. In this experiment  $n = 100$ . Other diagnostic plots are reported in Appendix D.

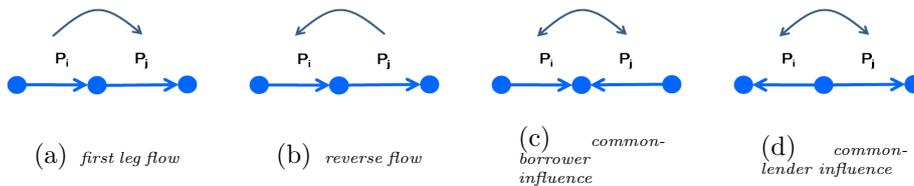
domly replaced (interchangeable) links of about 7 per cent.

From this result we can draw two conclusions. First, the observed connections are important; if we make a modest change to the connection pattern, the spillover effects are no longer significantly different from zero.<sup>68</sup> Second, if instead  $\phi$  becomes nil only when a large portion of links is changed, then the spillovers among rates would be driven by some omitted variable that is correlated with the actual network of loans but not with the simulated networks.

## 8.2 Changing Diffusion Flows

We have considered so far that the price of the loan of bank  $i$  to bank  $j$  affects the price of the loan of bank  $j$  to bank  $k$ , having basically assumed that the direction of the money flow drives the influence among prices. It is like saying that borrowers of a loan adjust their expected price as a lender after having observed the price experienced as a borrower. One can argue that the opposite is also true (hereafter *reverse flow*),<sup>69</sup> or that borrowers adjust the expected price of their loan depending on prices observed as a borrower too (hereafter *common-borrower influence*),<sup>70</sup> and finally, the same can be said of a lender (hereafter *common-lender influence*).<sup>71</sup> In this section we want to test whether making different assumptions on diffusion direction leads to different qualitative conclusions (Figure 9).

Figure 9: Influence Flows



Note that for both the *common-borrower influence* and *common-lender influence* we have two theoretical issues. The first one concerns the information diffusion. If diffusion is modeled in these ways a price signal can not move further than distance 2 through the network because it is a priori limited to the same lender (borrower) set of loans. The second issue is about exclusion restrictions. If the network of prices is conceived in this way, then it is composed of separated complete components.<sup>72</sup> It follows that we cannot deal with endogeneity as we did before because *transitive triads* (and more in general *complete cliques*) are formed by construction so that the *IV chain* (see Figure 7) is precluded and IVs are not based on an exclusion restriction anymore.<sup>73</sup> Figure 10 represents two explicative graphical exam-

<sup>68</sup>Observe that the portion of network topology that can be misspecified is not very small (7 per cent). It implies that even if we do not observe or we observe imprecisely a portion of the interbank network, our results on the existence of spillover effects still hold.

<sup>69</sup>More concretely, the price of the loan of bank  $i$  to bank  $j$  is affected by the price of the loan of bank  $j$  to bank  $k$ .

<sup>70</sup>The price of the loan of bank  $i$  to bank  $j$  affects the price of the loan of bank  $k$  to bank  $j$ .

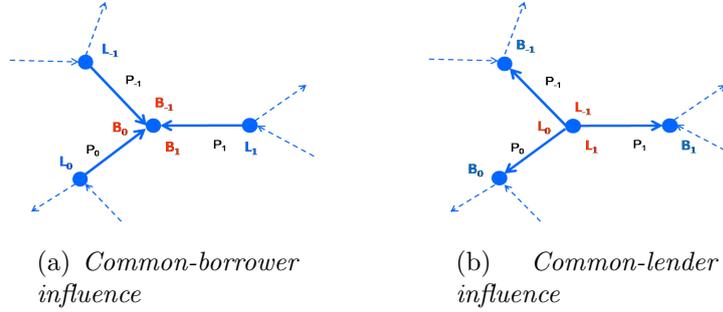
<sup>71</sup>The price of the loan of bank  $i$  to bank  $j$  affects the price of the loan of bank  $i$  to bank  $k$ .

<sup>72</sup>The adjacency matrix is thus composed of diagonal blocks.

<sup>73</sup>See Bramoullé et al. (2009) for more econometric details on the role of intransitive triads in network models. Lee (2007) studied the estimation of network models with separate components, but in the case of sparse network components. Graham (2008) proposed an estimator based on group size variance avoiding

ples of prices network constructed following *common-borrower influence* and *common-lender influence*.<sup>74</sup>

Figure 10: Absence of Exclusion Restriction



This implies that only a *reverse flow* can be consistently tested effectively. I also report the results for *common-borrower influence* and *common-lender influence*. Figure 22 shows the time series of  $\hat{\phi}_{m,t,2SLS}$ .<sup>75</sup> As theory predicts, estimates of *common-borrower influence* and *common-lender influence* are not reliable and are often out of parameter space ( $|\phi_{m,t,2SLS}| < 1$ ). The *reverse flow* shows a time evolution very close to the baseline model (see panel (d) of Figure 16), predicting the same high diffusion after big crises and suggesting that signals are reciprocal and move in both directions.

### 8.3 Considering Settlement Banks instead of Final Agents

Many studies use money market data from the Furfine algorithm; Afonso et al. (2011) is one example. One of the most common drawbacks of databases constructed using this algorithm is the lack of information on final agents. The algorithm matches two payments settled through the payment system, i.e. on settlement banks' accounts, and it is thus possible that those banks operate (as settlement agents) on behalf of other banks (final agents).<sup>76</sup> Missing this information can seriously jeopardize the validity of the analysis, leading to misspecification of actual counterparts of loans. Data on final agents are available in payment messages settled by T2, so that having them at hand allows the actual lender and borrower of a loan to be exactly matched.<sup>77</sup> In this section I consider settler banks instead of final agents. This exercise provides us with at least two interesting insights. First, it highlights differences between results when final agents are misspecified. Second, it can be seen as a falsification test. More specifically, it is likely that some banks are their own settlement banks but that others buy

sparseness assumptions. Recalling the *circularity* concept, used previously, the intuition is that in these cases its level is so high that IVs cannot solve the problem because of the absence of exclusion restrictions.

<sup>74</sup>Note that in these cases prices are segregated and each price influences (is influenced by) all the other prices preventing exclusion restrictions.

<sup>75</sup>The augmented model is considered, thus including  $AX_L$

<sup>76</sup>See Adams et al. (2008) for an analysis of tiering in payment systems.

<sup>77</sup>In principle, we do not expect price to depend on the lender or borrower being a settlement bank. The trading phase is often managed independently of the settlement phase in terms of price formation. Nevertheless, it would be interesting and insightful to test this assumption. It may be cumbersome and is thus left for future research.

the settlement service from other banks.<sup>78</sup> Suppose bank A, which has bank B as settlement bank, lends money to bank C, which is also a settlement bank. Settlement bank C is rightly considered to be a final agent (because it is a settlement bank) but B is wrongly regarded as the lender instead of A. From a network perspective we are simply misspecifying the node that the arc is pointed from, econometrically it means that we are also misspecifying the bank characteristics too. This section investigates whether the previous results change qualitatively and how much bias is produced by considering settlement banks instead of final agents.

Let us focus first on a descriptive assessment, following the same path as before. The Moran's I statistic for maturities from overnight to three days is plotted in Figure 23, so we can see that considering settlement banks leads to roughly the same time evolution of the index, in particular for short distances. Differences are notable for high distances.<sup>79</sup> Let us turn now to the econometric model. In Figure 24  $\hat{\phi}_{m,t,2SLS}$ , when settler banks are considered instead of final agents, is plotted. Figure 24 must be compared with the second row/first column panel of Figure 16. The qualitative results are very similar, peaks in diffusion are observed after the first and second sovereign crisis and coincide with those that emerged using final agents. Nevertheless, the magnitudes are significantly different and therefore inaccurate. When settler banks are considered instead of final agents, we estimate a  $\phi_{m,t}$  of roughly 0.2 in both the first and second sovereign crisis, while the actual values are 0.1 and 0.2 respectively. The diffusion after the first sovereign crisis is clearly overestimated. The conclusion is that the utility gained by having the final agents information is significant and the same analysis implemented considering settler banks may bias the estimation of the parameters. On the other hand, peaks of transmission are detected even if we consider settler banks. The same qualitative results hold for the other specifications and maturities.

## 9 Concluding Remarks

As a first contribution, this paper proposes an econometric procedure to test for and measure the strength of private information diffusion in a decentralized market. As a second contribution, the method is applied to the decentralized unsecured market for euro funds in order to assess the presence of this mechanism during a wide time span ranging from 2008 to 2012.

On the conceptual side, according to the theoretical literature on OTC markets, such as Babus and Kondor (2013) for example, private information may have an important role in a decentralized market with heterogeneous valuations of the exchanged asset. Spatial econometrics techniques were adapted to a network framework in which the outcome of arcs (bilateral trades) is modelled instead of the outcome of nodes (dealers).<sup>80</sup> A 2SLS estimator was proposed to test for private information diffusion, which also gives a quantification of diffusion strength, providing a multiplier for rate dispersion.<sup>81</sup> If present, this mechanism has a direct

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<sup>78</sup>Observe that settler banks are not proper intermediaries, they are more like service providers. I thus assume that the strategic interactions between two direct counterparties are not different from others between two counterparties that transact through an intermediary.

<sup>79</sup>Considering settler banks seems to increase the persistence of network-lag correlation. The intuition behind this is that settler banks are likely to sell this service to more banks and consequently it appears that distant prices are correlated simply because loans are more likely to be settled in the accounts of a smaller circle of (settlement) banks.

<sup>80</sup>As a minor methodological contribution, the paper may be seen as an application of spatial econometrics which is concerned about spillover effects among arcs instead of nodes.

<sup>81</sup>The multiplier measures the intensity of propagation through the interbank network after an idiosyncratic

role in defining the average market rates and their volatility, and an indirect one in determining debts of households and firms, via the pass-through from market to banking rates. In the same direction, the paper also proposes a new perspective from which to study the dynamics of the money markets and their turbulence.

