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Research Paper

How the interbank market becomes systemically dangerous: an agent-based network model of financial distress propagation

Matteo Serri,[1] Guido Caldarelli[2,3,4] and Giulio Cimini[2,3]

[1]Dipartimento Memotef, Università "Sapienza" Facoltà di Economia,
Via del Castro Laurenziano 9, 00161 Rome, Italy;
email: matteo.serri@gmail.com

[2]IMT School for Advanced Studies, Piazza S. Francesco 19, 55100 Lucca LU, Italy;
emails: giulio.cimini@imtlucca.it, guido.caldarelli@imtlucca.it

[3]Istituto dei Sistemi Complessi (ISC)-CNR, Via dei Taurini 19, 00185 Rome, Italy

[4]London Institute for Mathematical Sciences (LIMS), 35A South Street,
Mayfair, London W1K 2XF, UK

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ABSTRACT

Assessing the stability of economic systems is a fundamental research focus in economics that has become increasingly interdisciplinary in the currently troubled economic climate. In particular, much attention has been devoted to the interbank lending market as an important diffusion channel for financial distress during the recent crisis. In this paper, we study the stability of the interbank market to exogenous shocks using an agent-based network framework. Our model encompasses several ingredients that have been recognized in the literature as procyclical triggers of financial distress in the banking system: credit and liquidity shocks through bilateral exposures, liquidity hoarding due to counterparty creditworthiness deterioration, target leveraging policies and fire-sale spillovers. However, we exclude the possibility of central authorities intervention. We implement this framework on a data set of 183 European banks that

Corresponding author: G. Cimini

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were publicly traded between 2004 and 2013. We document the extreme fragility of the interbank lending market up to 2008, when a systemic crisis leads to total depletion of market equity with an increasing speed of market collapse. After 2008, the system is more resilient to systemic events in terms of residual market equity. However, the speed at which a crisis breaks out reaches a new maximum in 2011, and it never returns to the values observed before 2007. Our analysis points to the key role that crisis outbreak speed plays: it sets the maximum delay for central authorities intervention to be effective.

Keywords: financial contagion; systemic risk; financial networks; interbank lending market; agent-based models.

1 INTRODUCTION

The financial instability that characterized the last decade has made one thing clear to academics and regulators: the economy and the financial system are now so inherently complex that a multidisciplinary effort will be needed to disentangle the intertwined set of connections between the actors and institutions within them (Acemoglu *et al* 2015; Beale *et al* 2011; Gai *et al* 2011; Haubrich and Lo 2013; Musmeci *et al* 2015; Sorkin 2009). Indeed, the network structure of the financial system is now acknowledged as a potential trigger of instability (Bardoscia *et al* 2016; Chan-Lau *et al* 2009), hence the many recent studies on the origin of the crisis that investigate the interplay between network topology and contagion processes (an approach originally developed in statistical physics (see *Nature Physics* 2013)). Among the various subjects, researchers have particularly focused on the interbank lending market, namely the network of financial interlinkages between banks resulting from unsecured overnight loans. This system has been identified as one of the principal diffusion channels for financial distress during the 2007–8 crisis (Birch and Aste 2014; Bluhm and Krahnen 2011; Cont *et al* 2013; Gabrieli and Co-Pierre 2014; Georg 2013; Krause and Giansante 2012). After the collapse of Lehman Brothers, the interbank market froze, causing a severe liquidity drought throughout the financial system (Acharya and Merrouche 2013; Adrian and Shin 2008; Berrospide 2013; Brunnermeier 2009). Such a black swan was due to the collapse of different liquidity channels, eg, asset-backed commercial papers and repurchase agreements (repos), and to a burst in the spread between long-term and overnight interest rates (or the London Interbank Offered Rate–overnight indexed swap (Libor–OIS) spread; Brunnermeier (2009)). As this problem became systemic, central banking authorities intervened with extraordinary monetary policies to restore the solvency of the financial system.

Liquidity issues threaten the stability of the financial system by generating important spillover effects. Different subcategories of problems have been identified in the literature: funding liquidity, market liquidity, flight to liquidity quality, liquidity spirals, liquidity hoarding, market freeze and assets fire sales. Authors such as Acharya and Skeie (2011) and Brunnermeier and Pedersen (2009) have modeled liquidity dynamics using a theoretical approach. Others, such as Berrospide (2013) and Acharya and Merrouche (2013), have used empirical econometric analyses to study the causes of interest rate spreads. Eisenberg and Noe (2001) were the first to tame the complexity of the problem, using a theoretical approach that explicitly considered the set of interconnections within the financial system. Their work originated a flourishing line of research aimed at assessing the systemic importance of financial institutions under a network perspective (see, for example, Barucca *et al* 2016; Bluhm and Krahnen 2011; Gabrieli and Co-Pierre 2014; Greenwood *et al* 2015; Hausenblas *et al* 2015).

