



Epidemics of liquidity shortages in interbank markets

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HIGHLIGHTS

- We model liquidity-driven financial contagion by a SIR-like model.
- The interbank network structure appears crucial for epidemics of liquidity disease.
- The number of lenders explains bank riskiness more than the volume of loans.

ARTICLE INFO

Article history:

Received 24 July 2017

Received in revised form 5 March 2018

Available online 16 May 2018

Keywords:

Financial contagion

Liquidity shocks

Interbank lending market

Epidemic models

ABSTRACT

Financial contagion from liquidity shocks has been recently ascribed as a prominent driver of systemic risk in interbank lending markets. Building on standard compartment models used in epidemics, in this work we develop an EDB (Exposed–Distressed–Bankrupted) model for the dynamics of liquidity shocks reverberation between banks, and validate it on electronic market for interbank deposits data. We show that the interbank network was highly susceptible to liquidity contagion at the beginning of the 2007/2008 global financial crisis, and that the subsequent micro-prudential and liquidity hoarding policies adopted by banks increased the network resilience to systemic risk—yet with the undesired side effect of drying out liquidity from the market. We finally show that the individual riskiness of a bank is better captured by its network centrality than by its participation to the market, along with the currently debated concept of “too interconnected to fail”.

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1. Introduction

The 2007/2008 global financial crisis has raised important concerns on the stability of the financial system, in particular regarding its complex and interconnected nature [1–5]. Indeed, because of bilateral or indirect exposures between financial institutions, credit losses and funding shortcomings can spread through the system, with potential catastrophic consequences for the whole market [6–12]. Within this context, much attention has been devoted to assess systemic risk in the interbank lending market, namely the network of financial interlinkages resulting from overnight loans between banks [13–15]. Indeed, while interbank lending is crucial for banks to face fluctuating liquidity needs [16] and properly fuel the economy [17], the interbank market turns out to be rather fragile, as intra-system cash fluctuations alone have the potential to lead to systemic defaults [18], and exceptional liquidity shocks can lead to a complete market drought [2]. The latter scenario in particular characterized the period after the global financial crisis: banks held more liquid assets in anticipation of future expected losses and liquidity needs [19–21], and such a precautionary hoarding behavior caused

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a drastic increase of unsecured interbank borrowing rates for all but the shortest maturities [22]. The interbank market contraction was exacerbated even more by the massive liquidity injections from central banks, which instead of restoring interbank activity had the effect of replacing the market with the central banks balance sheets [23,24]

The stream of literature on systemic risk analysis for interbank markets has focused on two main aspects: the network-based characterization of the topological structure of the market [15,25–30], and the design of dynamics and metrics for the spread of financial distress over the network [1,31–39] including liquidity shocks [40–44]. In this work we add to this research field by proposing a modeling of liquidity-driven financial contagion in interbank networks through a compartment model similar to those commonly used in epidemiology [45,46]. In particular, by assuming that liquidity shocks propagate as an epidemic disease over the market, we adapt the well-known SIR (*Susceptible–Infected–Removed*) model [47–49] to the specific context of liquidity shocks interbank networks, and cast it as an EDB (*Exposed–Distressed–Bankrupted*) model. This is close to the work by Toivanen in the context of credit shocks [50]. We simulate such a dynamical model on the Italian interbank network e-MID (electronic market for interbank deposits) [15,27,29,30], analyzing liquidity contagion in relation with the structure and evolution of the network, and defining systemic risk through the resilience of individual banks and of the overall system to liquidity shocks.