On the empirical side, I tested private information diffusion in the euro unsecured money market. The proposed 2SLS estimator was computed for a wide time span from June 2008 to the end of 2012, estimates reveal that diffusion was not constantly at work during the period considered. It was considerable only during hot periods. This evidence indicates that market tensions and strong uncertainty (generated by the sovereign debt crises) allow individual evaluations to be heterogeneous and let the diffusion of private information take place. Deviance from the public signal seems to take place and have a network nature driven by the private signals that market participants send to each other. Diffusion has been found to flow in multiple directions through the interbank network.

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shock to a bank's valuation (about central bank money market value).

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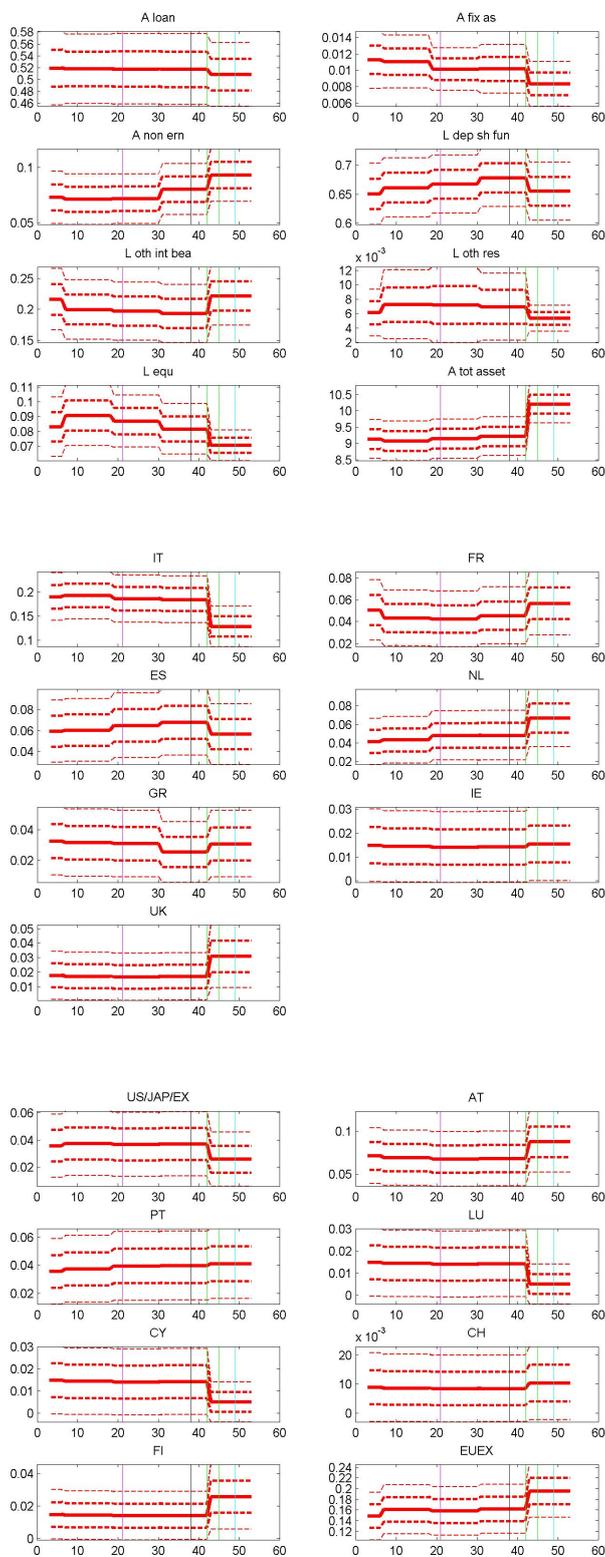
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# Figures

Figure 11: Sample mean of covariates



The bold line depicts the time series of sample mean, dashed lines represent respectively mean  $\pm 1/4$  and  $\pm 1/8$  standard deviation points. Standard deviation is scaled to improve the visibility of the time dynamic. The violet vertical line traces the first sovereign debt crisis, black vertical line traces the second sovereign debt crisis, the green lines trace LTROs and the light blue line traces the signal rate change in July 2012.

Figure 12: Number of banks operating in the market

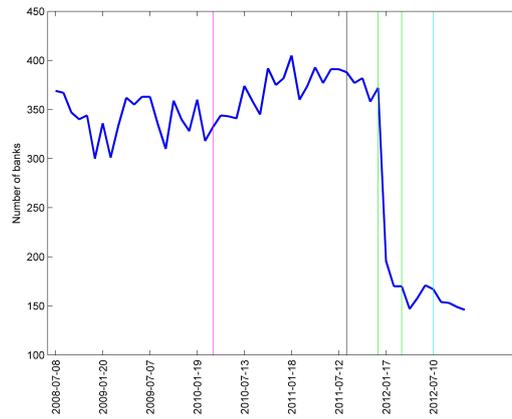
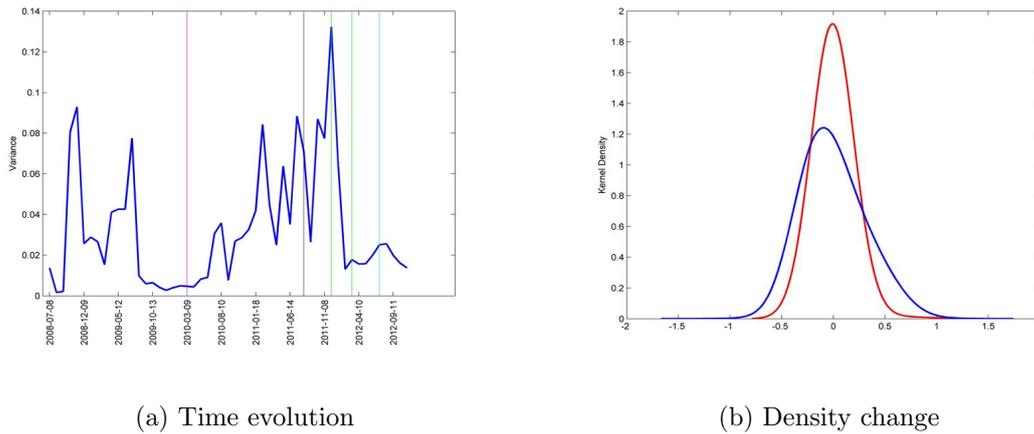


Figure 13: Price variance

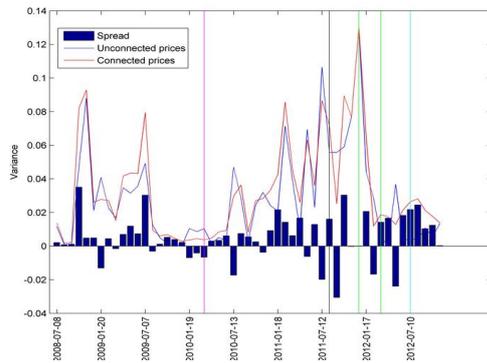


(a) Time evolution

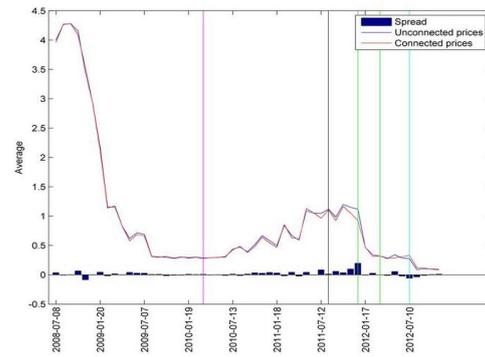
(b) Density change

Panel (a): the violet vertical line traces the first sovereign debt crisis, the black vertical line traces the second sovereign debt crisis, the green lines trace LTROs and the light blue line traces the signal rate change in July 2012. Maintenance periods are considered. Panel (b): kernel density of prices centered to zero. Bandwidth = 0.2, kernel = Normal. Red line: distribution of prices during the maintenance period from 2010-01-20 to 2010-02-09, blue line: distribution of prices during the maintenance period from 2011-07-13 to 2011-08-09.

Figure 14: Connected vs unconnected spreads



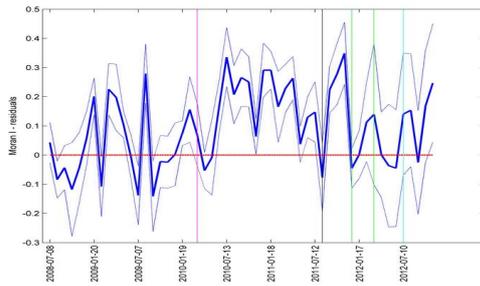
(a) Volatility



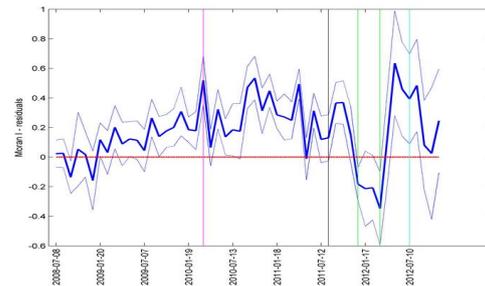
(b) Price

Violet vertical line traces the first sovereign debt crisis, the black vertical line traces the second sovereign debt crisis, the green lines trace LTROs and the light blue line traces the signal rate change in July 2012.

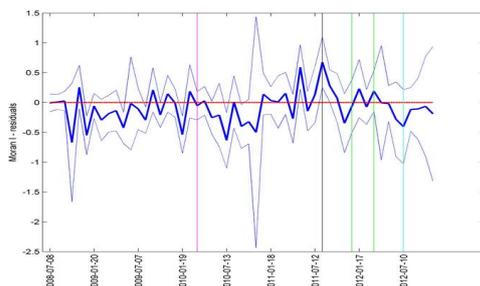
Figure 15: Moran's I statistic for longer maturities, computed for distances 1



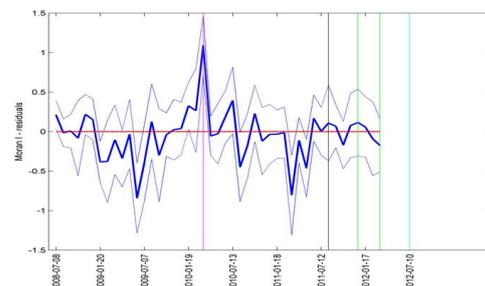
(a) from four to ten days



(b) from eleven days to one month



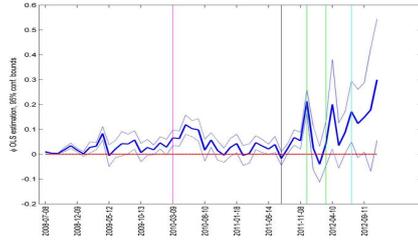
(c) from one month to three months



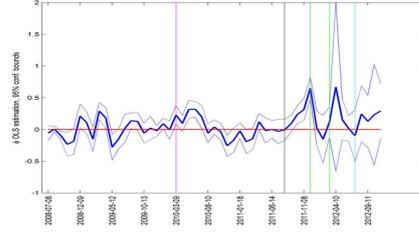
(d) from three months to one year

Violet vertical line traces the first sovereign debt crisis, the black vertical line traces the second sovereign debt crisis, the green lines trace LTROs and the light blue line traces the signal rate change in July 2012.