A second approach to dealing with the complexity of the financial system has been using agent-based models (ABMs). An ABM is a simulated framework in which several agents interact following optimal selfish strategies, creating spin-off effects such as the emergence of an endogenous trading market (Caporale *et al* 2009; Lucas *et al* 2014). The use of ABMs in economics and finance started in parallel with the development of calculators and computer science. The Santa Fe Institute Artificial Stock Market model was one of the first ABMs developed in the early 1990s, and it was later complemented with market orders (Lux and Marchesi 1999). Recent advances in ABM for financial stability studies include the work of Fischer and Riedler (2014), who showed the fundamental role of leverage in assessing systemic risk, and of Georg (2013) and Hałaj and Kok (2014), who modeled an emerging interbank market via a stylized trading mechanism. All these studies agree on the relevance of the topology of interactions for contagion mechanisms. Other studies, such as Cont *et al* (2013), Bookstaber *et al* (2014) and Klinger and Teplý (2014), consider an exogenous interbank network (data-driven or simulated) affected by shocks that induce an idiosyncratic response, such as the emergence of bank runs and fire sales. The aim is to evaluate systemic risk as well as find effective regulatory capital buffers and requirements to prevent cascade failures.

In this paper, we bring together these two approaches by introducing an ABM that describes the network dynamics of the interbank market. We build on the framework introduced by Chan-Lau *et al* (2009) and Krause and Giansante (2012), and later developed by Cimini and Serri (2016). We consider a data-driven network of bilateral exposures between banks (the agents of our model); these use micro-optimal rules to interact with each other and the rest of the financial system. We explicitly model various categories of spillover effects arising during financial crises, such as fire sales and interest rate jumps due to leverage targeting and the liquidity-hoarding behavior of banks. The modeled dynamics of procyclical policies then spread financial losses via credit and liquidity interconnections, and they may result in cascades of defaults.

In our approach, we just assume the existence of events in order to focus on the description of the dynamical evolution of the financial system. Our ABM can thus be used to stress test the robustness of the financial system to an external shock, which can either be absorbed or cause an avalanche of failures that eventually lead to the market freezing.

Note that the use of an ABM allows us to have a complete description of the system dynamics during a crisis (ie, out of the economic equilibrium), which would be very difficult to obtain by analytical modeling. The ABM presented here also allows us to consider a flow of events that is different from what actually happened during, for example, the 2007–8 financial crisis. In particular, we are interested in the scenario characterized by the absence of a lender of last resort, such as a central bank, whose monetary policies can completely redesign the market. Indeed, our aim is not to reproduce the real dynamics of the crisis, but to define the worst possible scenario without any quantitative easing or bailout programs from regulatory institutions. The rest of the paper is organized as follows. Section 2 reports our basic assumptions, while Section 3 offers a detailed description of the ABM framework. The results of our extensive simulation program are discussed in Section 4, and Section 5 concludes.

2 MODEL ASSUMPTIONS

The main ingredients of our model are the set of connections and the strategies of the agents. In order to define them, we make the choices listed below.

2.1 Network definition

- The interbank network is assumed to consist of loans with overnight (ON) duration. Thus, A_{ij} is the overall amount that bank i lends to bank j (ie, the interbank asset of i toward j), which corresponds to the liquidity $L_{ji} \equiv A_{ij}$ that j borrowed from i (ie, the interbank liability of j toward i). As contracts are of short duration (ON), we assume that links are continuously placed and immediately resolved and rolled over, so that the same (current) interest rate $r > 1$ applies to both assets and liabilities. In other words, the market dynamics we consider here is on a time scale that is longer than that of contracts duration.

- The network is derived from aggregate interbank exposures and obligations:

$$A_i = \sum_j A_{ij} \quad \text{and} \quad L_i = \sum_j L_{ij} \equiv \sum_j A_{ji}.$$

  We use the Bureau van Dijk Bankscope database, which contains the yearly aggregated balance-sheet information of $N = 183$ large European banks from

2004 to 2013.[1] We then employ the procedure described in Cimini *et al* (2015), which uses the fitness model of Caldarelli *et al* (2002) to build an ensemble of interbank networks from such aggregate data.

- For each bank i, the balance-sheet equation reads

$$E_i := A_i^{\mathrm{E}} - L_i^{\mathrm{E}} + r \sum_j A_{ij} - r \sum_j L_{ij}, \tag{2.1}$$

where A_i^{E} and L_i^{E} are, respectively, the external assets and liabilities of i. $A_i = A_i^{\mathrm{E}} + r \sum_j A_{ij}$ and $L_i = L_i^{\mathrm{E}} + r \sum_j L_{ij}$ are, respectively, the total amount of assets and liabilities (external plus interbank) held by i. For each bank i to be solvent, it must be $E_i > 0$.

2.2 Strategies definition

In order to build agent strategies and model dynamics, we take inspiration from the most important facts characterizing the crises.