In a nutshell, we show that the network topology of e-MID plays a fundamental and non-negligible role in the epidemics of liquidity distress, and that the total number of bank failures can assume very high values also when the initial shock is minimal. Importantly, systemic risk increases substantially just before the global financial crisis, and possibly goes back to pre-crisis values only long afterwards. The probability to go bankrupt turns out to be higher for banks accounting for larger shares of the interbank network; however, the number of lenders of a bank can statistically explain riskiness more than the total amount of money borrowed, in line with the recent paradigm shift from “too big to fail” to “too interconnected to fail” [51]. We complement this analysis with a network-based study of e-MID, providing additional evidence that the market underwent significant changes due to the financial turmoil—with less banks participating to the market and executing fewer and lesser loan transactions. Liquidity hoarding had a considerable impact also on the underlying network structure: hub banks basically disappeared, the number of reciprocal and three-party contracts dropped, and – in spite of the reduced systemic risk – at the end the network lost its efficiency in terms money flow within banks.

The rest of the paper is structured as follows. Section 2 recalls basic features and network characterization of the e-MID dataset, and Section 3 presents a network analysis of the data. The EDB contagion model is defined in Section 4, and model simulation results are reported in Section 5. Finally, Section 6 presents an econometric study of simulation outcomes, and Section 7 concludes.

2. e-MID data

The electronic Market for Interbank Deposits (e-MID) is a trading platform of unsecured money-market loans,¹ that is unique in the Euro area for being screen-based and fully electronic. e-MID covers the entire domestic overnight deposit market in Italy, but is open to both Italian and foreign banks, and a significant share of all liquidity deposit in the Euro area is traded through the e-MID platform [53]. The dataset we have at our disposal consists of all the interbank transactions finalized on e-MID from January 1999 to September 2012. For each contract we have information about the amount exchanged, the date and time, the interest rate, the IDs of the lender and of the borrower banks, and the contract maturity.²

Because of the data structure, e-MID (and interbank markets in general) is properly represented as a directed weighted network, where interbank loans constitute the direct exposures between banks and allow for the propagation of financial distress in the system. Here we focus on quarterly networks obtained by aggregating transactions over three months, as this time scale is enough to allow the emergence of complex interaction patterns [29]. To describe the network we employ the following notation. At quarter t , we have a system consisting of a set of N_t banks (the *nodes* of the network) and of L_t transactions among them—corresponding to the *links* connecting pairs of nodes. Transaction volumes are described by the $N_t \times N_t$ *weighted adjacency matrix* $\mathbf{W}(t)$, whose generic element $w_{ij}(t) \geq 0$ ($i, j = 1, \dots, N_t$) amounts to the overall loan that i granted to j (obtained by summing the single ON contracts resulting in a money flow from i to j). Analogously, the whole pattern of connections is described by the $N_t \times N_t$ *binary adjacency matrix* $\mathbf{A}(t)$, whose generic element $a_{ij}(t)$ equals 1 if a connection from node i to node j exists (*i.e.*, if bank j borrowed money from i during t so that $w_{ij}(t) > 0$), and 0 otherwise.³ The network built in this way is *directed*, meaning that in general $a_{ij}(t) \neq a_{ji}(t)$ and $w_{ij}(t) \neq w_{ji}(t)$ [27]. In the following we will restrict our analysis to the *weakly connected component* of the network, defined as the largest subnetwork in which any two nodes are connected to each other by a finite sequence of links (regardless of their direction). This restriction is particularly useful in the context of simulating epidemic cascades, as it eliminates the possibility that the infection cannot spread when starting from or stopping into sink nodes or isolated communities.

¹ An anonymous and collateralized segment of e-MID (New MIC) was introduced in February 2009 with the aim of improving the liquidity distribution within the euro area [52].

² Transactions can be ON (overnight), ONL (overnight long), TN (tomorrow next), TNL (tomorrow next long), SN (spot next), SNL (spot next long), 1W (one week), 1WL (one week long), 2W (two weeks), 3W (three weeks), 1M (one month), 2M (two months), 3M (three months), 4M (four months), 5M (five months), 6M (six months), 7M (seven months), 8M (eight months), 9M (nine month), 10M (ten months), 11M (eleven months), 1Y (one year). In this paper we use only overnight transactions, which represent the vast majority of trades (approximately 90%).

³ Note that as in e-MID banks do not lend money to themselves, it is $a_{ii} = w_{ii} = 0 \forall i$ by construction.

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