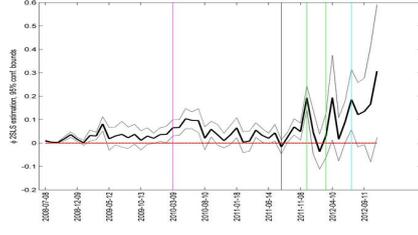
Figure 16: 2SLS and OLS estimation of  $\phi_{m,t}$ ,  $m =$  overnight to three day maturities



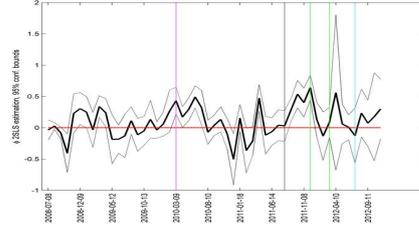
(a) OLS



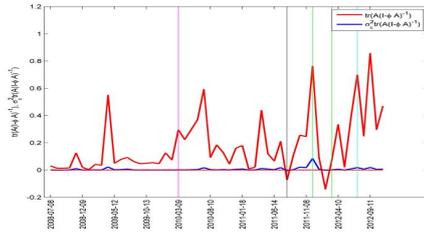
(b) OLS -  $AX_L$



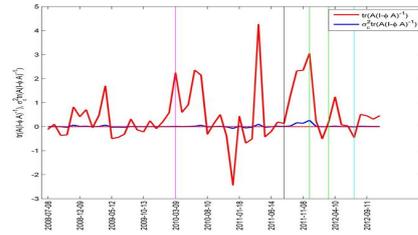
(c) 2SLS



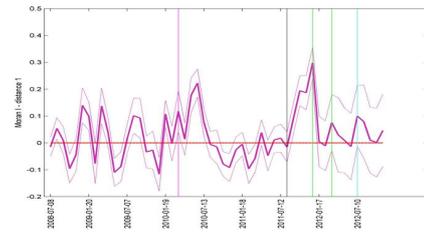
(d) 2SLS -  $AX_L$



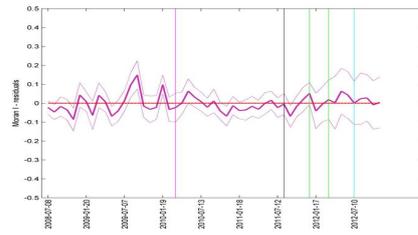
(e) Endogeneity



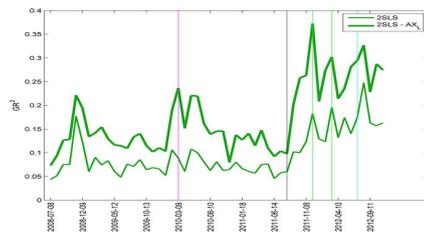
(f) Endogeneity -  $AX_L$



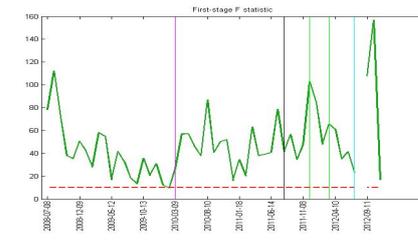
(g) Residuals Moran's I



(h) Residuals Moran's I -  $AX_L$



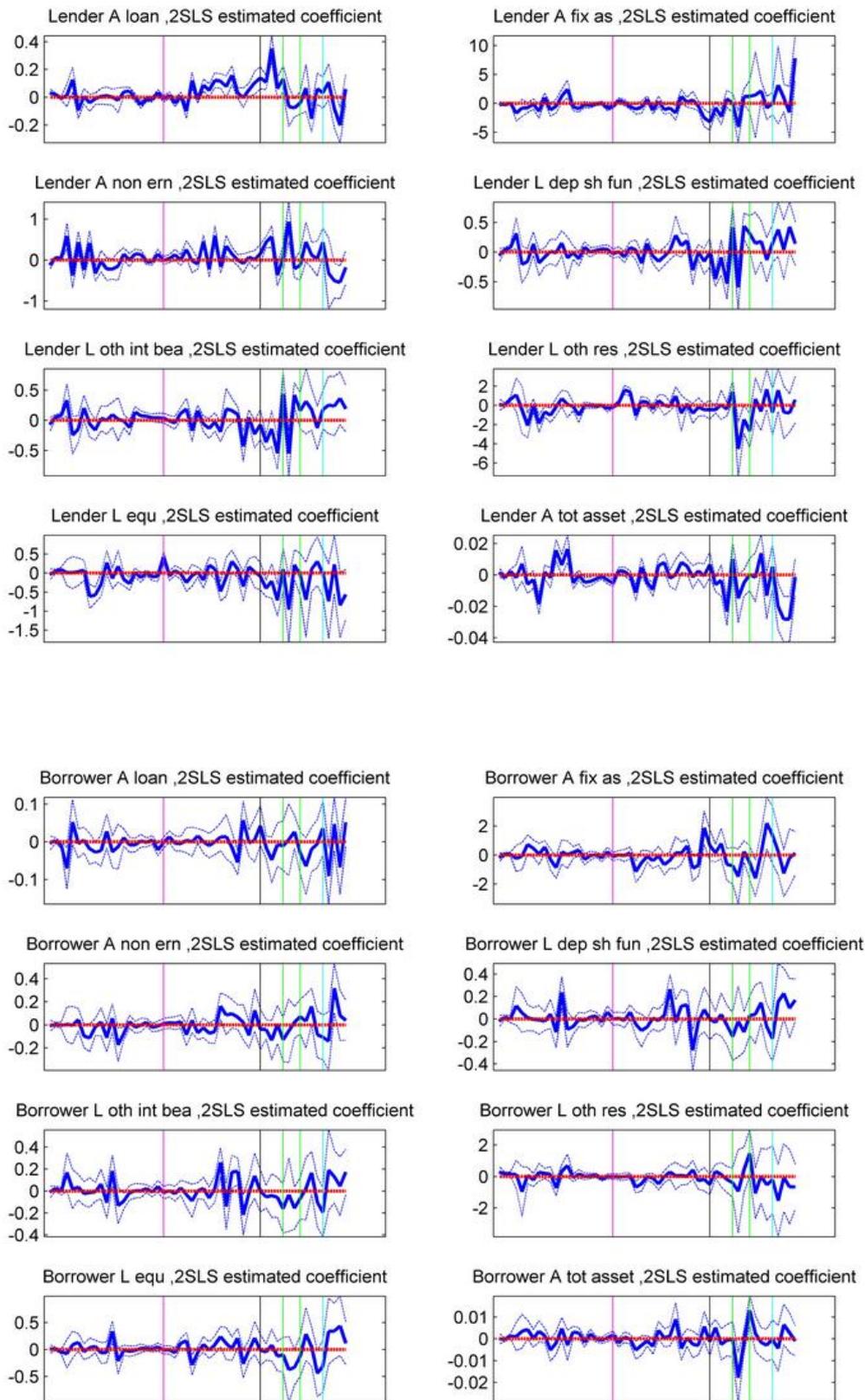
(i) Representation quality



(j) Instruments validity

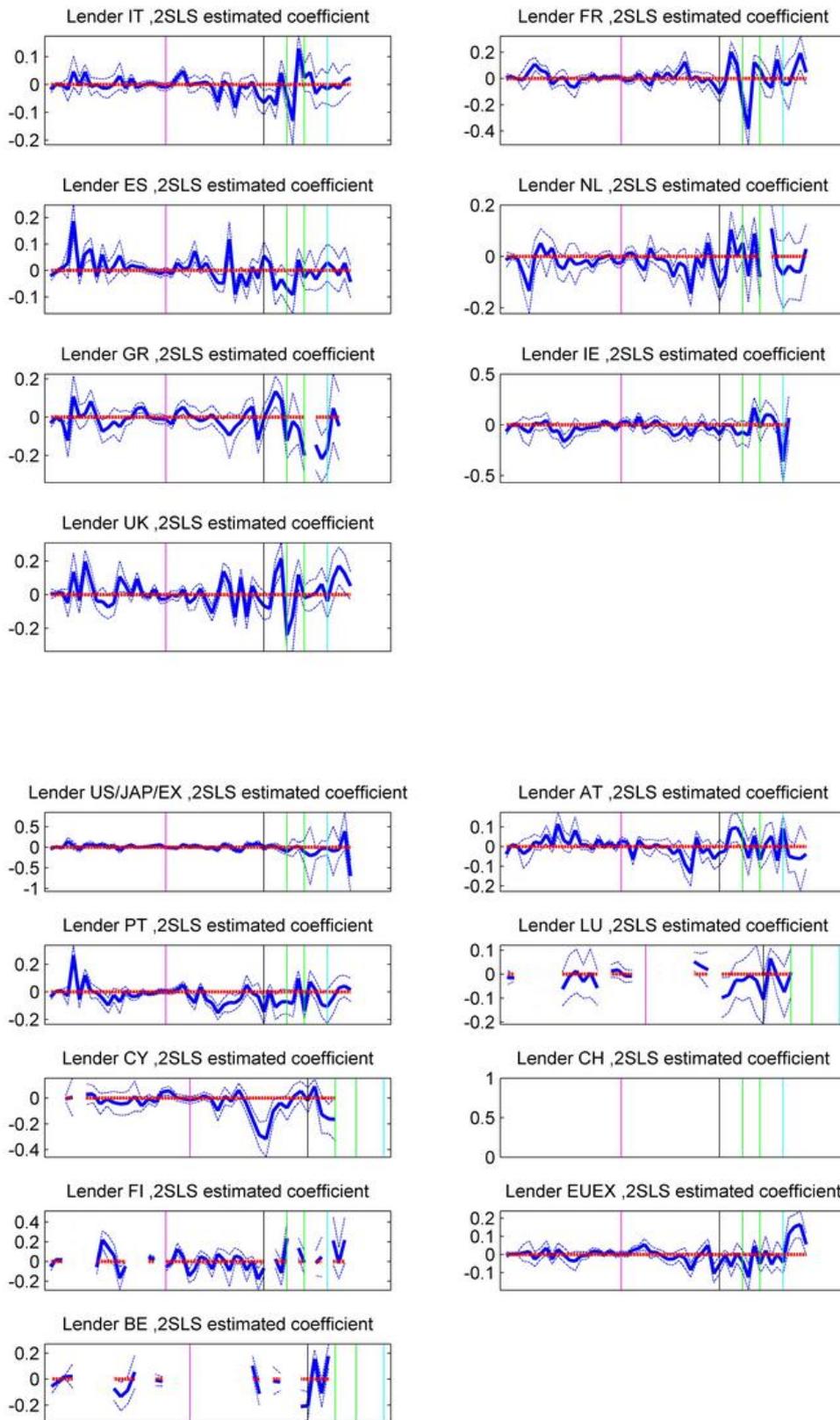
The dashed lines represent 95 percent confidence intervals. Violet vertical line traces the first sovereign debt crisis, the black vertical line traces the second sovereign debt crisis, the green lines trace LTROs and the light blue line traces the signal rate change in July 2012. Third row panels represent the estimated  $tr(A(I - \phi A)^{-1})$  and  $\sigma_\epsilon^2 tr(A(I - \phi A)^{-1})$  which measure the endogeneity issue in the observed network. Generalized  $R^2$  is used to evaluate representation quality. The dashed horizontal line in the last panel represents 10.