- If hit by a shock, a bank sells assets following a leverage-targeting policy in order to reinforce its reputation and the expectations of stakeholders.
- After the shock and during the realignment, worries about creditworthiness may cause a "flight to quality", for which banks withdraw liquidity from the market.
- Liquidity hoarding coupled with a constant liquidity demand triggers an increase of interbank interest rates and the consequent revaluation of interbank assets and liabilities.
- If a bank defaults, credit and funding shocks propagate through its bilateral exposures like a bank-run contagion on financial interbank contracts.
- Interbank network connections and fire-sale spillovers may lead to default cascades, with a consequent increase of liquidity hoarding and interest rates.
- In extreme conditions, the market freezes, triggering exacerbated fire sales.

3 MODEL DYNAMICS

Building on the above definitions and assumptions, we now specify the model dynamics of the interbank market (see Figure 1 for the flow chart of the model).

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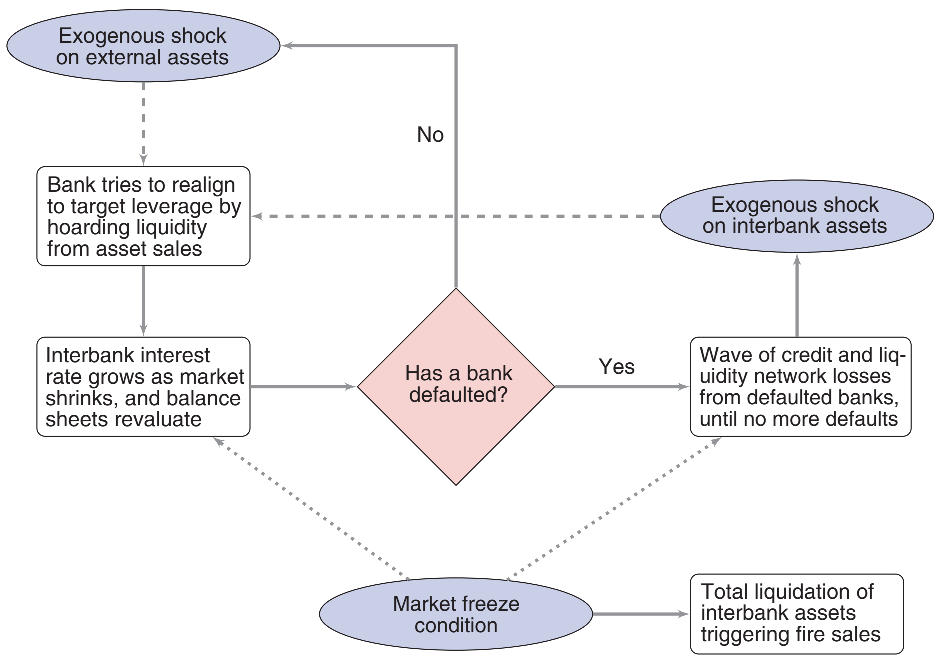
[1] Raw Bankscope data is available from Bureau van Dijk (http://bankscope.bvdinfo.com). We refer the reader to Battiston *et al* (2015) for all the details about the handling of missing data.

FIGURE 1 Flow chart of the ABM.



The dashed lines represent process inputs, while the dotted lines represent check functions.

3.1 Exogenous shock

- At a given time step $t = t_0$, bank s is hit by an exogenous shock, so that its external assets A_s^{E} decrease by a quantity Φ (Chan-Lau *et al* 2009; Krause and Giansante 2012):

$$A_s^{\mathrm{E}}(t_0 + 1) = A_s^{\mathrm{E}}(t_0) - \Phi \Rightarrow E_s(t_0 + 1) = E_s(t_0) - \Phi. \tag{3.1}$$

- At first, bank s tries to realign to its target leverage $B_s(t_0) = A_s(t_0)/E_s(t_0)$ by selling assets. To this end, the amount of assets to be sold is given by (Adrian and Shin 2008; Brunnermeier 2009)

$$\begin{aligned} A_s(t_0 + 1) - E_s(t_0 + 1)B_s(t_0) &= A_s(t_0) - \Phi - [E_s(t_0) - \Phi]\, B_s(t_0) \\ &= \Phi[B_s(t_0) - 1]. \end{aligned} \tag{3.2}$$

As bank s becomes increasingly worried about its financial situation, it adopts a microprudential policy (Acharya and Merrouche 2013; Berrospide 2013) by hoarding the liquidity granted by such sales. This means that its interbank loans are not rolled over for their entire amount. We thus assume that external and interbank assets are sold proportionally to their balance-sheet shares

$$f_s^{\mathrm{E}}(t_0) = A_s^{\mathrm{E}}(t_0)/A_s(t_0) \quad \text{and} \quad f_s^{\mathrm{I}}(t_0) = \sum_k A_{sk}(t_0)/A_s(t_0).$$

We further assume that interbank assets rescale proportionally to the contract's size; each loan $A_{sk}(t_0)$ decreases by an amount equal to $\Phi[B_s(t_0) - 1] f_s^{\mathrm{I}}(t_0)$ times the ratio of $A_{sk}(t_0)$ itself to the total exposure $\sum_k A_{sk}(t_0)$ of s. The net result is that part of the total value of the interbank market is lost. The consequent increase of counterparty and roll-over risk perceived in the market causes the interbank interest rate to go up (Acharya and Skeie 2011). In particular, we assume

$$\frac{\mathrm{d}r}{\mathrm{d}t} = r \ln(1+\alpha) \Longrightarrow r(t_0+1) = (1+\alpha) r(t_0) + \varepsilon, \tag{3.3}$$

where the factor $\alpha > 0$ is a small quantity that leaves the system stable, and ε is a random variable drawn from $\mathcal{N}[0, \sigma]$. Thus, interbank assets and liabilities increase as

$$A_{jk}(t_0+1) = \left[\frac{r(t_0+1)}{r(t_0)}\right] A_{jk}(t_0) \quad \text{and} \quad L_{jk}(t_0+1) = \left[\frac{r(t_0+1)}{r(t_0)}\right] L_{jk}(t_0),$$

respectively, for all j, k. Note that while the external assets sold by s have no impact on the balance sheet (models usually assume that the values of external assets do not change, as the most unbiased assumption is that the overall contribution of market fluctuations averages to zero), the liquidated interbank assets cause the bank's equity to shrink, as they do not get revalued by the new interest rate. Therefore, the target leverage of s is substantially respected, except for the non-appreciation of a part of its interbank assets (which is, however, minimal). Overall, the balance sheet of bank s becomes

$$\begin{aligned}
E_s(t_0+1) &= \{A_s^{\mathrm{E}}(t_0) - \Phi - \Phi[B_s(t_0) - 1] f_s^{\mathrm{E}}(t_0)\} \\
&\quad - \{L_s^{\mathrm{E}}(t_0) - \Phi[B_s(t_0) - 1] f_s^{\mathrm{E}}(t_0) - \Phi[B_s(t_0) - 1] f_s^{\mathrm{I}}(t_0)\} \\
&\quad + \left[\frac{r(t_0+1)}{r(t_0)}\right] \sum_k A_{sk}(t_0) \left\{1 - \frac{\Phi[B_s(t_0) - 1] f_s^{\mathrm{I}}(t_0)}{\sum_k A_{sk}(t_0)}\right\} \\
&\quad - \left[\frac{r(t_0+1)}{r(t_0)}\right] \sum_k L_{sk}(t_0) \\
&= E(t_0) - \Phi + [\alpha + \varepsilon / r(t_0)] \\
&\quad \times \left\{\sum_k [A_{sk}(t_0) - L_{sk}(t_0)] - \Phi[B_s(t_0) - 1] f_s^{\mathrm{I}}(t_0)\right\},
\end{aligned} \tag{3.4}$$

indicating that the equity of s has changed due to the external shock and the revaluation of its interbank contracts, except for the part that is not rolled over.

- Banks $\{i\}$ that borrow from s receive a funding shock, which is given by the interbank assets that s dries up for liquidity hoarding, and replace it with an external liability. Thus, their balance sheets become

$$E_i(t_0+1) = E_i(t_0) + [\alpha + \varepsilon/r(t_0)] \times \left\{ \sum_k [A_{ik}(t_0) - L_{ik}(t_0)] + \Phi[B_s(t_0) - 1]\frac{L_{is}(t_0)}{A_s(t_0)} \right\}. \tag{3.5}$$

- For all other banks $\{j\}$,

$$E_j(t_0+1) = E_j(t_0) + [\alpha + \varepsilon/r(t_0)] \left\{ \sum_k [A_{jk}(t_0) - L_{jk}(t_0)] \right\}. \tag{3.6}$$

These steps are repeated until a first default is triggered.

3.2 Cascade failures

- After some rounds of exogenous shocks, at iteration step t^* a given bank u becomes insolvent and defaults, meaning $E_u(t^*) \leqslant 0$. Bank u is removed from the system, but this event triggers a cascade of credit and liquidity losses in the interbank market (Chan-Lau *et al* 2009; Krause and Giansante 2012). We use a one-step debt-solvency rank dynamics (Cimini and Serri 2016) to model this process, ie, we have the following.

  (a) *Credit shocks*: bank u cannot meet its obligations, so every other bank j suffers a loss equal to $\lambda A_{ju}(t^*)$. Here, λ indicates the amount of loss given default. We set $\lambda = 1$ to consider only uncollateralized markets.

  (b) *Funding shocks*: banks are unable to replace all the liquidity previously granted by the defaulted institutions and thus need to sell their assets, triggering fire sales (Brunnermeier and Pedersen 2009). In particular, each bank j is able to replace only a fraction $(1-\rho)$ of the lost funding from u, and its assets trade at a discount: j must sell assets worth $[1 + \gamma(t^*)]\rho A_{uj}(t^*)$ in book value terms, corresponding to an overall loss of $\gamma(t^*)\rho A_{uj}(t^*)$.[2] Here, we set $\rho = 1$, meaning that banks actually cannot replace the lost funding from u and are thus forced to entirely replace the corresponding liquidity by asset sales.