Figure 17: 2SLS estimation time series of lender and borrower balance sheet covariates ( $\beta_{B,m,t}$  and  $\beta_{L,m,t}$ ),  $m =$  overnight to three day maturities



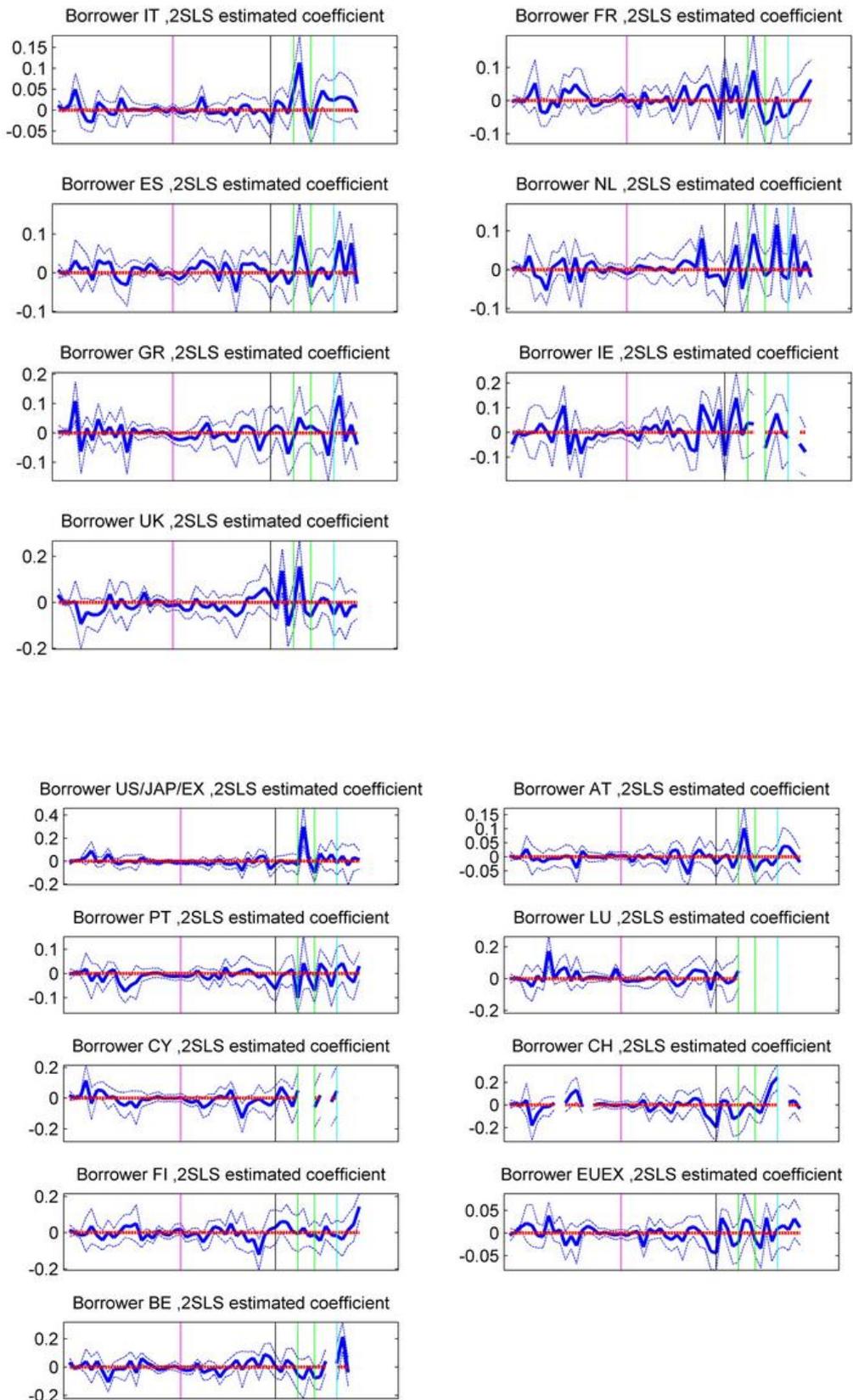
The dashed lines represent 95 percent confidence intervals. The horizontal axis is time ( $t$ ), the violet vertical line traces the first sovereign debt crisis, the black vertical line traces the second sovereign debt crisis, the green lines trace LTROs and the light blue line traces the signal rate change in July 2012. Missing dots refer to missing characteristic in the respective time period.

Figure 18: 2SLS estimation time series of lender country dummies ( $\beta_{B,m,t}$  and  $\beta_{L,m,t}$ ),  $m =$  overnight to three day maturities



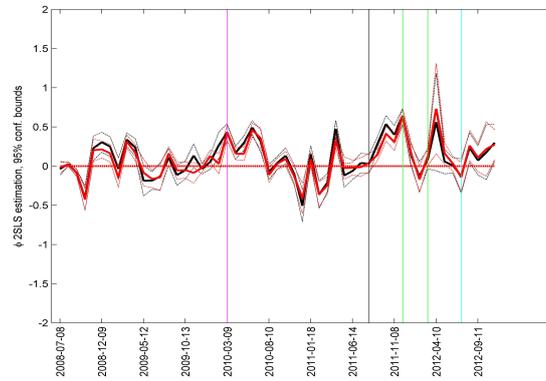
The dashed lines represent 95 percent confidence intervals. The horizontal axis is time ( $t$ ), the violet vertical line traces the first sovereign debt crisis, the black vertical line traces the second sovereign debt crisis, the green lines trace LTROs and the light blue line traces the signal rate change in July 2012. Missing dots refer to missing characteristic in the respective time period.

Figure 19: 2SLS estimation time series of borrower country dummies ( $\beta_{B,m,t}$  and  $\beta_{L,m,t}$ ),  $m =$  overnight to three day maturities



The dashed lines represent 95 percent confidence intervals. The horizontal axis is time ( $t$ ), the violet vertical line traces the first sovereign debt crisis, the black vertical line traces the second sovereign debt crisis, the green lines trace LTROs and the light blue line traces the signal rate change in July 2012. Missing dots refer to missing characteristic in the respective time period.

Figure 20: 2SLS and SC2SLS estimation time series of  $\phi_{m,t}$ , for maturities from one to three days



Black line represents 2SLS, Red line represents SC2SLS.

Figure 21: Robustness check: rewiring the network structure

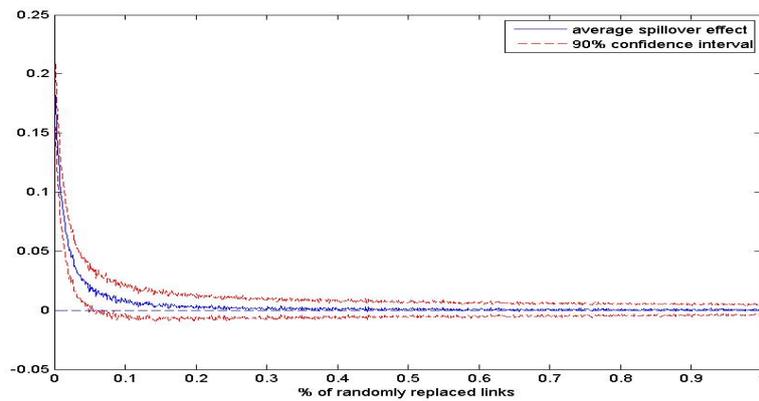
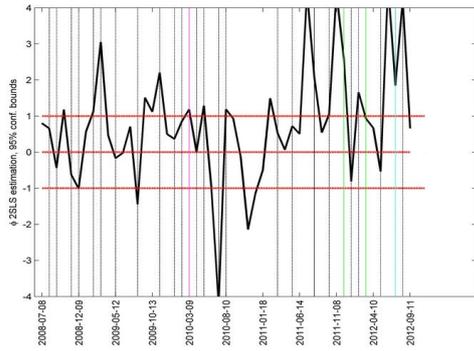
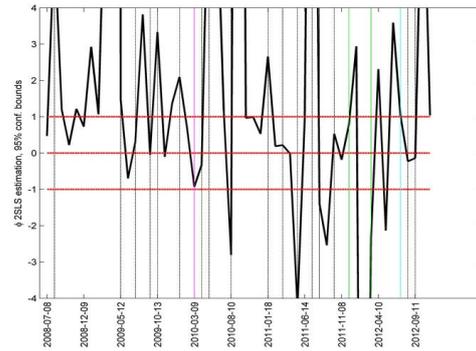


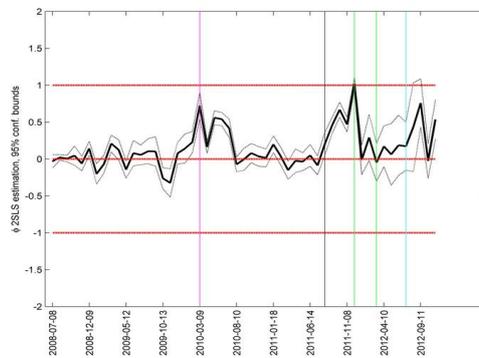
Figure 22: Changing influence flows



(a) *Common-borrower influence estimates*



(b) *Common-lender influence estimates*



(c) *Reverse flow estimates*

The dashed lines represent 95 percent confidence intervals. Violet vertical line traces the first sovereign debt crisis, the black vertical line traces the second sovereign debt crisis. Red horizontal lines are centered on zero and delimit the parameter space.