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[2] Following a common approach (Ellul *et al* 2011; Feldhütter 2012; Greenwood *et al* 2015), we assume that fire sales generate a linear impact on prices. Given that $Q(t^*) = \rho \sum_{j \neq u} A_{uj}(t^*)$

Overall, the balance sheet of a bank j connected to u becomes

$$E_j(t^*+1) = E_j(t^*) - \lambda A_{ju}(t^*) - \gamma(t^*)\rho A_{uj}(t^*). \tag{3.7}$$

If any other bank u' fails because of the suffered loss, the procedure above is repeated until no other bank fails.

- After the default cascade has ended, the net change of equity drives each survived bank to realign to its leverage before the cascade, and to liquidate some of its assets. Thus, the dynamics restart from the exogenous shock phase, even if the shock is endogenous this time. However, now the interbank market has shrunk significantly by a loss $\Delta E(t^*) = \sum_i E_i(t^*+1) - E_i(t^*) \leqslant 0$. This triggers a sudden interest rate increase, which we model by adding to (3.3), a source term that depends on the ratio of $\Delta E(t^*)$ to the exogenous shock Φ:

$$\frac{\mathrm{d}r}{\mathrm{d}t} = r\ln(1+\alpha) + \delta \ln\left[\frac{|\Delta E(t^*)|}{\Phi}\right]$$
$$\Longrightarrow r(t^*+1) = (1+\alpha)\,r(t^*) + \alpha\,\delta\,\log_{[\alpha+1]}\left[\frac{|\Delta E(t^*)|}{\Phi}\right] + \varepsilon. \tag{3.8}$$

  Thus, if $|\Delta E(t^*)| \simeq \Phi$, the interest rate grows by the same factor α as before; however, if $|\Delta E(t^*)| \gg \Phi$, the interest rate blows up. Overall, the equities of each bank s change according to (3.4) with $t_0 = t^*$, where, however, Φ is replaced by $E_s(t^*) - E_s(t^*+1)$, and the interest rate has changed according to (3.8).[3] This process may again trigger a default cascade. Otherwise, the exogenous shock dynamics continues afterwards.

3.3 Market freeze

The market freezes at iteration $t = t_\mathrm{c}$ when the total relative equity of the market $\sum_i E_i(t_\mathrm{c})/\sum_i E_i(0)$ becomes smaller than a critical ratio ϵ_c. At this point, interbank assets get totally liquidated. Whenever, for a given bank j, this liquidation is not enough to repay debts (that is, if $\chi_j(t_\mathrm{c}) = \sum_k[L_{jk}(t_\mathrm{c}) - A_{jk}(t_\mathrm{c})] > 0$), such a bank is forced to dispose of its external assets through a fire sale. However, unlike normal sales due to funding shocks, the market is now frozen, and the value of external assets is therefore enormously decreased. Thus, bank j must sell a fraction of assets worth

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is the total amount of assets to be liquidated, we have no price change when $Q(t^*) = 0$, and we assume that an asset's value vanishes when $Q(t^*) = C \equiv \sum_{ij} A_{ij}$ (ie, when the whole market has to be sold). Thus, we have a relative asset price change $\Delta p/p|_{t^*} = -Q(t^*)/C$. To obtain the corresponding $\gamma(t^*)$, we equate the loss $\gamma(t^*)\rho A_{uj}(t^*)$ to the amount sold $1 + \gamma(t^*)\rho A_{uj}(t^*)$ times $\Delta p/p|_{t^*}$, obtaining $\gamma(t^*) = [C/Q(t^*) - 1]^{-1}$.

[3] We consider a random sequence of survived banks to perform target leveraging sequentially.

TABLE 1 List of parameter values used in simulations.

Symbol	Value	Description
d	0.1	Density of the reconstructed interbank network
λ	1.0	Loss given default
ρ	1.0	Lost funding fraction to be replaced
Φ	10^8	Entity of the exogenous shock
r_0	1.0	Initial interest rate
α	10^{-3}	Interest rate increase factor
σ	10^{-3}	Variation of the random variable in the interest rate dynamics
δ	10^{-2}	Pre-factor of the source term for interest rate dynamics
ϵ_c	0.37	Critical ratio of residual equity for market freeze

$(1+\Gamma_c)\chi_j(t_c)$, with $\Gamma_c \gg \gamma(t_c)$. To evaluate the depricing factor Γ_c, we rescale $\gamma(t_c)$ by the relative wealth of potential buyers of fire-sold assets (Duarte and Eisenbach 2013), ie, their current wealth compared with the initial value

$$\Gamma_c = \gamma(t_c)\,\frac{\sum_i E_i(0)}{\sum_i\{E_i(t_c) - \chi_i(t_c)\Theta[\chi_i(t_c)]\}}; \tag{3.9}$$

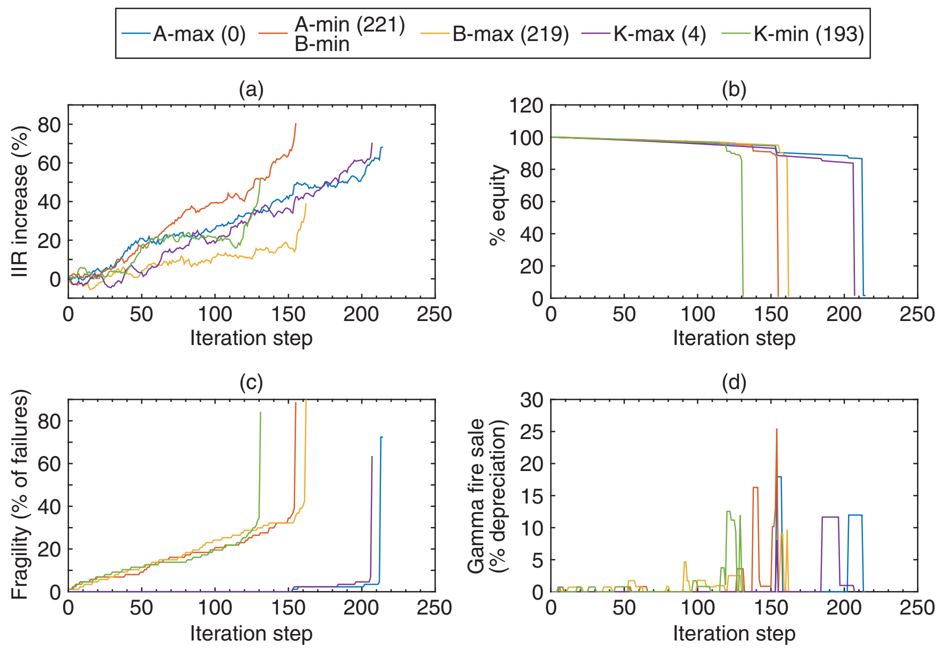
this means that, if the interbank market shrinks, it is more difficult to sell assets, and Γ_c grows. Note that to compute Γ_c, we subtract from the current total equity the total assets that must be fire sold (because these assets cannot be used to acquire other assets). The market freeze condition ends the ABM dynamics of the interbank market.

4 RESULTS

We now present results of our ABM simulations (Table 1 reports the list of parameter values we use). First, we look at the dynamics of a single realization of the system. Figures 2, 3 and 4 report results of the model run on balance-sheet data from some representative years: 2004, 2008 and 2013. These are the first and last years of the data set at our disposal, plus the year of the global financial crisis.[4] These figures show various important quantities characterizing the market at different iteration steps t: (a) interest rate, (b) percentage of total residual equity, (c) percentage of defaulted banks and (d) depricing factor γ. The different trajectories refer to different model configurations, in which we systematically hit a given bank s with the exogenous shock Φ. Thus, the line A-max (A-min) refers to s being the biggest (smallest) bank in terms of total assets; the line B-max (B-min) refers to s being the bank with the

[4] Results for other years are reported in the supplementary materials (Figures S1–S7), which are available online.

FIGURE 2 Dynamics of a single realization of the ABM built on balance-sheet data (2004).

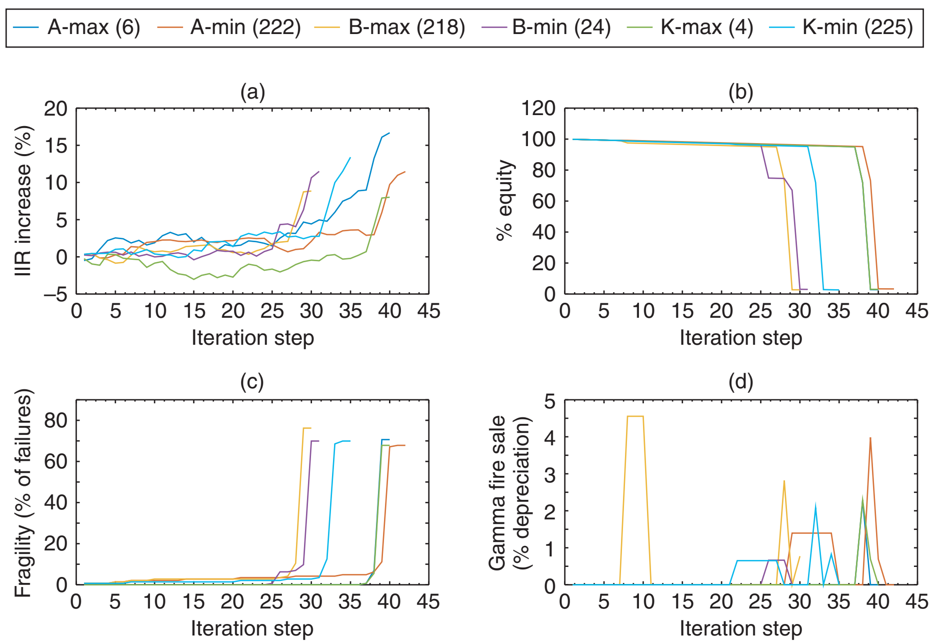


IIR denotes "interbank interest rate".

highest (lowest) leverage; and the line K-max (K-min) refers to s being the bank with the most (least) bilateral contracts in the interbank market.