Figure 23: Moran's I Statistic for maturities from one to three days, computed for distances from 1 to 10. Robustness check: settlement banks

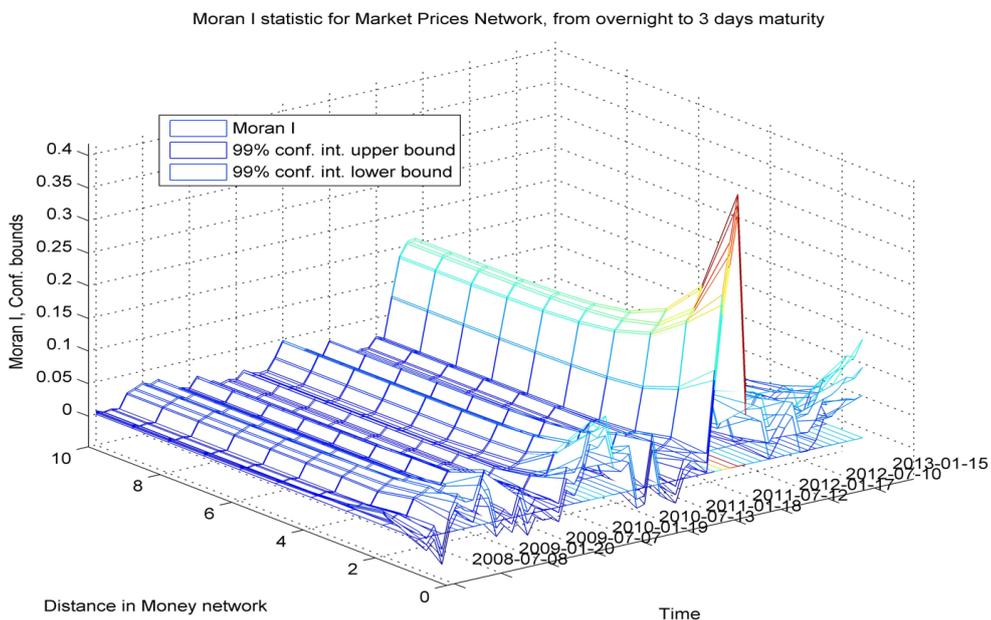
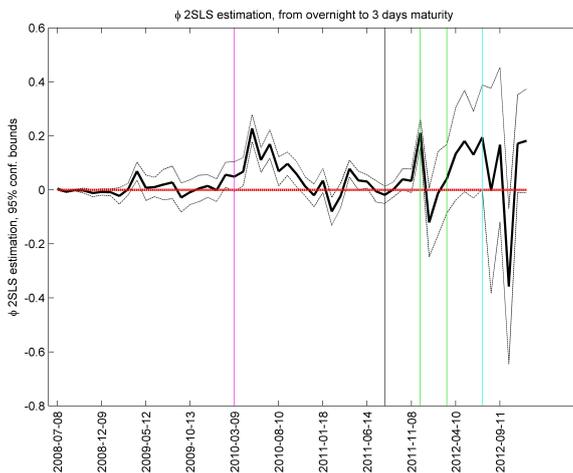


Figure 24: 2SLS estimation time series of  $\phi_{m,t}$ , for maturities from one to three days. Robustness check: settlement banks



# Tables

Table 1: Diffusion vs variance - Parameter estimates

Dependent Variable: loan's rate		
	$P$ (1)	<i>normalized P</i> (2)
Info Diffusion Strenght ( $\phi$ )	0.5367 *** (0.0726)	0.5367 *** (0.0726)
Lender A loan	0.3510 *** (0.0612)	1.1742 *** (0.2046)
Lender A fix as	-2.3042 ** (0.9200)	-7.7079 ** -30775
Lender A non ern	0.5731 *** (0.1745)	1.9171 *** (0.5838)
Lender L dep sh fun	-0.0893 (0.1976)	-0.2989 (0.6611)
Lender L oth int bea	-0.1417 (0.1987)	-0.4740 (0.6646)
Lender L oth res	0.0549 -10221	0.1838 -34190
Lender L equ	-0.2080 (0.3005)	-0.6959 -10051
Lender A tot asset	-0.0035 (0.0067)	-0.0116 (0.0223)
Lender IT	-0.0745 ** (0.0317)	-0.2493 ** (0.1059)
Lender FR	0.2036 *** (0.0511)	0.6811 *** (0.1710)
Lender ES	-0.0745 ** (0.0373)	-0.2492 ** (0.1248)
Lender NL	0.1056 ** (0.0464)	0.3531 ** (0.1551)
Lender GR	0.1356 ** (0.0530)	0.4536 ** (0.1772)
Lender IE	-0.0073 (0.0472)	-0.0244 (0.1579)
Lender UK	0.1296 ** (0.0508)	0.4336 ** (0.1701)
Lender US/JAP/EX	0.0271 (0.0487)	0.0906 (0.1630)
Lender AT	0.0906 * (0.0470)	0.3030 * (0.1573)
Lender PT	-0.1122 * (0.0608)	-0.3752 * (0.2033)
Lender LU	-0.0093 (0.0559)	-0.0309 (0.1871)
Lender CY	-0.1272 (0.0972)	-0.4256 (0.3252)
Lender FI	0.0267 (0.0637)	0.0894 (0.2132)
Lender EUEX	-0.0669 * (0.0367)	-0.2239 * (0.1228)
Lender BE	-0.1090 (0.0702)	-0.3648 (0.2349)
Borrower A loan	-0.0478 (0.0406)	-0.1598 (0.1357)
Borrower A fix as	0.8041 (0.7010)	26900 -23448
Borrower A non ern	-0.1332 (0.1127)	-0.4455 (0.3769)
Borrower L dep sh fun	0.0402 (0.1281)	0.1345 (0.4284)
Borrower L oth int bea	-0.0409 (0.1323)	-0.1367 (0.4426)
Borrower L oth res	0.1113	0.3724

	(0.5170)	-17295
Borrower L equ	0.0834	0.2791
	(0.1969)	(0.6588)
Borrower A tot asset	-0.0026	-0.0087
	(0.0048)	(0.0161)
Borrower IT	0.0145	0.0485
	(0.0269)	(0.0901)
Borrower FR	0.0456	0.1525
	(0.0462)	(0.1546)
Borrower ES	0.0079	0.0263
	(0.0348)	(0.1166)
Borrower NL	0.0638	0.2134
	(0.0396)	(0.1325)
Borrower GR	0.0129	0.0433
	(0.0509)	(0.1704)
Borrower IE	0.1403 **	0.4692 **
	(0.0681)	(0.2278)
Borrower UK	0.1378 **	0.4608 **
	(0.0627)	(0.2099)
Borrower US/JAP/EX	-0.0211	-0.0707
	(0.0511)	(0.1711)
Borrower AT	0.0089	0.0297
	(0.0369)	(0.1234)
Borrower PT	0.0027	0.0092
	(0.0422)	(0.1410)
Borrower LU	-0.0288	-0.0963
	(0.0801)	(0.2679)
Borrower CY	0.0188	0.0629
	(0.0562)	(0.1879)
Borrower CH	0.0336	0.1125
	(0.0818)	(0.2736)
Borrower FI	0.0589	0.1970
	(0.0643)	(0.2150)
Borrower EUEX	0.0111	0.0373
	(0.0258)	(0.0864)
Borrower BE	0.0513	0.1716
	(0.0536)	(0.1792)
Constant	1.0772 ***	3.6034 ***
	(0.2541)	(0.8499)
F-test first step	34.6168	34.6168
$R^2$	0.2141	0.2141
Contextual effects $A[X_L, X_B]$	Yes	Yes
Time interval	2011-09-14 - 2011-10-11	2011-09-14 - 2011-10-11
Maturities	1 to 3 days	1 to 3 days

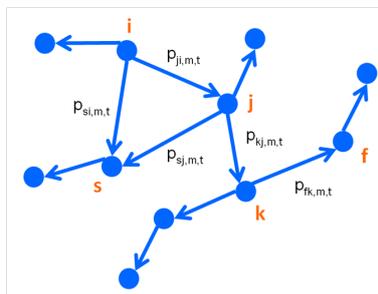
Notes: \* :  $p < 0.10$ ; \*\* :  $p < 0.05$ ; \*\*\* :  $p < 0.01$ . Only country fixed effects with more than 1% of observations are included in the model.

# APPENDICES

## Appendix A: A Decentralized Market Network

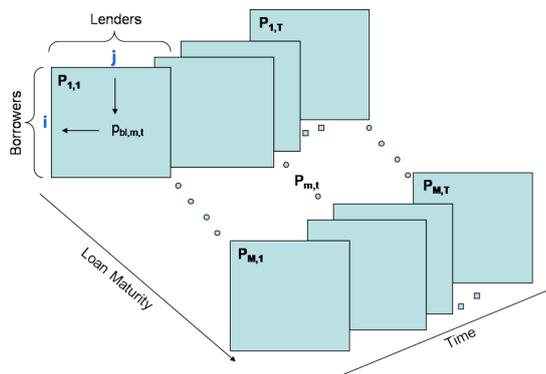
In this section we give a more technical explanation of how the prices' network is constructed and more generally how a network of links can be conceived. The database has a classical array structure,  $P_{BL,M,T} \equiv$  Set of prices associated with loans with banks  $L$  as lenders and banks  $B$  as borrowers with maturities  $M$  agreed at times  $T$ , the basic unit is  $p_{bl,m,t} \equiv$  the price of a loan of bank  $l$  to bank  $b$  of maturity  $m$  agreed at time  $t$ . If we take a slice of this array, say  $P_{BL,m,t} = P_{mt}$ , i.e all loans of maturity  $m$  at time  $t$ , we basically have a network of prices (Figure 25).

Figure 25: Price network among banks.  $P_{mt}$



$P_{mt}$  is a square matrix containing information about all prices of maturity  $m$  agreed at time  $t$ . The information structure can be seen as an array of networks, each of them is represented by a weighted adjacency matrix; see Figure 26. In classical network analysis the adjacency matrix contains the information about node connections so that each entry  $p_{bl,m,t}$  represents an arc pointed from  $l$  to  $b$ .

Figure 26: Information structure: networks array

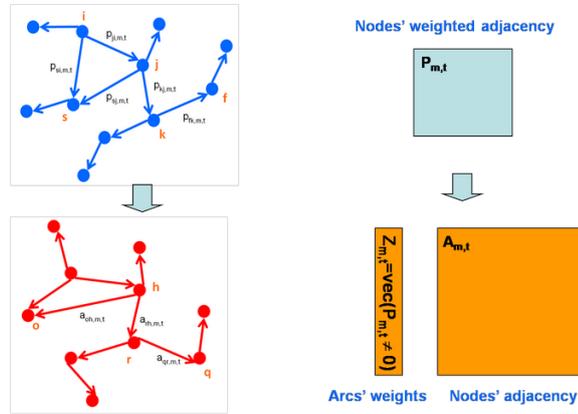


Spatial econometrics and network theory literature is mainly based on spillover among nodes, traced by the adjacency matrix. Our interest is in spillover among arcs (prices), so we need to switch from a node perspective to an arc one. The final goal is to obtain a matrix

that represents the adjacency of arcs (rather than nodes). This task can be accomplished, but it requires an arbitrary choice if the network is directed. Since we deal with loans, the direction of connections among banks matters and so we are obliged to set an *arcs adjacency* criterion. In Section 8.2 we discuss the possibility of setting different criteria and show the different results obtained.

Let  $F \equiv$  Set of possible couple of banks,  $A_{m,t} \equiv$  Adjacency matrix of  $F$  elements at  $t$  for maturity  $m$ , with a generic element  $a_{oh,m,t}$ . Let  $h = p_{ji,m,t}$  and  $o = p_{gs,m,t}$ , so that  $a_{oh,m,t} = 1$  iff  $j = s$  (i.e. the borrower of  $h$  is the lender of  $o$ ). The arbitrariness of this choice is discussed in Section 8.2. In terms of matrices we are basically representing the information contained in  $P_{m,t}$  with  $A_{m,t}$ , an arc adjacency matrix and  $Z_{m,t} = \text{vec}(P_{m,t} \neq 0)$ , a vector of prices, see Figure (27). With these two elements we are basically back to a classical network framework with a unit specific outcome  $Z_{m,t}$  and the unit adjacency information  $A_{m,t}$ .

Figure 27: From nodes to arc adjacency



## Appendix B.1: Standard Spatial Econometrics with Node-based Outcomes

Suppose we take the weighted average price (as a borrower) as the outcome of a node and the row-normalized matrix of exchanged volumes as network which spillover passes through.<sup>82</sup> This approach may prove problematic because of an in-built correlation induced between the outcome and its spatial lag, it may misspecify the estimated price transmission. Preventing this requires us to take prices (arcs) as the unit of analysis and consider their adjacency matrix.

Spatial Autoregressive models (SAR) usually have the following form:

$$y_i = \rho \sum_{j \neq i} g_{ij} y_j + \beta x_i + \epsilon_i \quad (14)$$

in matrix form

<sup>82</sup>This type of modelling is similar to that of Martinez and Leon (2014). They study the role of connectedness in the Mexican secured money market.

$$y = \rho Gy + \beta x + \epsilon \quad (15)$$

where  $y_i$  is a dependent random variable,  $G$  is a weighted adjacency matrix whose entry  $g_{ij}$  is equal different from zero if  $j$  influences  $i$  and 0 otherwise ( $g_{ii}$  is assumed to be zero),  $x_i$  is an independent variable and  $\epsilon_i$  is a residual. Where the estimate of  $\rho$  measures the spatial dependence in  $y$ . A spillover is in place if the  $i_{th}$  element of  $y$  ( $y_i$ ) is influenced by the  $i_{th}$  element of  $Gy$  ( $\sum_j g_{ij}y_j$ ), so  $G$  is informative in explaining similar  $y$  for adjacent observation. Note that here only  $G$  drives this possibility.

Suppose now we want to estimate the price transmission in a network in which  $i$  and  $j$  are connected by a contract they agreed. We observe  $p_{ij}$  and  $v_{ij}$ , as respectively the price and the volume of a loan of  $j$  to  $i$ . Let  $P$  and  $V$  be the relative matrices. Since in standard spatial econometrics models there is a node-specific outcome ( $p$ ) and a network  $G$  we can measure a node-specific outcome such as the average paid price as a borrower  $p_i = \frac{1}{\sum_{j \neq i} v_{ij}} \sum_{j \neq i} v_{ij} p_{ij}$  and set  $g_{ij} = \frac{v_{ij}}{\sum_{j \neq i} v_{ij}}$  as a generic element of  $G$ , having the following model:

$$p_i = \rho \sum g_{ij} p_j + \beta x_i + \epsilon_i \quad (16)$$

in matrix form

$$p = \rho Gp + \beta x + \epsilon \quad (17)$$

where

$$p = \text{diag}(GP')\iota \quad (18)$$

and  $\iota$  is a  $n \times 1$  vector of ones, so that

$$Gp = G \text{diag}(GP')\iota = \text{diag}(GP')G\iota \quad (19)$$

Note that if both the following conditions hold, these two vectors are correlated by construction

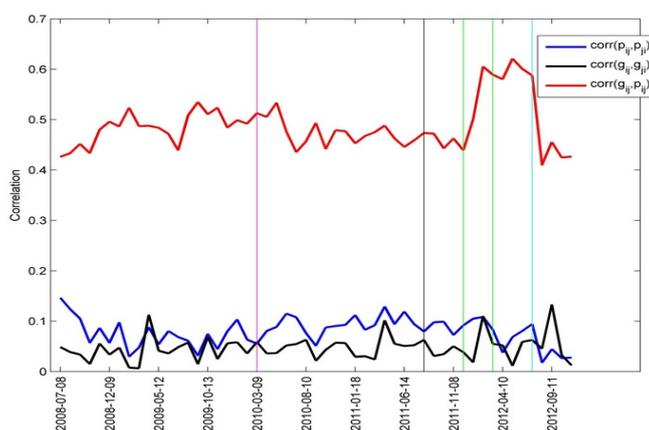
1.  $g_{ij} \not\propto p_{ij}$
2.  $g_{ij} \not\propto g_{ji}$  and  $p_{ij} \not\propto p_{ji}$ ,

and we automatically obtain an estimate of  $\rho$  significantly different from zero. The reason is that the generic  $i_{th}$  element of  $p$  is  $p_i = \sum_j g_{ij} p_{ij}$  while the generic  $i_{th}$  element of  $Gp$  is  $G_i p = \sum_j g_{ij} (\sum_k g_{jk} p_{jk})$ .  $p_i$  is a linear function of  $g_{ij}$ , thus this aspect completely changes the framework of model (14) in which the dependent variable is not a linear function of  $g_{ij}$ . If conditions (1) and (2) do hold we have that  $\text{cov}(g_{ij} p_{ij}, g_{ij} g_{ji} p_{ji}) \neq 0, \forall i, j$  and consequently  $\rho$  simply measures the in-built correlation of these two random variables constructed by similar combinations of the same set of initial random variables. Note that condition (1) basically states that if  $i$  and  $j$  agree on a contract, its price and relative quantity (with respect to total amount borrowed by  $i$ ) are correlated, which is a quite reasonable assumption. Condition (2) means that if there is a degree of reciprocity in prices and relative quantities then it will affect

the correlation between the dependent variable and its spatial lag a priori, without any real transmission at work. Condition (2) is more interesting from a network topology perspective, as it basically says that the correlation is autogenerated when reciprocity in contracts is observed and then a significant spatial correlation can be confounded with reciprocity. In addition symmetry is very common in money markets as it is very unlikely that  $P(g_{ij}|g_{ji}) = P(g_{ij})$ . In the sample considered here conditions (1) and (2) are plausible, as shown in Figure 28, where maturities from overnight to three days are considered, all of the observed correlations are high during the time span considered. It seems to be a constant feature of the unsecured money market. As mentioned before, the strongest relationship is between price and relative volume of contracts, on average roughly 0.5. Reciprocity in prices and relative volumes seems to be important as well. This feature of UMM might be evidence of *trust circles*. Higher maturities show a similar pattern and are not reported for brevity. The correlation between prices and quantities remains stable across maturities.

Figure 28: Prices and volumes correlations. Reciprocity and cross-correlation

Maturities from overnight to three days.



Violet vertical line traces the first sovereign debt crisis, the black vertical line traces the second sovereign debt crisis, the green lines trace LTROs and the light blue line traces the signal rate change in July 2012.

In addition to the in-built correlation among nodes outcome, in model (16) we have at least two additional problems. First, we include only borrower characteristics, implicitly assuming that lender characteristics do not matter in price bargaining, which is a rather strong assumption. Econometrically, it turns into an omitted variable problem. If we assume  $p_{ij} = f(x_i, x_j)$ , where  $f(\cdot)$  is a linear function of lender and borrower characteristics, omitting  $x_j$  in the model should lead to a biased estimation of  $\rho$  because of the correlation between  $p_i$  and  $x_j$ .