Looking at Figures 2–4, the first striking observation is that the ABM dynamics converge to the market freeze condition much faster in 2008 than in the other years. Indeed, the maximum interest rate that can be sustained by the market is also much lower in 2008. Actually, the final values of r reached in both 2004 and 2013 appear to be unreasonably high, meaning that the interbank market is rather stable to the proposed dynamics. The total residual equity in the market and the number of defaults have, as expected, a symmetrical trend, and the sudden drop of residual equity usually marks the transition to the market freeze state, where the assets' fire-sale depreciation γ is maximal. Note, however, that there is a significant difference between the "stable" years 2004 and 2013. In the first instance, the equity drop ends with the total depletion of the market, just as in 2008. In 2013, the system can absorb the first systemic crash, and falls into a state with nonzero residual equity. Market freeze is not triggered immediately, and even when it occurs it does not zero the value of the market. This points to the effectiveness of the new regulatory requirements on banks' balance

FIGURE 3 Dynamics of a single realization of the ABM built on balance-sheet data (2008).

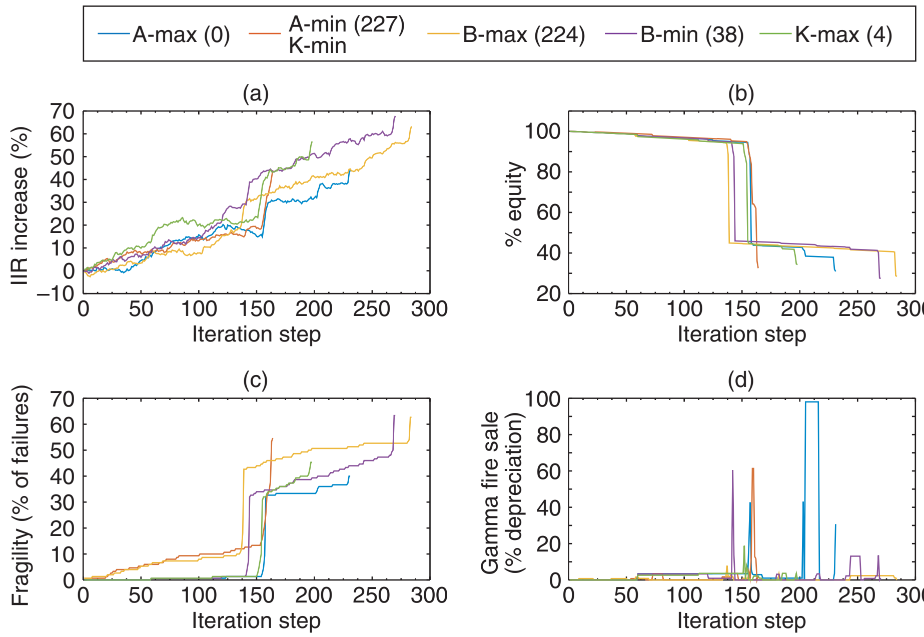


IIR denotes "interbank interest rate".

sheets, put in place after the crisis. Concerning the difference of system dynamics between the various shock configurations, we see in general that the convergence of the system to the market freeze is faster when the systematically shocked bank is "small" (ie, owns a few total assets and a few contracts, and typically has high leverage). "Big" and less leveraged banks are, indeed, more robust to an extensive exogenous shock, but they eventually fail, causing the same kind of market transition. The difference in behavior is less evident in 2013, suggesting that balance sheets became more homogeneous because of the new regulation.

We now discuss more robust results, which are obtained as averages over 1000 realizations of the ABM dynamics and for distributed exogenous shocks (the bank to be shocked is randomly drawn at each iteration). Figure 5 supports the findings outlined above: up to 2008–9, the final equity in the system $\sum_i E_i(t_c + 1)$ is basically zero, whereas after 2010 we observe a higher resilience of the system, with a residual equity around 30% even after the freezing of the interbank market. Figure 6 shows instead the length of the ABM dynamics, namely the number of iterations t_c for the system to converge to the market freeze. This indicator basically quantifies the

FIGURE 4 Dynamics of a single realization of the ABM built on balance-sheet data (2013).