A second issue is that model (16) can have weak IV using a 2SLS procedure in which the instruments are not an accurate approximation of optimal ones. If we use only  $Gx$  as instrument for  $Gp$ , its explicative power is going to be low as  $Gp$  is supposed to be a function of both lender and borrower characteristics, while  $Gx$  contains only borrower ones. One way of partially circumventing these issues may be to add the *contextual effects* in the model:

$$p_i = \rho \sum g_{ij} p_j + \beta x_i + \gamma \sum g_{ij} x_j + \epsilon_i \quad (20)$$

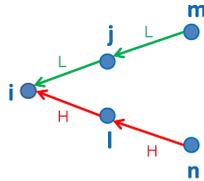
in matrix form

$$p = \rho Gp + \beta x + \gamma Gx + \epsilon \quad (21)$$

In this way the omitted variable problem is eliminated as well as the weak IV one.<sup>83</sup> The in-built correlation still holds.

Using a 2SLS is one way to mitigate this problem, but it is still an unsatisfying solution for another significant problem. Considering node-average flows in a network is not an efficient way to exploit the information. The intuition is that averaging (at the node level) can hide a real transmission at work. Let us provide a very simple example, considering the simplified network in Figure 29, where prices can be high (H) or low (L) with a symmetric deviance to 0. It is evident in such a network that price transmission is at work, if we take a node-average perspective, we have that  $p_i = 0$  and  $G_i p = 0$ , so we average out the transmission process at work at the *arc level* which can be signaled by  $p_{ij} = p_{jm} = L$  and  $p_{il} = p_{ln} = H$  taking a *node level* perspective. More formally, the issue lies in the difference between  $\text{corr}(p_{ij}, p_{jk})$  and  $\text{corr}(\sum_j g_{ij} p_{ij}, \sum_k g_{jk} p_{jk})$ .

Figure 29: Exploiting network information



Red arcs are high prices (H), while blue arcs are low prices (L)

Given all of these considerations, we take an arc perspective in measuring the price transmission.

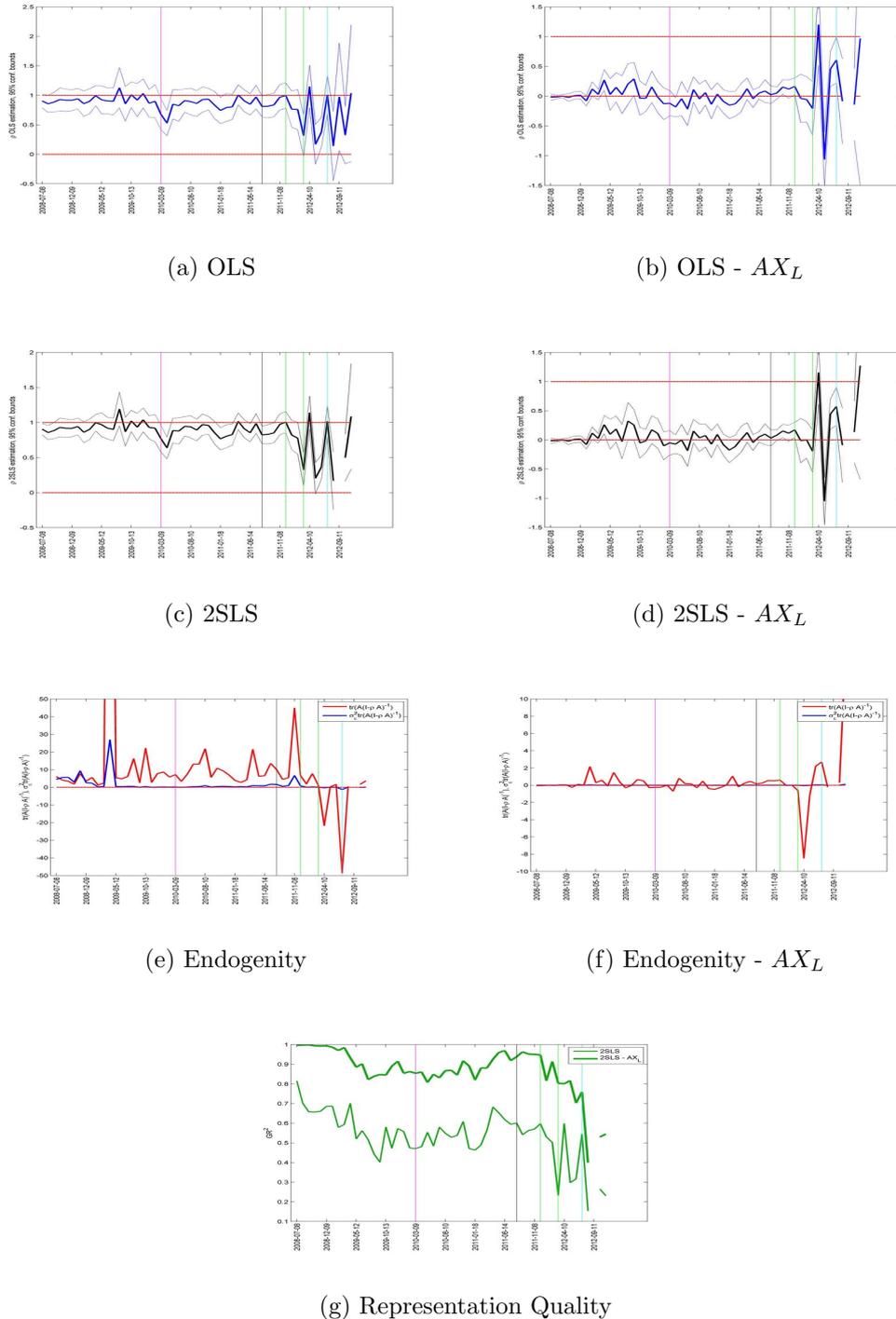
## Appendix B.2: Relative Empirical Results

We also estimated model (16) and (20) with our data in order to have, firstly, a comparison between the baseline model and a standard spatial econometrics approach with network-based outcomes and, second, an empirical check of the previous discussion. Time series of estimated parameters are reported in the same fashion as the baseline results (as in Figure 16 of Section 7). In Figure 30 the OLS and 2SLS estimates of  $\rho$  are reported for both models (16) and (20),  $\hat{\rho}$  derived from model (16) is always around one for both OLS and 2SLS (note that the parameter space is  $|\rho| \leq 1$  and consequently a large portion of point estimates are out

<sup>83</sup>Including  $Gx$  implies  $Gy$  to be projected on  $Gx$  and  $G^2x$  (with a low approximation of optimal instruments). Both lender and borrower characteristics are included so that IV should not be weak a priori.

of the acceptable range). This is a direct consequence of (i) in-built correlation, (ii) omitted variables and (iii) weak IVs. Including  $GX$  improves the reliability of estimates, OLS is almost always significantly different from zero varying around 0.4, while 2SLS is almost always not significantly different from zero varying floating around 0.1. As stated before, estimating model (20) can circumvent (ii) and (iii), but the in-built correlation (i) still prevents an informative estimation of price transmission and it flattens the time series, preventing the signaling power of a time-variation in  $\hat{p}$ . Note also that the *generalized*  $R^2$  is often close to 0.9 for model (20); again the in-built correlation gives an almost perfect explanation for  $p_i$  by construction.

Figure 30: Node outcome: 2SLS and OLS estimation of  $\rho_{m,t}$ ,  $m = \text{overnight to three day maturities}$



The dashed lines represent 95 percent confidence intervals. Violet vertical line traces the first sovereign debt crisis, the black vertical line traces the second sovereign debt crisis, the green lines trace LTROs and the light blue line traces the signal rate change in July 2012. Third row panels represent the estimated  $tr(A(I - \phi A)^{-1})$  and  $\sigma_\epsilon^2 tr(A(I - \phi A)^{-1})$  which measure the endogeneity issue in the observed network. Generalized  $R^2$  is used to evaluate representation quality.

## Appendix C: Including Network Measures

In this section we include network measures of lender and borrower in order to understand whether also controlling for the position in the money network changes the baseline results. Another interesting aspect to test is whether the position of lender (borrower) influences loan prices.<sup>84</sup> We take six network measures and include them in model (7) for both lender and borrower. All the listed measures are referred to a direct graph, represented by an adjacency matrix  $G$ .

### Degree Centrality

$$D_i^\pm = \frac{d_i^\pm}{(n-1)} \quad (22)$$

where  $d_i^\pm$  is the number of directed (+ if outdegree, - if indegree) links of node  $i$  and  $n$  is the number of nodes in the graph.

### Betweenness

$$B_i = \frac{1}{(n-1)(n-2)} \sum_{j=1}^n \sum_{k=1}^n \frac{\delta_{jk}^i}{\delta_{jk}} \quad (23)$$

where  $\delta_{jk}$  is the number of shortest paths between node  $j$  and node  $k$  and  $\delta_{jk}^i$  is the number of shortest paths between node  $j$  and node  $k$  through  $i$ .

### Clustering Coefficient

$$Cl_i^+ = \frac{\sum_{l \in N_i^+(g)} \sum_{k \in N_i^+(g)} g_{lk}}{n_i^+(g)[n_i^+(g) - 1]} \quad (24)$$

For all  $i$  such that  $i \in N'^+ \equiv \{i \in N | n_i^+(g) \geq 2\}$ , where  $N_i^+(g)$  is the outdegree-linked set of nodes for  $i$  and  $n_i^+(g)$  is the relative cardinality. For the other nodes the value is imposed equal to zero. Where  $g_{lk}$  is the  $(l, k)$  element of the adjacency matrix  $G$ .

$$Cl_i^- = \frac{\sum_{l \in N_i^-(g)} \sum_{k \in N_i^-(g)} g_{lk}}{n_i^-(g)[n_i^-(g) - 1]} \quad (25)$$

for all  $i$  such that  $i \in N'^- \equiv \{i \in N | n_i^-(g) \geq 2\}$ , where  $N_i^-(g)$  is the indegree-linked set of nodes for  $i$  and  $n_i^-(g)$  is the relative cardinality. For the other nodes the value is imposed equal to zero.

### Eigenvector Centrality

$$Ei^- = \frac{1}{\lambda_1} \sum_{j=1}^n g_{ij} E_j^- \quad (26)$$

where  $\lambda_1$  is the highest eigenvalue of  $G$ , the relative adjacency matrix.  $E^-$  is practically the right leading eigenvector of  $G$ . This centrality measure is different from the others above

---

<sup>84</sup>Note that the possible endogeneity of these measures is not accounted for.

because, in measuring a node's centrality, it gives a specific importance to each link (connected node) considering its relevance in terms of centrality.

$$Ei^+ = \frac{1}{\lambda_1} \sum_{j=1}^n g_{ji} E_j^+ \quad (27)$$

$Bo^+$  is practically the left leading eigenvector of  $G$ .

### Closeness Centrality

$$C_i^- = \frac{n-1}{\sum_{j \neq i} d(i, j)} \quad (28)$$

$$C_i^+ = \frac{n-1}{\sum_{j \neq i} d(j, i)} \quad (29)$$

where  $d(i, j)$  is the minimum path from node  $i$  to node  $j$ , if it does not exist, it is set at  $\infty$ .

**Closeness Centrality 2 (more informative)** The main closeness centrality problem is that it is zero whenever there is no link between  $i$  and one node in  $N$ , say  $j$ , because  $d(i, j)$  goes to infinity. This measure is devised in order to cope with the problem. We use this measure in the econometric analysis.

$$C2_i^- = \frac{1}{n-1} \sum_{j \neq i} \frac{1}{d(i, j)} \quad (30)$$

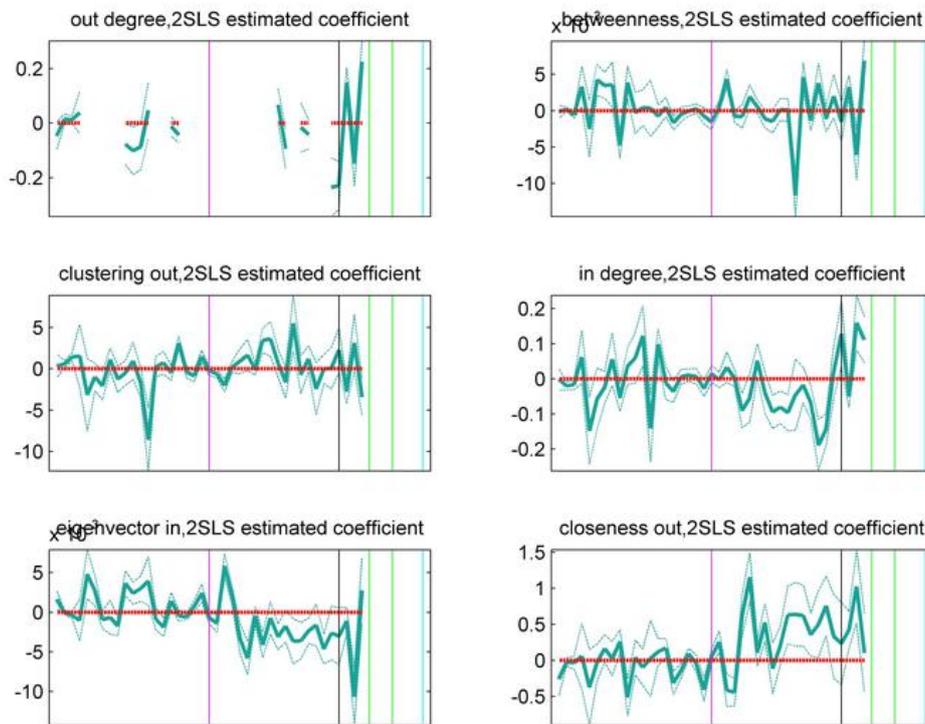
$$C2_i^+ = \frac{1}{n-1} \sum_{j \neq i} \frac{1}{d(j, i)} \quad (31)$$

The selected measures also have a behavioral interpretation: out-degree centrality, as a liquidity provider proxy; betweenness, as a money dealer proxy; out-degree clustering, as community liquidity leader; in-degree centrality as a best price seeker; eigenvector centrality, as information collector; out-degree closeness, as a market influencer. Time series of estimated coefficients are plotted in Figure 31 for lenders, and three measures appear important in the time interval between the first and second sovereign crisis, the higher the in-degree, the lower is the earning, while the higher the out-degree closeness, the higher is the earning for the lender. The eigenvector centrality has a positive impact on earnings before the first sovereign crisis, while it switches sign after the first sovereign crisis. For borrowers (Figure 32) only the betweenness is significant before the second sovereign crisis, signalling a smaller cost of money for 'dealer' banks. The estimated price transmission parameter is basically unchanged by the inclusion of network measures and is not reported for the sake of brevity.

## Appendix D: Simulation Experiment

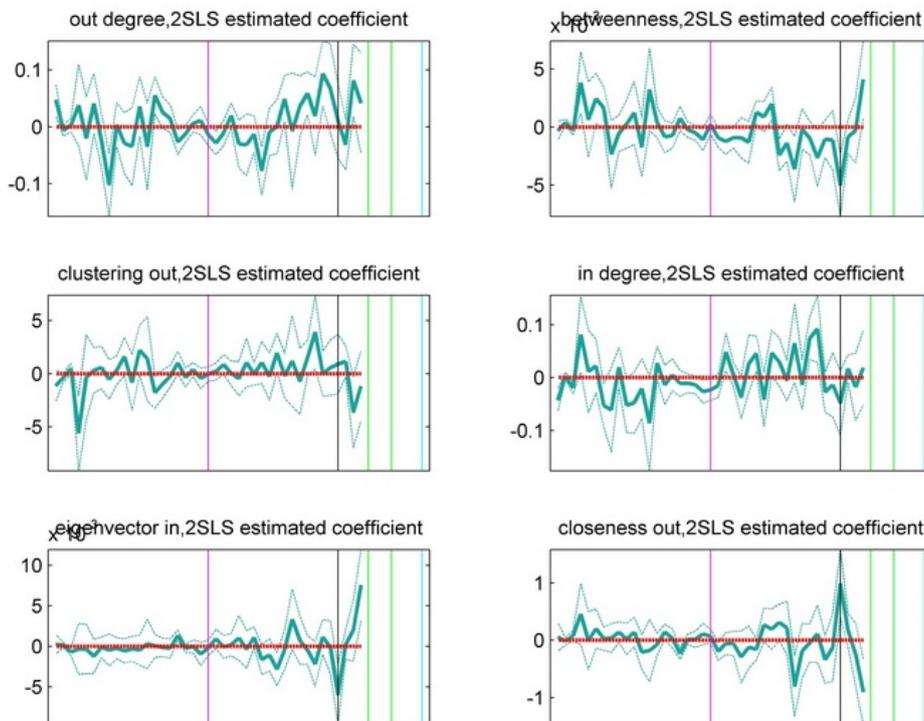
Figure 33 depicts the single draws, one hundred for each substitution rate. Figure 34 represents the t-statistics computed for each replication, while Figure 35 plots the average rejection rate of the null hypothesis (that there are no spillover effects) for each substitution rate.

Figure 31: 2SLS estimation time series of lender network measures for maturities from one to three days



The dashed lines represent 95 percent confidence intervals. The horizontal axis is time ( $t$ ), the violet vertical line traces the first sovereign debt crisis, the black vertical line traces the second sovereign debt crisis, the green lines trace LTROs and the light blue line traces the signal rate change in July 2012. Missing dots refer to missing characteristic in the respective time period.

Figure 32: 2SLS estimation time series of borrower network measures for maturities from one to three days.



The dashed lines represent 95 percent confidence intervals. The horizontal axis is time ( $t$ ), the violet vertical line traces the first sovereign debt crisis, the black vertical line traces the second sovereign debt crisis, the green lines trace LTROs and the light blue line traces the signal rate change in July 2012. Missing dots refer to missing characteristic in the respective time period.

Figure 33: Robustness check: single parameter draws

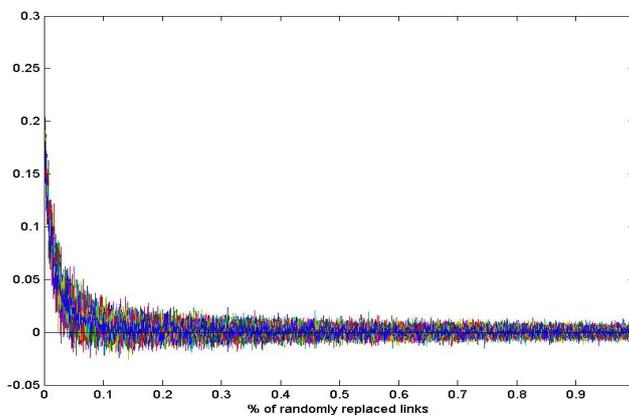


Figure 34: Robustness check: t-statistics

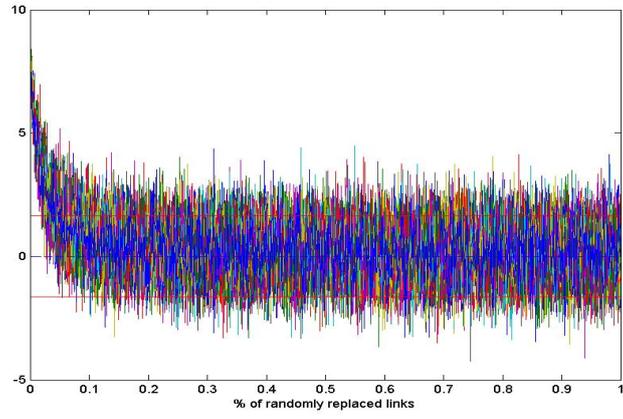
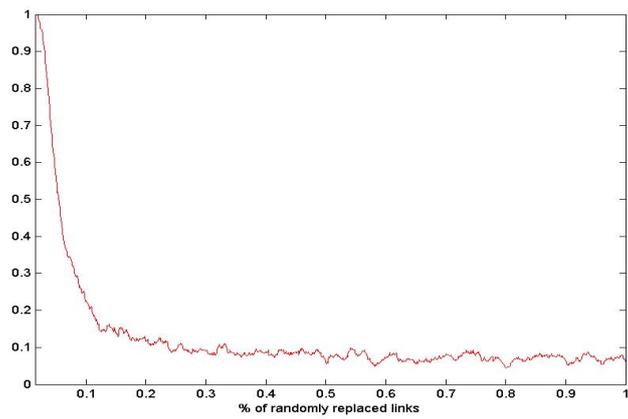


Figure 35: Robustness check: rejection rates



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