IIR denotes "interbank interest rate".

maximum delay allowed for a regulatory intervention aimed at taming the crisis spiral. Notably, the minimum value of t_c is six times smaller in 2008 than in 2012. We see that the system monotonically loses its resilience before the global crisis and increases it afterwards. Yet, according to our previous analysis, the system converges to its final state in different ways for the early and late years of our data set. In particular, the first drop of total equity can well represent the outbreak of the crisis event. We thus introduce the half-life of the system, $t_{1/2}$, as the iteration step at which the total equity in the system is halved, ie,

$$\sum_i E(t_{1/2}) = \frac{1}{2} \sum_i E(0).$$

In the whole range of years considered, this iteration corresponds to the earliest substantial equity drop. As Figure 7 shows, $t_{1/2}$ behaves differently from t_c: there is an additional minimum in 2011 (the year of the European sovereign bond crisis), and the more resilient markets are now those long before the global financial crisis. Overall, according to our results, 2008 marked the transition between a regime in

FIGURE 5 Final relative equity in the system after the market freeze, $\sum_i E_i(t_c + 1)/\sum_i E_i(0)$, averaged over 1000 ABM run-on balance sheet data for different years.

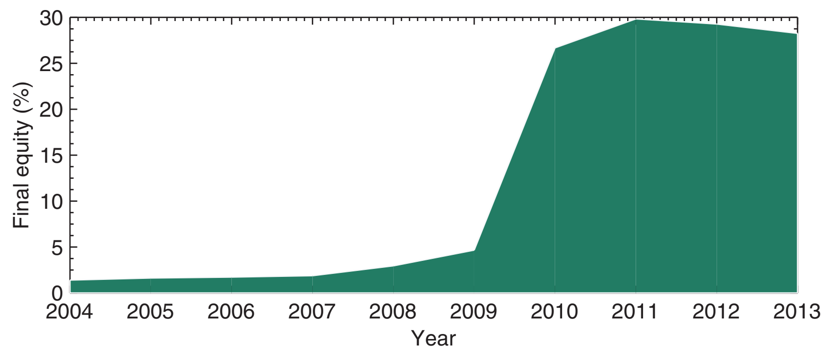
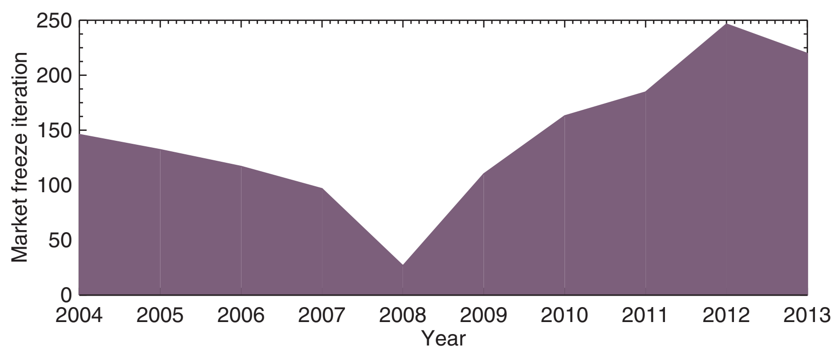


FIGURE 6 Final iteration t_c of the dynamics (market freeze condition), averaged over 1000 ABM run-on balance sheet data for different years.



which a crisis was hard to trigger but would lead to a total market crash, and a regime in which a crisis was easier to trigger but during which part of the system would be likely to survive.

5 DISCUSSION

In this paper, we have designed an ABM to mimic the dynamics of the interbank lending market during financial crises. The model relies on banks' balance sheets as its only data source, and it is built on simple assumptions regarding banks' strategic

FIGURE 7 Half-life $t_{1/2}$ of the total equity in the market, averaged over 1000 ABM run-on balance sheet data for different years.

behavior during periods of financial distress. We find that as we get close to the global financial crisis of 2008, the system becomes less stable in terms of time to collapse. This feature persists after the crisis, and another peak of instability is observed in 2011. However, the consequences of a crisis are much more severe (in terms of overall losses) before 2009, as afterwards new regulations made banks' balance positions more solid.

Here, we focused on the dynamics interbank market because of its crucial role as liquidity provider to the financial system (Allen *et al* 2014) and the economy in general (Gabbi *et al* 2015). As this system results from the usually uncollateralized (over-the-counter) bilateral contracts between banks, it is rather sensitive to market movements (Smaga *et al* 2016); it can dry up under exceptional circumstances (Brunnermeier 2009), becoming one of the main vehicles of distress spreading in the financial system. The dynamics of the interbank market is driven by the leverage-targeting and liquidity-hoarding behaviors of banks. These selfish strategies may consolidate individual banks' positions, but they also spread financial distress through spin-off effects such as interest rate increases and fire-sale spillovers; these, in turn, induce other banks to adopt similar procyclic behavior. Exceptional monetary policies by central banks are usually implemented to sustain the interbank market during periods of deteriorated creditworthiness and distributed distress. However, in order to assess the stability of the system, in our model we did not include the possibility of a regulatory intervention or bailouts. Indeed, by measuring the speed at which the crisis breaks out, we provide a temporal window for implemented anti-cyclical policies to be effective in mitigating the crisis.

DECLARATION OF INTEREST

The authors report no conflicts of interest. The authors alone are responsible for the content and writing of the paper.

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